JAIME ALBERTO MOSQUERA SÁNCHEZ

**Controle ativo de distúrbios harmônicos em veículos
híbridos orientado por métricas de qualidade sonora**

São Carlos
2017

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Controle ativo de distúrbios harmônicos em veículos híbridos orientado por métricas de qualidade sonora

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Prof. Dr. Leopoldo P. R. de Oliveira

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**Sound quality driven active control of
periodic disturbances for hybrid vehicles**

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Sound quality driven active control of periodic disturbance for hybrid vehicles

Corrected Version

PhD Thesis presented to the Graduate Program in Mechanical Engineering of the São Carlos School of Engineering of the University of São Paulo, Brazil, and to the Faculty of Engineering Science of the Arenberg Doctoral School of the KU Leuven, Belgium, in partial fulfilment of the requirements for the dual degree of Doctor in Mechanical Engineering (USP) and Doctor in Engineering Science (KU Leuven).

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*"If you want to go fast, go alone. If you want to go far, go together."
(African proverb)*

Resumo

MOSQUERA-SÁNCHEZ, J. A. **Controle ativo de distúrbios periódicos em veículos híbridos orientado por métricas de qualidade sonora**. 2017. 228 f. Tese (Doutorado em Engenharia Mecânica) - Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, e Faculdade das Ciências da Engenharia, Escola Doutoral da Universidade Católica de Leuven, Leuven, 2017.

Veículos elétricos e híbridos surgem como uma resposta da indústria automotiva ao desafio de se implementarem tecnologias limpas e sustentáveis de propulsão, em função do potencial esgotamento de combustíveis fósseis. A integração do motor elétrico ao trem-de-força neste tipo de veículos apresenta novas sensações auditivas aos passageiros. A grande quantidade de componentes espectrais, bem como a largura de banda que esse tipo de ruído abrange, caracterizam-se como desafios para as atuais abordagens de controle de ruído, vibração e aspereza veicular. Nenhuma das técnicas atuais abrange problemas vibro-acústicos de baixas, médias e altas frequências simultaneamente, ao tanto que poucos métodos encaram esses aspectos do ponto de vista da percepção humana. Esta pesquisa propõe uma metodologia para melhoria da qualidade sonora do ruído gerado por trens de força híbridos, percebido pelos passageiros no interior de veículos. O método proposto baseia-se no uso extensivo de sistemas ativos de equalização de ruído, que se mostram capazes de promover a melhoria da qualidade sonora de distúrbios harmônicos, por meio da manipulação das funções de magnitude e de fase relativa. Uma extensão destes sistemas para ambientes multicanal também foi desenvolvida, na base da solução de desafios relativos às interferências entre canais. Métricas objetivas de qualidade sonora (*Loudness, Roughness, Sharpness e Tonality*) são utilizadas para se avaliar o desempenho, bem como guiar o processo de otimização concorrente, que é parte da metodologia proposta para o desenvolvimento destes controladores. A verificação das técnicas propostas é realizada por meio de experimentos, usando estímulos auditivos realísticos de trens de força híbridos, que visam promover a melhoria da qualidade sonora em uma ou mais posições no interior da cabine. Os resultados apresentam percentagens de sucesso acima de 90%, o que demonstra que a metodologia proposta é promissora, não somente para controle de ruído de trens-de-força híbridos, mas também quaisquer distúrbios periódicos com

características similares.

Palavras-chave: Controle ativo multicanal de qualidade sonora; distúrbio periódico; otimização multi-objetivo de qualidade sonora; qualidade sonora; veículo elétrico híbrido.

Abstract

MOSQUERA-SÁNCHEZ, J. A. **Sound quality-driven active control of periodic disturbance for hybrid vehicles**. 2017. 228 p. Thesis (Doctor in Mechanical Engineering) - São Carlos School of Engineering, University of São Paulo, São Carlos and Faculty of Engineering Science, Arenberg Doctoral School, Catholic University of Leuven, Leuven, 2017.

Hybrid and electric vehicles (HEVs) arise as a response of the automotive industry to the quest of implementing clean and sustainable propulsion, face to the potential scarcity of fossil fuels. The integration of the electric motor to the powertrain in this sort of vehicles presents acoustic stimuli that elicit new perceptions. The large number of spectral components, as well as the bandwidth of the hybrid electric powertrain noise, pose new challenges to current noise, vibration and harshness approaches. None of the state-of-the-art techniques is able to simultaneously tackle low-, mid- and high-frequency issues, and probably just a handful of them take the auditory perception as a fundamental design criteria. This research proposes a framework for enhancing the sound quality (SQ) of the hybrid electric powertrain noise that is perceived inside the passenger compartment. The proposed method relies on the extensive use of active noise equalizer systems, which are capable of modifying the SQ of harmonic disturbances by means of profiling their magnitude and relative-phase functions. An extension of single-channel active noise equalizers to multichannel environments has been developed and the challenges related to cross-channel interferences tackled, which allows simultaneous active sound profiling for a number of listeners. In addition, as Loudness, Roughness, Sharpness and Tonality are the most relevant SQ metrics for HEVs noise, they have been used as performance metrics in the concurrent optimization analysis that drives the control design method. The proposed method is verified experimentally with realistic hybrid electric powertrain noise, by attaining SQ improvement for either single or multiple locations within a scaled vehicle mock-up. The results show success rates in excess of 90%, which indicate the proposed method is promising, not only for HEVs noise, but also for a variety of periodic disturbances with similar features.

Keywords: Hybrid electric vehicle; multichannel active sound quality control; multi-

objective sound quality optimization; periodic disturbance; sound quality.

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List of Symbols

Active Control

α	2μ
β	Lagrange multiplier
δ	Constraint factor of a least mean squares algorithm
Δ_j	Minimum phase delay between the j -th sensor and all the actuators
$\{\check{U}_j, \check{u}_j\}$	Estimate of the control output signal of an array, related to the j -th sensor
$\{C, c\}$	Command signal
$\{D'', d''\}$	Correct primary signal estimate
$\{D', d'\}$	Incorrect primary signal estimate
$\{D, d\}$	Primary signal (disturbance)
$\{E', e'\}$	Pseudoerror signal
$\{E, e\}$	Error signal
$\{W, w\}$	Adaptive filter
$\{X'', x''\}$	Filtered reference signal with both direct and coupling paths
$\{X', x'\}$	Filtered reference signal by a single path
$\{X, x\}$	Reference signal
μ	Step size of a least mean squares algorithm
ϕ	Absolute phase of a secondary path representation (in rad)
B_j	Power of a system reference signal, related to the j -th sensor

Mechanics

$\gamma_{\mathcal{K}}$	Coefficient of stiffness proportionality
$\gamma_{\mathcal{M}}$	Coefficient of mass proportionality
$\mathcal{D}$	Damping matrix
$\mathcal{K}$	Stiffness matrix

$\mathcal{M}$	Mass matrix
Kk	Arbitrary stiffness value

Index

j	Index of summation
k	Fourier bin
l	Time-domain block processing
m	m -th sensor/actuator pair (microphone/loudspeaker)
n	Discrete time
r	Harmonic
t	Continuous time
z	Z-transform

Multi-objective Optimization (MOO)

μ	Relevance of inputs (symbol redefined to keep the EE method terminology)
σ	Non-linear and/or interactions amongst inputs (EE method)
η_c	Distribution index for the simulated binary crossover operator
η_m	Distribution index for the polynomial mutation operator
$\mathcal{E}_j$	Euclidean distance of the j -th individual w.r.t the origin of coordinates
$\mathcal{P}$	Population size
$\mathcal{Q}$	Number of associated SQ metrics to the MOO
$\mathcal{V}$	Number of associated tones to the MOO
ψ_j	Step size for assessing the EE of the j -th input variable
y	Number of discrete levels for assessing the EE method

Set of Numbers

$\mathbb{C}$	Complex
$\mathbb{N}$	Natural
$\mathbb{R}$	Real

Mathematical Operator

$\{\exp; e\}$	Exponential function

$\lfloor a \rfloor$	Round down function (floor)
$\mathbb{E}$	Expectation
$\mathcal{F}$	Discrete Fourier transform
$\mathcal{H}$	Hilbert transform
∇_A	Partial derivative w.r.t. A
$diag()$	Diagonal matrix
$min()$	Minimum: smallest value of a set
$mod(a, b)$	a modulo b function
$*$	Time-domain, linear convolution
$\star$	Time-domain correlation
Re	Real part of a number
Im	Imaginary part of a number

Acoustics and Psychoacoustics

$\mathbb{W}$	Number of tonal components
$\mathcal{N}$	Loudness
$\mathcal{N}'$	Specific Loudness
$\mathcal{N}_{acc}$	Accessory Loudness
$\mathcal{R}$	Roughness
$\mathcal{S}$	Sharpness
$\mathcal{T}$	Tonality
$\mathbf{X}$	Set of calibration weights
a_{pa}	Correction coefficients for the peripheral auditory system
a_{pf}	Correction coefficients for the acoustic propagation condition (free/diffuse field)
c_f	Correction factors for one-third-octave-band levels in the Loudness algorithm
c_v	Correction factors for the lowest one-third-octave-band level in the Loudness algorithm
h	Sharpness' weighting function
L_C	Corrected sound pressure level
L_E	Excitation level

L_P	Sound pressure level (SPL)
L_X	Sound pressure level excess
L_{ETQ}	Absolute threshold of hearing
p	Acoustic pressure
p_C	Corrected acoustic pressure
p_{ref}	Reference acoustic pressure ($20 \mu Pa$)
q	Roughness' correction function for the carrier frequency
SL	Set of slopes for excitation level calculations
SLR	Predefined specific Loudness ranges
SLS	Steepness of the specific Loudness pattern
V	Number of identified tonal candidates
WS	Weighted spectrum
Y_j	Background noise that surrounds the j -th tonal candidate

Superscript

(a)	Amplitude gain factor
(p)	Relative-phase shift factor
-1	Matrix or operator inverse
$\bar{A}$	Complex conjugate (bar)
$\tilde{A}$	Estimate of the matrix $\mathbf{A}$ with coupling terms (inverted hat)
$\hat{A}$	Estimate of the matrix $\mathbf{A}$ with no coupling terms (hat)
H	Hermitian transpose
L	Left-side
Lo	Lower bound
R	Right-side
T	Transpose
Up	Upper bound

State-space

$\mathcal{A}$	State matrix
$\mathcal{B}$	Input matrix
$\mathcal{C}$	Output matrix

$\mathcal{G}$ Feedthrough matrix

Misc.

Ω Frequency vector at which a system has been identified

$\mathcal{Z}$ Critical band frequency (in Bark)

ω Frequency (in rad/s)

A Matrix (capital, boldface font)

θ Relative-phase angle of a signal (in rad)

a Amplitude (in Pa)

b Cross-corelation

env Envelope function

F Vector function

f Frequency (in Hz)

f_{mod} Modulation frequency

F_s Sampling rate

G Amplitude of a signal

g Gain factor

I Identity matrix

i Imaginary unit

J Cost function

K Number of Fourier bins

L Length of discrete Fourier transform

M Total amount of sensor/actuator pairs (microphones/loudspeakers)

mi Modulation index

N Total amount of samples in a given timeframe

O Amount of tones to be controlled, $O \leq R$

P Lagrange function

Q Length of FIR filter that represents a single secondary path estimate.

R Total amount of harmonics in a multitone sound

R^2 Coefficient of determination

S Secondary path

s Microphone sensitivity (in Pa.V⁻¹)

T_s	Sampling period
v	Electric signal
Y	Vector (in boldface)

Acronym

AC	Alternating current
ADC	Analog-digital converter
AM	Amplitude modulated
ANC	Active noise control
ANE	Active noise equalizer
ASQC	Active sound quality control
DAC	Digital-analog converter
DC	Direct current
DFT	Discrete Fourier transform
DoF	Degree of freedom
DSP	Digital signal processing
EE	Elementary effects
EM	Electric motor
EV	Electric vehicle
FFT	Fast Fourier transform
FFTW	Fastest Fourier transform in the West
FIR	Finite impulse response
FRF	Frequency response function
GA	Genetic algorithm
HEV	Hybrid electric vehicle
ICE	Internal combustion engine
IMC	Internal model control
IRF	Impulse response function
JND	Just-noticeable difference
LMS	Least mean squares
LTI	Linear, time-invariant
MIMO	Multiple input, multiple output

MOO	Multi-objective optimization
NSGA	Non-dominated sorting genetic algorithm
NVH	Noise, vibration, and harshness
OAT	One factor at a time
PZT	Lead zirconate titanate
RLS	Recursive least squares
RMS	Root mean square
SAP	Sensor-actuator pair
SISO	Single input, single output
SP	Spectral pitch
SPEA	Strength Pareto evolutionary algorithm
SPL	Sound pressure level
SQ	Sound quality
SQP	Sequential quadratic programming
SRM	Switched reluctance motor

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Chapter 1

Introduction

THIS manuscript presents a novel methodology to enhance the sound quality (SQ) of the powertrain noise, for single or multiple listeners within the passenger cavity of hybrid electric vehicles (HEVs). The proposed methodology comprises original contributions in the fields of signal processing, active noise control (ANC) and SQ, combined with state-of-the-art techniques for optimizing multi-objective engineering problems. The effectiveness of the proposed method is experimentally demonstrated by using a laboratory workbench that assessed a number of realistic periodic disturbances, synthesized from measurements of the noise emitted by the powertrain in a commercial HEV. Through innovative multichannel active sound quality control (ASQC) systems that deal with cross-coupling amongst channels, the SQ of stationary powertrain noises has been improved at a number of locations within the workbench cavity. The concurrent optimization of relevant SQ metrics to the sort of noises of concern has been used to guide the multichannel active sound profiling tasks, needed to attain improved soundscapes. The results have proven that the proposed methodology is also able to tackle sounds with similar spectral features to that of the hybrid electric powertrain noise.

This manuscript is the result of a four year, double-degree doctoral programme in the field of machine and system dynamics. The first two years, which were spent at the Department of Mechanical Engineering of the São Carlos School of Engineering of the University of São Paulo (EESC/USP), Brazil, were devoted to gain insights on multi-objective optimization techniques, as well as to implement these techniques in search of improved soundscapes for periodic disturbances, as quantified by SQ metrics. The third year, which was spent at the Production Engineering, Machine Design and Automation Division of the Department of Mechanical Engineering of the KU Leuven (PMA/KU Leuven), Belgium, concerned with the development of multichannel active control techniques that allow the independent-zone implementation of optimized targets for several listeners inside cavities. The last year was dedicated to the numerical and experimental verification of the proposed framework at the EESC/USP, Brazil.

This chapter serves as a contextualization of the main goals of the present research in the history, development and future of HEVs. This chapter also puts forward some strengths and weaknesses of the state-of-the-art solutions in the engineering problem of concern. Original outcomes from this research are briefly discussed and contrasted with existing solutions, as a form of motivating the subsequent chapters. This chapter ends by sketching out the outline of this manuscript.

1.1 Problem statement

Nowadays, economical and environmental aspects compel the automotive industry to make an outright turn towards cost-effective but reliable, eco-friendly and sustainable machine and system design (GOVINDSWAMY et al., 2009; ASIMAKOPOULOS et al., 2010; GONZÁLEZ-PALENCIA et al., 2012; SINGH et al., 2014; SKIPPON, 2014; GUO et al., 2015; JAMES et al., 2016; DIEZ-IBARBIA et al., 2017). In this direction, the possibility of electrifying vehicle powertrains has become one of the main subjects of research in the industry, on the basis that the electric motor (EM), which arguably exhibits better performance than the internal-combustion engine (ICE), is a cleaner source of motive power (SOVACOOOL; HIRSH, 2009; ASIMAKOPOULOS et al., 2010; LA et al., 2011; GUO et al., 2015; LABEYE et al., 2016; CAMPELLO-VICENTE et al., 2017). Attributes such as its high performance, still at low rotation speeds, its zero emission operation, as well as its reduced manufacturing costs, make the EM to be the preferred choice among the available propulsion technologies, which still aims at meeting these goals.

Since the duration of power supply for EMs is currently seen to not suffice large journeys, diverse levels of powertrain electrification have then been proposed (CHAN, 2007; GOVINDSWAMY et al., 2009; GENUIT, 2010; RUST; GRAF, 2010; VARNHAGEN et al., 2011; GUO et al., 2015). While the electric vehicle (EV) is intended for short trips, e.g. operation in cities, the HEV benefits from integrating ICEs to its powertrain for extending its autonomy, thus being able to accomplish large journeys. Even so, although the cost of HEVs, as compared with standard ICE-propelled cars, is currently not so affordable for all sorts of markets (CHAN, 2007; GOVINDSWAMY et al., 2009; SOVACOOOL; HIRSH, 2009), they did have succeeded in positioning themselves as the preferred customer choice amongst electrified cars (SCHNEIDER, 2012; CAMPELLO-VICENTE et al., 2017). The extended autonomy is mostly acknowledged (SKIPPON, 2014), while still relying on the use of clean sources that provide motive power (LABEYE et al., 2016).

Vehicles provided with hybrid powertrains typically comprise of an important number of parts that operate in different modes, which depend on the current rotation speed, load, breaking and/or recharging regimes (CHAN, 2007; GAO et al., 2007; GUO et al., 2015). Some operation modes even demand the parts to co-operate amongst them (FUJIMOTO et al., 2012; SARRAZIN et al., 2012). For the sake of illustration, Fig. 1.1 shows a

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diagram of a HEV that highlights some new added parts to the typical ICE-propelled powertrain. As one would intuitively reason, the interaction amongst those subsystems would make the emitted vibro-acoustic field to sound substantially different from that of the ICE itself (AUWERAER et al., 2011; SARRAZIN et al., 2012). For instance, according to the Toyota Prius 2010 Manual (MITCHELL, 2016), the auditory stimulus perceived at the interior of the vehicle may be dominated by either the EM or the ICE, which depends on the vehicle operation regime, e.g. the ICE sound may become more apparent when accelerating abruptly. Moreover, the power inverter, which is the part that commands the speed regime of the EM, cf. power electronics block in Fig. 1.1, generates new audible components that are multiples of the switching frequency of the driver. The presence of new audible components in the noise will arguably elicit other than the impressions ICE-propelled vehicles typically evoke (GENUIT, 2010).

Figure 1.1: *Schematics of a hybrid electric vehicle.*

Source: WebDevStudios (visited in 2016).

Another modern engineering improvement that points at the same directions is the use of lightweight materials for assembling passenger cabins, which enhances vehicle autonomy (CHAN, 2007; GONZÁLEZ-PALENCIA et al., 2012; BEIN et al., 2016). Lightweight vehicle cabins are also proven to confer more safety to the passengers (CHEAH; HEYWOOD, 2011; GONZÁLEZ-PALENCIA et al., 2012). However, it is at this juncture where vibro-acoustics come into play, since panels built with low-mass materials often exhibit poor vibro-acoustic transmission properties, which may cause the passengers to be more exposed to incoming sound fields from the powertrain. On the contrary, aside from typical bulky solutions, complete isolation of the powertrain noise transmission

may prevent the occupants to be aware of the operation regime of the vehicle. As a consequence, cabin vibro-acoustics is seen as a puzzling trade-off between the enhancement of both vehicle autonomy and passenger safety via lightweight materials, and the improvement, or at least the preservation, of the current noise, vibration and harshness (NVH) comfort of the vehicle (ANTONI et al., 2013).

Physical features of the hybrid electric powertrain noise

To detail some facts on this new sort of auditory stimuli, Fig. 1.2(a) shows the spectrogram of a measurement of the acoustic pressure signal generated by a commercial hybrid powertrain, which operates in a mode such that both the ICE and the EM co-operate between each other during a run-up. This signal has been acquired by placing a microphone under the engine compartment. Figure 1.2(b) refers to the same measurement, after performing the second generation Vold-Kalman order-tracking algorithm (VOLD et al., 1997), which is intended to extract both amplitude and relative-phase functions of the engine/motor orders. The visual inspection of Figs. 1.2(a) and (b) renders the following observations:

- The time-frequency pattern of the noise contains a large amount of narrowband components that comes from both motive power generators.
- While the harmonics generated by the ICE, together with some other ones generated by the EM, increase their frequency as the rotating speed increases, other harmonics coming from the EM hold their frequency unaltered, regardless of the rotating regime. There also seems to be other ones that decrease their frequency as the rotating speed increases. This combination would render a rather odd auditory experience, as compared to the typical ICE-induced one.
- The energy of the harmonics is mainly located within the bandwidth comprised between 50 Hz and 3000 Hz. This bandwidth is way larger than the one in which ICE-induced noise typically falls, e.g. 50 Hz – 500 Hz.
- Crossing amongst spectral lines is also found as a normal occurrence along the run-up. This fact leads to infer that having harmonics very close among each other in the frequency domain is also a common instance in this new sort of auditory stimuli (SARRAZIN et al., 2012).

For the ICE-propelled vehicle user who is willing to take a step towards HEVs, it will not be an easy auditory experience to get used to the fact of having such a large amount of harmonics, in which some of them keep their frequency unaltered, while still having others that grow upwards and downwards, as the rotating speed changes along a run-up/run-down. Moreover, another novel but unexpected HEV

Figure 1.2: Time-frequency analysis of measured hybrid electric powertrain noise: (a) downsampled time history; (b) synthesized time history from an order-tracking extracted from the downsampled time history. Measurement acquired at 204.8 kHz and downsampled to 20.48 kHz.

sound feature for the ICE-propelled car user, is the fact that the spectral lines in the auditory stimulus spread in a larger bandwidth (GOVINDSWAMY et al., 2009). These NVH aspects may prevent HEVs to be more accepted by customers (DIEZ-IBARBIA et al., 2017), even when its environmental and safety features are proven to be better than the ones

of the ICE-propelled vehicle.

SQ features of the hybrid electric powertrain noise

The relationship between the physical parameters of technical sounds and the human auditory perception is also currently one of the spotlights of the automotive industry (BRIZON; MEDEIROS, 2012). The possibility for tailoring the residual powertrain noise to provide the driver and passengers with relevant auditory information on the operation regime of the vehicle (KUO et al., 1997; DIEGO et al., 2004; GONZÁLEZ et al., 2006; KUO et al., 2007; WANG et al., 2010), or even for enhancing customer perceptions (GONZÁLEZ et al., 2003; REES; ELLIOTT, 2006) of, e.g. vehicle quality, powerfulness, sportiveness, luxury, reliability, quietness, among others (JAY, 2007), also allows the manufacturers to boost their products with unique and distinctive sound marks (FASTL, 2005; KUO et al., 2008; OLIVEIRA et al., 2010; SHIN; CHEONG, 2010; WANG et al., 2013; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b). At this point, SQ techniques come in handy for supporting auditory-oriented procedures, since they bridge the gap between objective vibro-acoustics and the human auditory response, by means of models that objectively quantify auditory perceptions.

Whereas it is still possible to cope with the unusual amount of harmonics and spectral crossings amongst them in the hybrid electric powertrain noise, by merely following SQ techniques applied for ICE noise, the fact that its spectrum spreads over a larger bandwidth, sometimes in excess of 4 kHz, does demand the inclusion of more auditory dimensions to the problem, namely other than the widely used low-frequency Loudness (GONZÁLEZ et al., 2003; JEON et al., 2007; LEE, 2008; OLIVEIRA et al., 2009; NYKÄNEN; SIRKKA, 2009; SHIN et al., 2009; SHIN; CHEONG, 2010; CHO et al., 2011; TAN et al., 2012; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b) and Roughness (GONZÁLEZ et al., 2003; JANSSENS et al., 2007; JEON et al., 2007; LEE, 2008; OLIVEIRA et al., 2009; LEE et al., 2010; SHIN; CHEONG, 2010; CHO et al., 2011; WANG et al., 2013; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b; DRAGONETTI et al., 2017). In fact, some recent works on NVH aspects of HEVs (GOVINDSWAMY et al., 2009; MOLLET et al., 2015; GUO et al., 2015) put forward the need for developing SQ approaches that face tonal, narrowband and sharp sounds, which are the novel high-frequency occurrences in the noise that come with integration of the EM in the powertrain. Then, high-frequency SQ metrics, namely Sharpness (GONZÁLEZ et al., 2003; JEON et al., 2007; LEE, 2008; NYKÄNEN; SIRKKA, 2009; SHIN; CHEONG, 2010; CHO et al., 2011; SARRAZIN et al., 2012) and Tonality (GONZÁLEZ et al., 2003; ZHANG; SHRESTHA, 2003; SHIN et al., 2009; SARRAZIN et al., 2012; DRAGONETTI et al., 2017), should be accounted for when objectively diagnosing -and controlling- the SQ of hybrid electric powertrain noise.

Figure 1.3 illustrates the evolution of the four SQ metrics cited above, as a function of the rotation speed. The analyzed auditory stimulus is the run-up measured in a commercial HEV, plotted in Fig. 1.2(b). Since the ICE and EM do not necessarily operate

at the same speed regime, the calculation of the rotation speed of EM is based on both the gear ratio between the gears that link the ICE and EM to the driveline, as well as on the speed regime of the ICE measured by a tachometer. The unusual SQ occurrences, in contrast to the typical ICE-propelled powertrain noise, are listed below:

Figure 1.3: SQ profiles of the downsampled measurement in Fig. 1.2(b).

- The Loudness increase is proportional to the rotation speed, and this is, at its turn, due to the proportional power increase of the spectral lines along the run-up, cf. Fig. 1.2.
- Roughness behaves in a similar form as in ICE sounds, in which high levels are observed at low rotation speeds, as a result of the high harmonic overcrowding in some frequency bands (cf. first 5 s in Fig. 1.2). The Roughness profile starts at high values, mainly due to the harmonics coming from the ICE that are crowded in the low-frequency bandwidth. The difference in the Roughness behavior between the ICE and the hybrid electric powertrain noise relies on the fact that the large number of crossings among spectral lines along the run-up causes this metric to not demonstrate a clear trend, thus showing sharp "oscillations" around its "expected value", along the run-up.
- Sharpness also starts at high values, presumably due to the high-frequency narrowband components coming from the EM, at the very beginning of the run-up. Interactions amongst the harmonics are seen to cause Sharpness to drop off during

the initial rotation speeds, wherein Roughness and Tonality metrics are dominant. As from around 100 RPM, Sharpness again increases, which could be due to the power of the high-frequency harmonics coming from both ICE and EM. From around 300 RPM onwards, this metric gets eventually stabilized at 1.4 acum, due to the high level of the EM harmonic at 5 kHz that becomes apparent from 15 s on. At that point, it is worth noticing that the spectral line at 5 kHz is a harmonic of the fundamental switching frequency (2.5 kHz) of the power inverter that drives the EM.

- Tonality starts at high values, which is also presumably due to the level and spectral location of the harmonics coming from the EM. Its relevance starts falling down as the rotating speed increases, due to the Loudness increase. This metric stabilizes around the same case as in Sharpness, i.e. around 300 RPM, due to the power and spectral location of the EM harmonic at 5 kHz.

These remarks indicate that important SQ occurrences in hybrid electric powertrain noise might be ignored, if high-frequency SQ descriptors like Sharpness and Tonality were not taken into account, namely: (i) the participation of the high-frequency harmonics from the EM, particularly the one at 5 kHz and (ii) the tonal relevance of the EM harmonics, which has been widely claimed in the specialized literature (GOVINDSWAMY et al., 2009; SARRAZIN et al., 2012; MOLLET et al., 2015; GUO et al., 2015; DRAGONETTI et al., 2017).

An even more challenging matter lies in the fact that customers do not usually share their standpoints about vehicle attributes. This is due to a large amount of variables that influence subjective judgments, e.g. sex, race, age, location, among others. Skippon (2014), for instance, reports on substantial gender differences elicited by customers from the United Kingdom, in which male customers were found to prefer sporty vehicle noise, whereas female participants showed inclinations for low-level vehicle noise. Besides being able to handle the sound qualities of the hybrid electric powertrain noise, the methodology that is pursued in this research should also cope with that variety of opinions, in order to truly meet specific auditory expectations.

SQ control of periodic disturbances: feasible approaches for HEVs

The solution for the engineering challenge that arises at this point should respond to *how to enhance the sound qualities of the hybrid electric powertrain noise, such that the resulting sound field perceived within the passenger cavity elicits the right and improved perceptions from the occupants*. The problem at hand reaches a higher complexity level, given the need to account for the variety of standpoints on how a vehicle, particularly a hybrid electric one, should sound in its interior.

When it comes to modifying the interior sound field in vehicles, the literature reports on some theories and techniques that are worth discussing, in searching for a framework that allows *positively improving* the powertrain noise in HEVs:

- *Solutions at source level:* the improvement of NVH aspects in HEVs has mostly been approached by focusing efforts on the EM design. In this regard, researchers are increasingly adopting the switched reluctance motor (SRM), instead of vibro-acoustically better performing induction and permanent-magnet synchronous motors (POLLOCK; WU, 1997; CHAN, 2007; JAMES et al., 2016; MOLLET et al., 2016), due to its increased power -high torque- density, high tolerance fault capability, high tolerance to high temperatures, and its quite affordable manufacturing cost. However, since the SRM causes important vibro-acoustic energy radiation that tends to aggravate with certain load conditions (COLBY et al., 1996), NVH specialists are on their way to improve its dynamic behavior, by means of either:
  - innovative geometric designs (BALAMURUGAN; ARUMUGAM, 2005) that helps counterbalancing the existing radial forces due to non-uniform air gap (COLBY et al., 1996; KAMALAKANNAN et al., 2011), or
  - applying active control techniques for cancelling radial forces that arise from the torque production mechanism itself (POLLOCK; WU, 1997; CHAI et al., 2006), or
  - designing the modal behavior of the stator, such that resonance effects when the excitation of the SRM phases coincides with any of its vibration modes are reduced (COLBY et al., 1996; CAI et al., 2001; BALAMURUGAN; ARUMUGAM, 2005; SUN et al., 2007; KAMALAKANNAN et al., 2011)..

In particular, the specialized literature mostly states that the radial attractive force between stator and rotor is the main source of acoustic noise (CHAI et al., 2006; JAMES et al., 2016; MOLLET et al., 2016; DRAGONETTI et al., 2017), which is a consequence of the torque production mechanism itself. For the sake of illustration of the terminology, Fig. 1.4 shows some relevant parts of a SRM, e.g. rotor, stator, phases and windings.

From a number of studies on the design of SRMs that aims at improving NVH features in vehicles, it is worth to mention the one by Sun et al. (2007), which thoroughly describes the origin of acoustic SRM noise, as well as proposes solutions that deserve some discussion. The authors have proposed increasing the SRM structural resonances, based on two premises: (i) to broaden the speed scope of the motor, and (ii) *to lower the level of acoustic noise* that might arise from having high-level displacements at low frequencies. They reported on a modal analysis of a real SRM, in which 30 SRM resonances were found in between 1127.3

Figure 1.4: Schematic of a 8/10 switched reluctance motor.

Source: Lee et al. (2014).

Hz and 7270.9 Hz. The authors concluded that assembling SRMs by following given geometric design parameters, both its acoustic and thermal behavior will be improved. Although by lowering acoustic/vibration levels the dynamical behavior of machines and systems usually turns out to be improved, the fact that the resonances of the stator structure have been "shifted" from mid- to high frequencies, reveals that the authors implicitly targeted Loudness as the relevant descriptor, in a prominently high-frequency noise scenario. At that point, it would be interesting to assess the noise via high-frequency SQ metrics such as Sharpness and Tonality, to see whether this line of thought is actually improving the human auditory perception or not. It is possible that other auditory phenomena related to those high-frequency perceptions have been raised, which depend on both the level and spectral location of the harmonic components.

Little effort has been made on investigating the influence of the ICE on the NVH of HEVs. The typical approach to the problem lies in using active engine mounts (OLSSON, 2006). Since the ICE role in HEVs is restricted to support propulsion and recharging tasks, downsized engines with optimized fuel consumption may also be implemented to the powertrain. In this case, the ICE sound design is focused on resembling the time-frequency pattern of typical 4/6/8-cylinder engines, by means of actively suppressing high-frequency engine orders, such that the resulting improved auditory stimulus also serves as a signal for the driver to change the gears, at the times at which fuel consumption is nearly optimal (SONTACCHI et al., 2016). The implementation of rotary (Wankel) engines, rather than reciprocating ones, has also been shown to improve vehicle weight and autonomy requirements, as they exhibit high power-to-weight ratio, but at the somewhat worthless cost of degrading the fuel efficiency (RUST; GRAF, 2010; VARNHAGEN et al., 2011). Rust & Graf (2010) then propose operating Wankel ICEs at certain stationary speed/load

regimes, in which the fuel efficiency has been shown to be optimal. The SQ improvement of the resulting stationary ICE noise could then be approached by state-of-the-art techniques. Other solutions that are aimed at reducing airborne ICE noise include the use of box labyrinths for housing (RUST; GRAF, 2010), as well as the addition of rubber dampers between fins, which are attached to the ICE for improving both acoustic and thermal responses (SINGH et al., 2014).

In summary, since the time-frequency patterns of the variety of commercial ICEs are similar between each other, which show no more than 40 engine orders (between 50 and 2000 Hz), current state-of-the-art active NVH and SQ techniques are able to enhance both vibro-acoustic and psycho-acoustic responses.

- *Solutions at path level*: a number of solutions have been proposed to deal with incoming airborne and/or structure borne noise within the passenger cavity in vehicles. The main objective of the NVH solutions *at the path level* is to improve the transmission features of the energy transfer paths, so as to deliver a desired amount of vibro-acoustic energy, or even no energy at all, at the receiver side.

The specialized literature classifies these solutions in two groups, as a function of their effectiveness at certain bandwidths, namely *low-frequency* solutions, which are the ones between 50 Hz and 1 kHz, and the *mid/high-frequency* solutions, which start from 1 kHz onwards (MELLER; NIEDŹWIECKI, 2014). The intense research and technological advances reported on each of those groups have made these frequency bounds to increasingly overlap between each other. On the one hand, Mei et al. (2012) experimentally demonstrated that passive control at frequencies as low as 172 Hz, with an impressive absorption rate of 86% of the incident acoustical energy, is possible with thin elastic membranes decorated with designed patterns of rigid platelets, which are referred to as *metamaterials* (LIU et al., 2000; MEMOLI et al., 2017). On the other hand, although some research has drawn attention on the possibility of extending typical *low-frequency, active solutions* (ROUT et al., 2015; WU et al., 2015), this research experimentally demonstrates that adaptive control schemes can be applied to tackle sounds with relevant spectral lines, as high as 3 kHz, provided that the high-frequency dynamics of the system can be accurately identified, as well as the associated computational cost for representing the system can be afforded.

An alternative classification for these solutions is based on whether they need or not additional energy to operate (STALLAERT et al., 2010), as follows:

- *Passive solutions*: this sort of solutions is typically bulky (SHOURESHI; KNUREK, 1996), which, despite having exceptional transmission rejection properties (CAMINO; ARRUDA, 2009), may jeopardize vehicle dynamic performance and

energy efficiency (TAN et al., 2012; CHEER; ELLIOTT, 2016). However, as mentioned before, the so-called *metamaterials* do offer the NVH specialist a great opportunity of controlling vibro-acoustic energy at specific low-, mid- and high-frequency bands. This novel paradigm in passive NVH control methods owns highly desirable mechanical characteristics for the application at hand, e.g. high stiffness with low mass, still exhibiting outstanding rejection levels to the transmission of vibro-acoustic energy (CLAEYS et al., 2013; CLAEYS et al., 2016; RUIZ et al., 2016). The frequency band(s) at which energy rejection is desired is tunable via design parameters, such as the geometrical design of cells, host structure and proper choice of building materials. It is at that point where passive methods, including those based on metamaterials, fall short in providing other than overall energy reduction solutions, which are of prime importance in SQ tasks. A given SQ target in a noise radiated by a rotating machine, might demand equalization or even amplification of its spectral components, apart from cancellation, and this is the reason why passive methods find a strong limitation in the intended application. To the best of our knowledge, neither any traditional passive solution nor any of those based on metamaterials has reported such an important feature. Moreover, the so-called *stop bands*, which are created at the frequencies of interest, are a function of both geometrical parameters and constituting material of the unit cells and host structure (CLAEYS et al., 2013), so the resulting attenuation (or amplification) factor of the metamaterial could only be set up by redesigning the panel/structure. Hence, when it comes to meeting a variety of stand-points on how a HEV should sound, the latter fact might demand customized panel design, which would entail the car maker to incur in additional costs to satisfy such specific auditory expectations.

- *Active*: as from the patent of Lueg (1934), active solutions have largely been investigated by a number of researchers worldwide, so this sort of solutions is currently in a mature stage. Contrary to the passive solutions, the methods and technologies in this group own the key feature of easily tuning their output to provide relevant SQ goals, at the cost of requiring external energy to operate. In particular, the so-called *Active Noise Equalizer* (ANE) systems (KUO et al., 1997; DIEGO et al., 2004; GONZÁLEZ et al., 2006; REES; ELLIOTT, 2006; KUO et al., 2007; OLIVEIRA et al., 2010; WANG et al., 2010; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b; MOSQUERA-SÁNCHEZ et al., 2017a; MOSQUERA-SÁNCHEZ et al., 2017b; LIU et al., 2017) are narrowband control schemes that allow tailoring the time-frequency pattern of a sound towards other than pure-reduction targets, by means of amplitude gains, and/or relative-phase shift parameters. Relevant operation modes such as cancellation, reduction, amplification,

relative-phase shifts, or even the preservation of the spectral components of the sound field free of external influences, are attainable with such adaptive systems. ANEs are mainly based on the Internal Model Control (IMC) scheme (REES; ELLIOTT, 2006; KINNEY et al., 2007), which requires a sufficiently accurate representation of the transfer path dynamics to operate precisely. Thus, when high-frequency sounds are of concern, active solutions are currently seen to not operate properly, once that a huge amount of computation, which is a function of both the sampling rate and the existing passive damping that can deal with long impulse response function (IRF) tails, will be needed to accurately represent the actual high-frequency vibro-acoustic dynamics. The implementation of control schemes with such complex and costly internal model representations can only be afforded currently by advanced Digital Signal Processing (DSP) boards.

An important issue observed in current active solutions, when addressing multiple listeners, is the fact that when implementing control actions at a given location for attaining a targeted SQ goal, interferences at other locations of interest may arise via acoustic coupling, as a result of the linear superposition that occurs between the sound that reaches these locations and the signal intended for the position to be controlled. In this research, a set of multichannel control schemes are formulated to overcome such a limitation, based on the algorithmic handling of the acoustic coupling, such that cross-channel interferences can be resolved by means of counterbalancing signals. These novel multichannel systems enable the NVH designer to implement independent, enhanced soundscapes for a number of listeners within the passengers cavity.

In summary, provided that computational issues regarding system identification and real-time implementation can be overcome, active solutions should be the preferred choice for improving the perception of periodic disturbances within the passenger cavity. These techniques have shown to drive the incoming vibro-acoustic field towards targeted spectra, by means of amplitude/relative-phase gain/shift factors, of which the adaptation and implementation do not involve changes in the hardware.

- *Solutions at receiver level*: the implementation of solutions for improving the auditory perception of vibro-acoustic fields at the receiver level generally implies using either headphones or earphones (CHANG et al., 2016). Although critical mobility applications, e.g. aircraft, do demand the use of solutions such as those of this group, mainly for addressing speech intelligibility issues in the presence of high-level noise (LIU et al., 2006; ALMEIDA-AGURTO et al., 2011; GERGES, 2012), automotive ap-

plications find these solutions unnecessary and impractical, since noise level and communication needs are way less critical (WANG et al., 2007). Notwithstanding, the combination of this approach with multichannel active solutions would allow the independent enhancement of the powertrain noise for each listener within the passenger cavity in a straightforward way, once that the cavity dynamics do not come into play, which in turn allows reducing the complexity of the control plant representation while canceling the interaction amongst channels due to acoustic coupling.

In summary, it has been shown that, while solutions at source level and passive treatments demand specific and costly designs, active solutions become promising techniques to tailor the sound field produced by the hybrid electric powertrain, since they can easily be *tuned* towards different targets, still with the same hardware. The implementation of active solutions loads the vehicle mass minimally (OLIVEIRA et al., 2008; WILLS et al., 2008; OLIVEIRA et al., 2009), which complies with other car maker goals on maximizing the vehicle autonomy, even in the case of cabins built in with lightweight materials. However, for the active solutions to become feasible in the engineering problem of concern, the following particular issues should be overcome:

- The system identification procedure should provide a sufficiently accurate representation of the plant dynamics, such that the active control schemes can operate stable, precise, and in real-time.
- Their operation for multiple listeners should ensure free-of-interference control actions, since the control action intended for a (set of) position(s) must not imply interferences at other relevant positions.

The proposed solution: active control of powertrain noise guided by SQ metrics

The purpose of this research is to present a framework to enhance the auditory perception of periodic disturbances, which copes with the possibility of adapting a sound field towards diverse and concurrently optimal SQ targets to each of the four auditory dimensions associated to the sort of noises of concern: Loudness, Roughness, Sharpness and Tonality. In particular, the noise induced by hybrid electric powertrains, which is structure borne and measured at a number of relevant locations in the vehicle cabin, is tackled through innovative multichannel distributed systems that deliver independent-zone active sound profiling control actions.

In general terms, the proposed framework for the SQ enhancement of the hybrid electric powertrain noise involves four key steps: (i) the diagnosis of the SQ of the sound measured in the passengers' cabin; (ii) the search for enhanced conditions for the sound; (iii) the real-time implementation of the SQ targets via SISO/MIMO active sound quality

Figure 1.5: Block diagram of the proposed framework for enhancing the SQ of periodic disturbance in HEVs.

control schemes; and (iv) the assessment of the controlled sound, to verify whether the implemented control tasks did effectively improve its qualities, as prescribed in the optimization stage. When multiple listeners are to be accounted for, the proposed procedure can be followed independently for each sensor location, provided that the active method for implementing the optimized SQ targets ensures free-of-interference control actions. Figure. 1.5 summarizes the proposed framework.

More details on the four key steps of the proposed method are briefly described below:

1. *Diagnostics of the SQ of the noise:* with the measurement of the acoustic pressure signal of the stationary powertrain noise at hand, SQ metrics are calculated to determine its *scores*. For the sake of clarification, an example on a real noise acquired from a hybrid electric powertrain, when accelerating while operating

in an ICE/EM mode, is shown in Fig. 1.2. This sound has been decomposed in a number of stationary rotating speeds, from which single scalar values that represent each of the assessed SQ metrics, i.e. Loudness, Roughness, Sharpness and Tonality, are assigned. The SQ assessment of the powertrain run-up is shown in Fig. 1.3. These SQ values will be referred to as *the SQ scores of the sound* hereafter.

2. *Searching for enhanced SQ conditions*: since all the associated SQ metrics are functions of the amplitude of the sound spectrum, this step is devoted to finding the best equalization of its spectral components, such that the resulting sound shows an enhanced SQ condition. In other words, this step intends to concurrently improve the SQ scores of the sound, by means of equalizing its spectral components. Since a number of amplitude combinations need to be tested, this approach might demand a large amount of computation. Moreover, by taking advantage of the stationary nature of the noises being tackled, the computationally costly time-domain SQ models are rewritten in the frequency domain. The enhanced sound, of which the SQ scores have been improved by means of its spectral equalization, is expected to meet the auditory expectations of a (set of) listener(s). When a certain solution does not meet the expectations of the targeted (set of) listener(s), the NVH specialist can easily choose amongst the optimum solutions in the *Pareto front* that results from the concurrent optimization. This key step in the proposed methodology is further detailed below:

- (a) *Frequency-domain SQ models*: time-domain SQ models use computationally costly operations. By exploiting the fact that the addressed sound fields have stationary statistics during uptime, mathematical models of each of the four SQ metrics are rewritten into the frequency domain. These newly derived SQ algorithms are provided with tuning parameters that account for differences between time- and frequency-domain SQ models, which are caused by the spectral leakage observed in time-to-frequency-domain transforms (GUIRAO; GARAVILLA, 1976; DANIEL; WEBER, 1997; HOELDRICH; PFLUEGER, 1999; PRESS-NITZER; MCADAMS, 1999; BAENE et al., 2004; KOHLRAUSCH et al., 2005; FASTL; ZWICKER, 2007; JANSSENS et al., 2007; WANG et al., 2013). The frequency-domain models that use amplitude, frequency and relative-phase data of the sound obtained in Step 1 allow assessing both the original SQ scores, as well as variations given by a number of amplitude changes, at a noticeably reduced computational cost.
- (b) *Sensitivity analyses*: since the hybrid electric powertrain noise has a large amount of harmonics, cf. Fig. 1.2, sensitivity analyses based on the method of the *elementary effects* is first calculated over the noise spectrum, aiming at identifying the harmonics that cause the largest variations on each of the SQ

metrics. In this way, besides allowing the multi-objective optimization step to deal with a reduced-order search space, the proposed sensitivity analyses enable the active control step to be focused on just a few harmonics, which in turn will result in a reduction on the energy requirements of the proposed SISO/MIMO control schemes.

- (c) *Searching for the best set of SQ scores*: based on the premise that a reduced set of the most sensitive harmonics is retrieved by the previous step, the investigation for better SQ scores is performed by following either exhaustive search routines, or by evolutionary multi-objective solvers, namely the Non-Dominated Sorting Genetic Algorithm, *NSGA-II* (DEB et al., 2002), or the Strength Pareto Evolutionary Algorithm, *SPEA2* (ZITZLER; THIELE, 1999; ZITZLER et al., 2001). The search space for the optimization routines is given by the reduced set of variables obtained from the previous step. Since the involved SQ metrics are often conflicting objectives to pursue, its concurrent optimization provides compromise -Pareto- frontiers.
3. *Real-time implementation*: the implementation of the optimized SQ targets is carried out by the proposed single/multi-channel ANE systems. Based on the original amplitude values of the harmonics and the optimized amplitude values obtained with the optimization step, the control parameters needed to attain the SQ goals are derived. In this way, it is expected that the controlled sound exhibits, in practice, improved sound qualities. Moreover, when facing multiple listeners, the attainment of the optimized SQ targets is carried out by the proposed multichannel control schemes that deal with cross-channel interferences. Three multichannel control schemes, derived in both time and frequency domains, are proposed for tackling a variety of sounds and sensor/actuator placements (SAPs). Performance and implementation aspects such as stability, convergence speed, computational complexity, as well as the influence of existing passive damping and the SAP placement, are approached by means of computer simulations and experiments. The so-called multichannel *Algorithm 1*, which is able to deal with the amplitude function of sounds, is the fastest proposed control scheme, but its computation cost is rather high. A cost-effective option, namely *Algorithm 2*, has been derived from *Algorithm 1* in an attempt to provide a multichannel system that still delivers independent-zone equalization at a reduced computation cost. However, *Algorithm 2* shows inferior convergence speed, as compared to *Algorithm 1*, due to simplifications made onto the formulation. Finally, the multichannel *Algorithm 3* has been proposed to tackle both amplitude and relative-phase functions of sounds, which also features the key ability of dealing with cross-channel interferences (MOSQUERA-SÁNCHEZ et al., 2017a).

4. *SQ assessment of controlled sound*: the resulting time histories from applying the designed control actions are eventually assessed via time-domain SQ models. The final SQ scores are compared with the ones that were designed in the optimization stage. This comparison will allow the determination of the *success percentage* in attaining the optimized soundscapes. In this manner, this research shows that Loudness, Sharpness and Tonality-based SQ targets designed for the hybrid electric powertrain noise can be experimentally attained with success percentages above 93%. However, Roughness-based SQ targets have been just accomplished with a success percentage on the order of 80%. While computer simulations have demonstrated that SQ targets in the hybrid electric powertrain noise can be attained with success percentages above 97% for all of the metrics, the experimental results have unveiled that both the time- and frequency-domain Roughness algorithms have important differences, which could not be solved by means of the proposed calibration procedure.

The effectiveness of the proposed framework is experimentally demonstrated with a 1:3-scaled vehicle mock-up, instrumented with four SAPs at locations that emulate driver, co-driver and rear passengers. A number of stationary periodic sounds, whose time-frequency patterns have been extracted from the data in Fig. 1.2, are used to excite the mock-up, while ten different optimal solutions have been tested on the sound, at each of the four intended locations. The controlled sound is eventually assessed by the time-domain SQ models, which, as mentioned before, enables the comparison between optimized and attained SQ scores. While Loudness, Sharpness and Tonality-based SQ targets were attained with a high level of accuracy, some discrepancies between optimized and attained Roughness-based SQ targets were observed. SISO experiments at the driver's position, as well as numerical simulations, have been carried out to gain insights on these discrepancies. Nevertheless, the results prove that the proposed framework is able to drive the perception of the hybrid electric powertrain noise towards enhanced SQ scores, still for multiple listeners, and with a minimum of requirements on both energy and hardware mass load for a vehicle. Other technical sounds with spectral features similar to those of the hybrid electric powertrain noise, e.g. stationary, narrowband, harmonic ICE and Diesel noises, can also benefit from the proposed method to enhance their SQ.

The proposed methodology is much in line with current engineering directions in designing and building affordable, reliable, eco-friendly and sustainable machines and systems (ALIVE, 2012; BEIN et al., 2016; EMVEM, 2013).

1.2 Objectives

Main objective

The main objective of this research is to design, simulate and implement strategies for enhancing the auditory perception of periodic disturbances, based on active noise equalizer systems that are guided by sound quality criteria. The proposed framework is especially designed for dealing with the noise transmitted from the powertrain via structural paths, which may require enhancement of its sound qualities at a number of locations within the passenger cavity in hybrid electric vehicles.

Specific objectives

- To determine the relationship between physical and psycho-acoustical parameters of the signals and systems involved in eliciting acoustic images within the passenger cavity in HEVs.
- To determine the requirements that the control/instrumentation devices should meet to allow for the successful implementation of the developed systems.
- To conduct numerical/experimental studies on the propagation of harmonic noises within cavities, in order to evaluate the influence of the sensor/actuator locations on the performance of the proposed multichannel control systems.
- To propose a design framework that tackles the challenges from the initial harmonic noise analysis to the prescription of targets and parameters for the active control implementation.
- To implement active noise equalizer actions that aim at enhancing the sound quality of hybrid powertrain-induced disturbances, by using multichannel control systems.
- To verify the performance of the developed control systems in attaining the proposed sound quality targets, in both numerical and experimental way.

1.3 Original contributions

- Contributions on active sound profiling and active sound quality control:
    - *SISO ASQC*: A single-channel active sound quality control scheme that deals with the magnitude and relative-phase functions of harmonic sound has been proposed. Its convergence process was derived in such a way that impulsive
-

events that might occur during uptime can be mitigated. The effectiveness of this control algorithm was demonstrated by means of hybrid simulations, i.e. computer simulations using measured transfer paths (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b).

- *Frequency mismatch correction for ASQC*: A scheme for correcting the frequency mismatch of narrowband active sound profiling systems has been proposed and implemented in the aforementioned ASQC. This algorithm relies on the estimation of the relative-phase of the targeted tones of the sound during uptime, which allows the implementation of an α - β -filter-like estimator that provides measures of the instantaneous frequency. The effectiveness of this scheme was numerically assessed by integrating this estimator in the aforementioned single-channel controller (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014a).
- *MIMO amplitude ASQC*: This work introduces a set of control schemes to deal with multichannel active sound profiling. These systems independently profile the magnitude of tonal components for different listeners within a closed domain. They feature different strategies to deal with the compromises between convergence, stability, performance and computational cost. The proposed controllers have been numerically and experimentally tested with both simple synthesized disturbances and real electric motor noise (MOSQUERA-SÁNCHEZ et al., 2015; MOSQUERA-SÁNCHEZ et al., 2017a; MOSQUERA-SÁNCHEZ et al., 2017b).
- *MIMO amplitude and relative-phase ASQC*: A multichannel active sound quality control scheme that deals with the magnitude and relative-phase functions of harmonic sounds is proposed. This algorithm features a novel scheme that allows for the compensation for cross-channel interferences, which enables the implementation of independent sound quality targets for each targeted sensor location. This controller has also been tested against simple synthesized disturbances and real electric motor noise (MOSQUERA-SÁNCHEZ et al., 2015; MOSQUERA-SÁNCHEZ et al., 2017a; MOSQUERA-SÁNCHEZ et al., 2017b).
- Contributions on sound quality analysis, optimization and tuning via active control:
  - *Control design framework*: This work proposes a general framework for tackling the complex task of defining control parameters that will meet perception expectations in terms of SQ metrics. This is done via concurrent optimization of the SQ metrics of the (hybrid electric powertrain) noise disturbance. A number of intermediate steps that render the process feasible are also

proposed and thoroughly analyzed:

- * A first assessment shows the effectiveness of the proposed multi-objective optimization (MOO) approach to prescribe control parameters that meet SQ targets for internal combustion engine noise (MOSQUERA-SÁNCHEZ et al., 2013).
- * Two evolutionary solvers are tested in an MOO that deals with the complete set of SQ metrics for an electric-motor noise; the targets have been attained again by the SISO ASQC tuned with the proposed MOO method (MOSQUERA-SÁNCHEZ et al., 2014).
- * This method is finally shown effective in dealing with MIMO ASQC design, attaining SQ targets for multiple metrics and multiple listeners within a closed domain (MOSQUERA-SÁNCHEZ et al., 2015) and (MOSQUERA-SÁNCHEZ et al., 2016).

1.4 Outline

Chapter 1 introduces the engineering problem that is addressed in this manuscript. Goals and original outcomes of this research are also described.

Chapter 2 addresses the issue of profiling periodic sounds at a number of sensor locations within cavities. This chapter presents three time- and frequency-domain multichannel active sound profiling systems that deal with interferences amongst channels, due to acoustic coupling. The possibility of performing free-of-interference active sound profiling for multiple locations will allow the MOO procedures to be independently carried out from one another location. Computer simulations verify the robustness of the proposed multichannel control schemes faced with plant magnitude variations.

Chapter 3 serves as an introduction for the multi-objective SQ optimization procedures, to be discussed in Chapter 4. In this chapter, important facts that motivate the time-domain SQ models to be rewritten in the frequency domain are presented. Differences between time- and frequency-domain SQ models that arise from the fact that the frequency-domain ones are not affected by numerical spectral leakage artifacts are solved, by means of a non-linear curve-fitting problem that provides a set of optimized tuning parameters.

Chapter 4 presents the proposed multi-objective SQ optimization problem, intended to find the best SQ scores for a given periodic sound. Sensitivity analyses based on the elementary effects method are proposed, in order to reduce the complexity of the optimization problem. The resulting set of harmonics, provided with proper

amplitude bounds, is first investigated through exhaustive searches that exploit a number of amplitude value combinations for searching for improved SQ scores. Afterwards, the problem is tackled in a real multi-objective fashion, in which two widely known genetic-algorithm (GA)-inspired multi-objective solvers have been tested. Chapter 4 also discusses on how to choose the solver parameters, such that the optimization routines converge to the optimal Pareto fronts. This Chapter eventually presents application examples on a synthesized periodic sound from a real measurement of a hybrid electric powertrain noise, which is measured at four positions within the experimental workbench cavity.

Chapter 5 provides the link between optimization and implementation steps, in terms of the actual implementation of optimized SQ targets over a number of periodic disturbances. Single-input, single-output (SISO) and multiple-input, multiple-output (MIMO) control schemes are discussed. Their effectiveness in attaining the desired optimized SQ targets is assessed by using time-domain SQ models on the controlled time histories.

Chapter 6 ends this manuscript with concluding remarks and directions for future research.

Chapter 2

Multichannel active periodic sound profiling

THIS chapter is concerned with the development of multichannel control schemes for the active sound quality control of periodic disturbances transmitted via structure borne within cavities. The proposed multichannel control schemes feature an innovative mechanism to counterbalance for cross-channel interferences, which have been determined as the root for current decentralized control schemes to not properly attain active sound profiling tasks for multiple listeners. Performance and implementation aspects of the control schemes are thoroughly discussed in this chapter. This chapter ends with a benchmarking of the centralized, decentralized and proposed multichannel control schemes, by means of computer simulations.

2.1 Introduction

Based on the principle of linear superposition of acoustic signals, ANC has emerged some decades ago as a promising technique for mitigating undesired sound fields (KUO; MORGAN, 1996; ELLIOTT, 2001). Engineering applications, such as automotive cavity interior, take advantage of such techniques to *enhance* (OLIVEIRA et al., 2009), instead of merely *reduce*, the noise generated by the operation of machines, by means of *balancing* the amplitudes (REES; ELLIOTT, 2006; KUO et al., 2008; OLIVEIRA et al., 2009; OLIVEIRA et al., 2010; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b), or *shifting* the relative phases (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b), towards desired SQ targets (MOSQUERA-SÁNCHEZ et al., 2013; MOSQUERA-SÁNCHEZ et al., 2015). This principle still holds for the so-called *active sound profiling* (REES; ELLIOTT, 2006) and *active sound quality control* (ASQC) techniques (GONZÁLEZ et al., 2003; GONZÁLEZ et al., 2006; KUO et al., 2007; KUO et al., 2008; OLIVEIRA et al., 2010; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b), which are variants of the ANC technique featuring a specialized algorithmic handling of the error signal. These are,

for the time being, the only available tools for the control designer to actively enhance the auditory qualities of such sound fields.

Active control techniques offer basically two strategies for implementing the controller that acts onto the plant, namely *feedback*, where the mitigation of a *disturbance signal* is pursued through the insertion of preprocessed physical variables that are measured from the same plant, and *feedforward*, whose implementation makes use of *a priori* information extracted from the disturbance, which enables the synthesis of a *reference signal*, with compatible physical parameters, e.g. amplitude, frequency, and relative phase, to those of the disturbance (HANSEN et al., 2012; WU et al., 2014). This strategy makes feedforward systems to be suitable for the control of acoustic noises with localized energy content, which is much the case of the noise radiated by rotating machines that exhibits spectral components related to the rotation regime, and whose energy is focused into narrow frequency regions (KUO; MORGAN, 1996). On the other hand, the feedback strategy is especially suitable for the control of acoustic noises with energy content that spreads into broad frequency regions, which would be the case of, e.g. road/wind noise in automotive applications, or even impacts that can excite the -entire- dynamics of the plant (OLSSON, 2006; SWEVERS et al., 2007). This does not mean that feedback systems can not be applied for controlling narrowband disturbances, some application examples are given by Bohn et al. (2004), Wu et al. (2014), but the effectiveness of these schemes are often inferior to that of the feedforward schemes (SEBA et al., 2005).

With regard to interior noise control in automotive applications, while for feedback systems active actuation onto structural systems is targeted, due to the possibility of realizing *quasi-collocated* SAPs, i.e. both the sensor and the actuator are placed onto -nigh- DoFs (OLIVEIRA et al., 2009), which in turn brings advantages in controllability and observability aspects, feedforward systems are able to manage large phase losses, mainly due to the fact that these systems are implicitly devised for disturbances whose statistics remains unchanged along uptime. This in turn enables feedforward control schemes to operate in *non-collocated* SAP arrangements, i.e. the sensor and the actuator placed onto -possibly- distant DoFs, which is a rather common situation in automotive applications, where a number of listeners are placed in locations at which it is not physically possible to implement SAPs (BISNETTE et al., 2006). Even so, since the size of the zone of quiet created by feedforward ANC/ASQC systems becomes a concern, as the frequency of the noise to be controlled increases (GARCIA-BONITO et al., 1997; ARDEKANI; ABDULLA, 2014), it would also be desired that the SAPs are disposed in a quasi-collocated fashion. However, applications like the automotive ones often restricts the locations for the placement of sensors and actuators, and hence the operation of feedback control schemes might be strongly hindered, in contrast to feedforward systems that have been proven to manage large phase losses, as a consequence of being

suitable to deal with -quasi-stationary disturbances.

SISO feedforward active sound profiling and ASQC techniques have been demonstrated to be effective in enhancing the auditory qualities of periodic noises at a single location within an enclosure (GONZÁLEZ et al., 2003; KUO et al., 2008; OLIVEIRA et al., 2009; OLIVEIRA et al., 2009; OLIVEIRA et al., 2010; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b). Moreover, decentralized MIMO ANC systems might be envisaged as a promising means to independently profile sound at a number of target locations, provided these control schemes are able to deal with the control signals that reach a given error sensor and that might cause interferences on the sound at each location. The fundamentals of current decentralized ANC systems rely upon simplifying the centralized formulation, by focusing the target of each control unit on a reduced -or a single- set of sensors (KUO; MORGAN, 1996). Thus, this decentralization strategy might be interesting from the point of view of independent-zone sound profiling, however, since the control units have nothing but their own information to converge, i.e. the dynamics between an actuator and a reduced set of sensors, cross-channel interferences may prevent the proper attainment of targeted operation modes on the sound at each sensor location, due to the computationally neglected coupling between channels (ZHANG et al., 2013).

A number of strategies have then been proposed for dealing with the interaction amongst control units in decentralized control schemes, which can be clustered in two lines of thought, as follows:

- Optimization of the sensor/actuator placement (ELLIOTT; BOUCHER, 1994; BAEK; ELLIOTT, 1995; ELGRICHI; ZEHEB, 1997; BERKHOFF, 2001; LEBOUCHER et al., 2002; DIEGO et al., 2004; CHO et al., 2015; TRINDADE et al., 2015; GAUTHIER et al., 2016): this solution would be the most effective one for accomplishing free-of-interference, multichannel active sound profiling, since the placement of sensors and actuators based on a cost function that relies on obtaining diagonally dominant control matrices, would make each control unit to independently converge from each other. However, it has been found that impracticable SAP placements might be found by following this guideline, especially in closed domains with fairly apparent modal features. Thus, some applications, such as automotive interior, would be unable to take advantage of.
- Restriction to the control output (ELLIOTT; BOUCHER, 1994; QIU; HANSEN, 2001; CHEER; ELLIOTT, 2015): in applications where the SAP positioning is rather restricted, or even fixed, instabilities would arise as a result of defective placement for certain discrete frequencies. The SAP placement has been determined as one of the causes that makes the matrix $\mathbf{A}(z) \in \mathbb{C}^{M \times M} = \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ to show eigenvalues with negative real parts, where M is the number of SAPs, $\mathbf{S}(z)$ is the control matrix containing diagonal and coupling terms, and $\hat{\mathbf{S}}(z) = \text{diag}(\mathbf{S}(z))$ is an estimate of

the terms at the main diagonal of $\mathbf{S}(z)$. The stabilization of such an arrangement can be assured by limiting the output of the control units. However, it has been observed that this stabilization strategy is not enough to ensure free-of-interference, active sound profiling, as the regularization parameter has just the necessary value to turn the control matrix into stable, which would still lead to some degree of interference amongst channels. Previous research has also shown that rather large constraint values would be required, in order to avoid cross-channel interferences, at the worthless cost of degrading the control performance, sometimes to such an extent that no improvement is obtained from its implementation (MOSQUERA-SÁNCHEZ et al., 2015).

Since the aim of the state-of-the-art techniques for decentralizing ANC schemes is to attain the same performance as the multichannel centralized scheme (FERRER et al., 2015), with less computational and wiring costs (ELLIOTT; BOUCHER, 1994), independent sound profiling for a number of listeners in closed domains seems currently unfeasible. The reason for that is the requirement for low cross-channel interferences, which would otherwise deteriorate the auditory qualities at neighboring positions. Furthermore, from the point of view of ASQC, it is an unacceptable result that the enhancement of the auditory perception for a given listener would come at the expenses of the other listeners.

This Chapter introduces three multichannel feedforward control schemes for profiling the amplitude and/or the relative-phase functions of periodic disturbances. The main novelty that these control schemes bring is that of accounting for cross-channel interferences due to acoustic coupling, by sending counterbalance signals that compensate for interferences caused on the sound. Its operation then relies on exchanging data amongst channels, in order to compensate for amplitude and/or relative-phase interferences the signals coming from other control units may cause in the sound. While compensation for interferences takes place at each error sensor location, the control units profile either the amplitude or the relative-phase function, or a combination of both, so as to realize the targeted control aims at a number of locations within a cavity. The control performance is not degraded due to the implementation of control output constraints, as long as the real parts of the eigenvalues of $\mathbf{A}(z)$ are positive. When such a condition is met (ELLIOTT; BOUCHER, 1994), the proposed multichannel control scheme should be able to accomplish the maximum theoretical amplification and reduction amplitude bounds, as well as relative-phase shifts between $-\pi$ rad and π rad, in a free-of-interference fashion.

Although computational benefits that come from pure-decentralized systems, such as low-cost and scalability, are sacrificed as a result of the need for communication between channels and intensive filtering tasks, the main benefit of this technique is to provide the listeners with improved, independent soundscapes for the same sound. This

feature allows, for instance, that a few harmonics might be targeted for control at certain locations, while others are focused at different locations, with the right attainment of sound quality targets at all of the intended locations. Since the proposed control schemes are sensitive to the global behavior of the acoustic system, rather than merely sensitive to discrete and/or local behaviors, they have been clustered within the class of *distributed* MIMO control schemes (HU et al., 2015; TRINDADE et al., 2015).

Computer simulations carried out on a simplified 8 degrees-of-freedom (DoF) MIMO numerical model, benchmark the tuning performance of the proposed control schemes against the centralized and pure-decentralized ones. Results from the simulations are appended at the end of this Chapter (Section 2.6), in order to verify the performance and effectiveness of the proposed multichannel control schemes in attaining independent-zone active sound profiling tasks for multiple listeners.

2.2 Multichannel active sound profiling systems

In this section, definitions and mathematical notation are introduced, by deriving the current theory and algorithms for decentralized multichannel active sound profiling. This decentralization framework is first examined from the point of view of the operation of each control unit. The time-domain control loop for single-frequency sounds is derived and its extension to the multifrequency sound is then obtained, by transforming relevant mathematical entities into the frequency domain (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b). Convergence and stability features of these control loops are eventually examined in terms of the overall system operation.

Derivation of the control algorithms

Since the objective of the control actions is to independently profile a periodic sound at a number of sensor locations, by means of either balancing the amplitudes, or shifting the relative phases of the harmonics, the kind of multichannel algorithm that minimizes *independent* cost functions becomes of interest. Hence, based on the demonstrated effectiveness of SISO systems in profiling periodic sounds (REES; ELLIOTT, 2006; KUO et al., 2007; KUO et al., 2008; OLIVEIRA et al., 2009; OLIVEIRA et al., 2010; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b), the proposed approach to the problem consists on placing a single sensor at each of the M targeted locations, together with as many actuators as sensors. Such an arrangement leads to $M \times M$ secondary paths, from which only M secondary paths should be identified, according to the current decentralization strategy for multichannel control schemes, illustrated in Fig. 2.1.

Figure 2.1: Block diagrams of state-of-the-art decentralized multichannel control schemes: (a) time-domain version; (b) frequency-domain version.

Time-domain adaptive algorithm

Each control unit measures residual, or error signals at corresponding locations, as follows:

$$\begin{aligned} e_m[n] &= d_m[n] - \sum_{j=1}^M S_{(m,j)}(z) * \{\mathbf{w}_j^T[n] \mathbf{x}[n]\}, \\ &= d_m[n] - \sum_{j=1}^M S_{(m,j)}(z) * u_j[n], \end{aligned} \quad (2.1)$$

where $\{e_m[n], d_m[n]\} \in \mathbb{C}$ are the error and the primary sound signals, respectively, as measured at the m^{th} location, at the discrete time n ; $u_j[n] \in \mathbb{C}$ is the control signal of the j^{th} control unit; $\mathbf{w}_j[n+1] \in \mathbb{R}^{L \times 1}$ is the order L , finite impulse response (FIR) representation of the j^{th} adaptive controller at time $n+1$; superscript T denotes array transposition; operator $(*)$ denotes time-domain linear convolution; $S_{(m,j)}(z)$ is the z -transform representation of the actual secondary path between sensor m and j^{th} actuator and $\mathbf{x}[n] \in \mathbb{C}^{L \times 1}$ is a L -point buffer for the reference signal that, for the time being, is assumed as a single-frequency signal:

$$x[n] = G e^{i(\omega n + \theta)}, \quad (2.2)$$

with $\{G, \omega, \theta\}$ being its amplitude, frequency and relative phase, respectively, and whose frequency equals the one of the primary sound; and $i \in \mathbb{C} \equiv \sqrt{-1}$ is the imaginary unit.

The *pseudoerror* signal $e'[n] \in \mathbb{C}$ for the m^{th} control unit is defined, by means of the SISO, internal model control (IMC) scheme (REES; ELLIOTT, 2006; KINNEY et al., 2007), as follows:

$$d'_m[n] \equiv e_m[n] + [\hat{\mathbf{S}}_{(m,m)}^T[n] \mathbf{u}_j[n]] \quad (2.3a)$$

$$e'_m[n] \equiv e_m[n] - g_m(d'_m[n]), \quad (2.3b)$$

where $\hat{\mathbf{S}}_{(m,m)}[n] \in \mathbb{R}^{Q \times 1}$ is the internal FIR model of the actual acoustic path between sensor m and actuator m ; $\mathbf{u}[n]$ is a Q -point buffer of time-domain samples of $u[n]$; $d'_m[n]$ is the "estimated" primary sound; and $g \in \mathbb{R}^{[0, 2]}$ is a gain factor, with $g = 0$ being the *cancellation* mode, $0 < g < 1$ is the *reduction* mode, $g = 1$ the *inactive* mode, and $1 < g \leq 2$ the *amplification* one. It is worth noticing that, for arriving at Eq. 2.3, the summation in Eq. 2.1 has been deliberately dropped out, which implies that only the "direct estimated secondary path" $\hat{S}_{(m,m)}(z)$ has been taken into account to "estimate" $d'_m[n]$.

The control target is stated upon Eq. 2.3b, in the form of a cost function to be

minimized by each control unit, as follows:

$$J_m = \mathbb{E} \left\langle (e'_m[n])^2 \right\rangle \approx (e'_m[n])^2 \quad (2.4)$$

$$s.t. (\mathbf{w}_m[n])^2 = 1,$$

where J_m denotes a cost function for the m^{th} control unit; and the expectation operator $\mathbb{E}$ applied upon the squared pseudoerror signal is approximated by its instantaneous value. A constraint on the adaptive controller weights is also enforced in Eq. 2.4, which aims at limiting the control effort of the m^{th} control unit. This constraint is handled by using a Lagrange multiplier (ELLIOTT; BAEK, 1996), as follows:

$$P_m = \overline{e'_m[n]} e'_m[n] + \beta_m [(\mathbf{w}_m[n])^2 - 1], \quad (2.5)$$

where P_m is the Lagrange function and $\beta_m \in \mathbb{R}$ is a Lagrange multiplier.

A least-mean-squares (LMS) updating rule can be derived from Eq. 2.5, by substituting it into the complex-domain, iterative algorithm:

$$\mathbf{w}_m[n+1] = \mathbf{w}_m[n] - \mu_m [Re(\nabla_{\mathbf{w}} P_m) + i Im(\nabla_{\mathbf{w}} P_m)], \quad (2.6)$$

where μ_m is the step size of the iterative algorithm; $\nabla_{\mathbf{w}}$ denotes partial derivative wrt. $\mathbf{w}$; and $\{Re, Im\}$ denote real and imaginary parts of a number, respectively, which yields:

$$\mathbf{w}_m[n+1] = \delta_m \mathbf{w}_m[n] + \alpha_m \left\{ \overline{\mathbf{x}'_{(m,m)}[n]} e'_m[n] \right\}, \quad (2.7)$$

where $\alpha_m \equiv 2\mu_m$; $\delta_m = 1 - \alpha_m\beta_m$; and:

$$\mathbf{x}'_{(m,m)}[n] \equiv \hat{\mathbf{S}}_{(m,m)}^T[n] \mathbf{x}[n] \quad (2.8)$$

is the filtered reference signal by the *direct* secondary path, which is also known as the *leaky*, LMS algorithm. Equation 2.8 is size-compatible by making $\mathbf{x}_{(m,m)}[n] \in \mathbb{C}^{Q \times 1}$.

The m^{th} time-domain, control signal is then realized by performing:

$$u_m[n] = \mathbf{w}_m^T[n] \mathbf{x}[n], \quad (2.9)$$

which closes the loop of the m^{th} time-domain, active sound profiling control unit in the decentralized control scheme.

Frequency-domain adaptive algorithm

The frequency-domain version of the above derived multichannel control scheme is also of interest, once that multi-harmonic sounds composed by R pure-sinusoids,

$$\mathbf{x}[n] = \sum_{r=1}^R G_r e^{i(\omega_r n + \theta_r)}, \quad (2.10)$$

can be locally profiled by using a single adaptive controller (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b). Thus, the time-domain cost function in Eq. 2.4 is redefined, by using the frequency-domain, pseudoerror signal $\mathbf{E}'_m[l] \in \mathbb{C}^{K \times 1} \equiv [E'_{(0,m)}[l], \dots, E'_{(K-1,m)}[l]]^T$, as follows:

$$\begin{aligned} J_{(k,m)} &= \mathbb{E} \left\langle (E'_{(k,m)}[l])^2 \right\rangle \approx (E'_{(k,m)}[l])^2 \\ \text{s.t. } (W_{(k,m)}[l])^2 &= 1, \end{aligned} \quad (2.11)$$

where $K = L$ is the length of the discrete Fourier transform; subscript $k = [0, K - 1]$ is the Fourier bin index; $\mathbf{W}_m[l] \in \mathbb{C}^{K \times 1} \equiv [W_{(0,m)}[l], \dots, W_{(K-1,m)}[l]]^T$ is the frequency-domain representation of the adaptive controller weights $\mathbf{w}_m[n]$; and $l = nLTs$ is the time-domain, block index, with $Ts \equiv (1/Fs)$ being the sampling period of the system.

To calculate $\mathbf{E}'_m[l]$ in a similar form as in the time-domain version of this control unit (cf. Eq. 2.3), L time-domain samples of both $e_m[n]$ (Eq. 2.1), and of $d'_m[n]$ (Eq. 2.3), should be taken in order to render K -point, run-time discrete Fourier transforms, once each $LTs[s]$, as follows:

$$\begin{aligned} \mathbf{E}'_m[l] &= \mathbf{E}_m[l] - \mathbf{g}_m \{\mathbf{D}'_m[l]\}; \\ \mathbf{E}_m[l] &= \mathcal{F} \left\{ [e_m[lL - 1] \dots e_m[lL - L]]^T \right\}; \\ \mathbf{D}'_m[l] &= \mathcal{F} \left\{ [d'_m[lL - 1] \dots d'_m[lL - L]]^T \right\}, \end{aligned} \quad (2.12)$$

where $\{\mathbf{E}_m[l], \mathbf{D}'_m[l]\} \in \mathbb{C}^{K \times 1}$ are the frequency-domain versions of both error and "estimated primary disturbance" signals, respectively; $\mathbf{g} \in [0, 2]^{K \times 1}$ is a vector of K gains for each Fourier bin, with bounds defined in Eq. 2.3; and the operator $\mathcal{F}$ denotes a discrete Fourier transform.

The cost function in Eq. 2.11 is handled in a similar form as in its time-domain counterpart (cf. Eq. 2.5), as follows:

$$P_{(k,m)} = \overline{E'_{(k,m)}[l]} E'_{(k,m)}[l] + \beta_{(k,m)} \left[(\overline{W_{(k,m)}[l]} W_{(k,m)}[l]) - 1 \right] \quad (2.13)$$

A frequency-domain LMS updating rule is then obtained by substituting Eq. 2.13 into Eq. 2.6, with obvious notation changes, i.e. $\mathbf{w}_m[n] \leftarrow W_{(k,m)}[l]$, and by following

definitions given in Eq. 2.12; which eventually yields in:

$$W_{(k,m)}[l+1] = \delta_{(k,m)} W_{(k,m)}[l] + \alpha_{(k,m)} \left\{ \overline{X'_{(k,m,m)}[l]} E'_{(k,m)}[l] \right\}, \quad (2.14)$$

where $\alpha_{(k,m)} \equiv 2\mu_{(k,m)}$; $\delta_{(k,m)} \equiv 1 - \alpha_{(k,m)}\beta_{(k,m)}$; $\overline{X'_{(k,m,m)}[l]} \in \mathbb{C}$ is the complex conjugate of the k^{th} Fourier bin of the frequency-domain representation of the filtered reference signal $x[n]$ by using $\hat{S}_{(m,m)}(z)$ (cf. Eq. 2.8):

$$\mathbf{X}'_{(m,m)}[l] = \mathcal{F} \left\{ [x'_{(m,m)}[lL-1] \dots x'_{(m,m)}[lL-L]]^T \right\} \quad (2.15)$$

The expression in Eq. 2.14 is also termed as the frequency-domain, *leaky* LMS algorithm. Notice that the subscript k has been made explicit in Eqs. 2.11, 2.13, and 2.14, for highlighting that the frequency-domain cost function should be optimized for each Fourier bin, at each of the M error sensor locations.

For the most general case of complex-domain primary sound, the time-domain control signal is realized by taking the inverse discrete Fourier transform of the resulting adaptive filter $\mathbf{W}_m[l+1]$ in Eq. 2.14, as follows (KUO et al., 2008; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b):

$$\mathbf{w}_m[n+1] = \mathcal{F}^{-1} \{ \mathbf{W}_m[l+1] \}, \quad (2.16)$$

and by calculating the control output using Eq. 2.9, which closes the loop of the m^{th} frequency-domain active sound profiling controller. Moreover, a computational saving results from dealing with real-valued primary sounds, which is the common case in active sound profiling tasks. It consists on just taking $(K/2 + 1)$ Fourier bins, which makes Eq. 2.14 to be calculated only $(K/2 + 1)$ times at each iteration, and the time-domain controller will then be realized by appending the complex conjugate part of the $k = [1, \dots, K/2 - 1]$ Fourier bins, as follows:

$$\mathbf{W}_m[l+1] = [\mathbf{W}_{(k=0,\dots,K/2;m)}^T[l+1], \mathbf{W}_{(k=1,\dots,K/2-1;m)}^H[l+1]]^T, \quad (2.17)$$

and by calculating Eq. 2.16 by using Eq. 2.17. In this form, the loop for the m^{th} frequency-domain controller for real-valued signals is closed.

The sequence of calculations stated in Eqs. 2.16, 2.17 and 2.9 is also known as the *delayless structure* (KUO et al., 2008). This strategy, besides alleviating frequency-domain artifacts that arise from the circular convolution involved in attempting to generate the control signal, also overcomes delays in the block-by-block processing involved in Eqs. 2.12 and 2.15.

Convergence and stability aspects

Since the time-domain LMS updating rule stated in Eq. 2.7 only differs from that of the frequency-domain in Eq. 2.14 in the time-domain index ($l = nLTs$), the convergence analysis will only be conducted for the latter one. Similar remarks can be extended to the time-domain version of this control scheme. In the following derivation, the subscript k is dropped out for notation simplicity.

Convergence

Following Elliott & Boucher (1994) procedure for *combining the effects of simultaneous adjustment of each control unit with the coupling*, Eq. 2.12 is rewritten in matrix form:

$$\mathbf{E}'[l] = \mathbf{E}[l] - \mathbf{g}\mathbf{D}'[l], \quad (2.18a)$$

$$\mathbf{E}[l] = \mathbf{D}[l] - \mathbf{S} \{ \mathbf{W}[l]X[l] \}, \quad (2.18b)$$

where $\mathbf{E}'[l] \in \mathbb{C}^{M \times 1}$ contains M frequency-domain pseudoerror signals; $\mathbf{g} \in \mathbb{R}^{M \times M}$ contains gain factors at the main diagonal for the M control units; $\mathbf{D}'[l] \in \mathbb{C}^{M \times 1}$ is the -incorrect- estimate of $\mathbf{D}[l]$ and $\mathbf{E}[l] \in \mathbb{C}^{M \times 1}$ contains M frequency-domain error signals, as redefined in matrix form in Eq. 2.18b, with matrix entities defined as follows: $\mathbf{D}[l] \in \mathbb{C}^{M \times 1}$ contains the frequency-domain representation of the actual primary sound; $\mathbf{S} \in \mathbb{C}^{M \times M} \leftarrow \mathbf{S}(z)$ is the full-matrix, steady-state approximation of the secondary paths, with each term representing its magnitude and phase at frequency ω ; $\mathbf{W}[l] \in \mathbb{C}^{M \times 1}$ contains frequency-domain adaptive weights at block-index time l ; and $X[l] \in \mathbb{C} \xleftarrow{\mathcal{F}} \mathbf{x}[n]$ is the frequency-domain representation of the reference signal, which is supposed to be correlated to the primary sound at all error sensors. This is the physically meaningful case, in which the primary sound with frequency ω propagates within a closed domain and control is required at all sensor locations, at that frequency.

Equation 2.14 is rewritten in matrix form, as follows:

$$\mathbf{W}[l+1] = (\mathbf{I} - \alpha\beta) \mathbf{W}[l] + \alpha\mathbf{X}'^H[l]\mathbf{E}'[l], \quad (2.19)$$

where $\mathbf{W}[l+1] \in \mathbb{C}^{M \times 1}$ contains frequency-domain, adaptive weights of the M control units, at block-index time $l+1$; $\mathbf{I}$ is the complex identity matrix of order M ; $\{\alpha, \beta\} \in \mathbb{R}^{M \times M}$ are diagonal matrices containing step sizes and constraint values for the M control units, respectively; and $\mathbf{X}'[l] \in \mathbb{C}^{M \times M}$ is the matrix that comes from arranging the frequency-domain versions of the filtered reference signal, by just using the *direct secondary paths* $\hat{S}_{(j,j)}(z)$, $j = 1 \dots M$, which is defined as follows (ELLIOTT; BOUCHER,

1994; KUO; MORGAN, 1996):

$$\mathbf{X}'[l] = \mathcal{F} \left\{ \hat{\mathbf{S}}_{(j,j)}^H[n] \mathbf{x}[n] \right\} \equiv \quad (2.20)$$

$$\begin{bmatrix} \mathcal{F} \left\{ \hat{\mathbf{S}}_{(1,1)}^H[n] \mathbf{x}[n] \right\} & 0 & \cdots & 0 \\ 0 & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(2,2)}^H[n] \mathbf{x}[n] \right\} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(M,M)}^H[n] \mathbf{x}[n] \right\} \end{bmatrix}$$

where $\mathbf{x}[n] \in \mathbb{C}^{Q \times 1}$ is a Q -point buffer for the single-frequency reference signal defined in Eq. 2.2.

By substituting Eqs. 2.18a, 2.18b and 2.20 in Eq. 2.19, it follows that:

$$\begin{aligned} \mathbf{W}[l+1] &= \mathbf{W}[l] + \alpha \left\{ -\beta \mathbf{W}[l] + \mathbf{X}'^H[l] \mathbf{D}[l] \right. \\ &\quad \left. - \mathbf{g} \mathbf{X}'^H[l] \mathbf{D}'[l] - \mathbf{X}'^H[l] \mathbf{S} \mathbf{W}[l+1] \mathbf{X}[l] \right\} \end{aligned} \quad (2.21)$$

Provided that $\mathbf{x}[n]$ is an unitary-amplitude, single-frequency, zero-phase reference signal with frequency ω , as stated in Eq. 2.2, both $\mathbf{X}'[l]$ and $\mathbf{S} \mathbf{X}[l]$ in Eq. 2.21 are nothing but $\hat{\mathbf{S}}(z)$ and $\mathbf{S}(z)$ themselves, respectively. Furthermore, it is said that the decentralized control scheme has converged when $\mathbf{W}[l+1] = \mathbf{W}[l]$, which implies that suitable values for α have been provided in Eq. 2.21, so that the term in curly braces in Eq. 2.21 equals zero. Thus, by examining the term in curly braces in Eq. 2.21, it follows that:

$$\mathbf{W} = \left[\hat{\mathbf{S}}^H (\mathbf{D} - \mathbf{g} \mathbf{D}') \right] \left[\beta + \hat{\mathbf{S}}^H \mathbf{S} \right]^{-1}, \quad (2.22)$$

is the set of adaptive weights the control units should converge to attain desired sound profiling goals, provided the second term in brackets has an inverse. In Eq. 2.22 it is straightforward to see that, as $\mathbf{g} = 0$ and a single β is given for the entire algorithm, the derived expression equals that of the derived one by Elliott & Boucher (1994), for the steady-state of $u[n]$.

Stability

The stability of the above derived multichannel active sound profiling system is dictated by the positiveness of the real part of the eigenvalues of $\mathbf{A} = \beta + \hat{\mathbf{S}}^H \mathbf{S}$, as excited at ω (ELLIOTT; BOUCHER, 1994). When $\beta = 0$, then $\mathbf{A} = \hat{\mathbf{S}}^H \mathbf{S}$. On the one hand, centralized control schemes "see" the full control matrix $\mathbf{S}(z)$ (GONZÁLEZ et al., 2006), hence $\hat{\mathbf{S}}^H$ is nothing but its exact hermitian transpose, provided that $\hat{\mathbf{S}}(z) \approx \mathbf{S}(z)$, and thus the stability is always assured. On the other hand, current decentralized control schemes are forced to just "see" the diagonal entries of $\mathbf{S}(z)$, (cf. Eq. 2.19), which causes matrix $\mathbf{A}$ to not always have all its eigenvalues with positive real parts. In view of such statements,

two strategies have been proposed to realize a stable, decentralized multichannel system at frequency ω (ELLIOTT; BOUCHER, 1994):

- SAP positioning: the SAP placement plays a fundamental role in realizing a stable, decentralized multichannel control scheme, once that, when the non-diagonal entries of $|\mathbf{S}(z)|$ are greater than the main diagonal ones, $\mathbf{A}$ could become ill-conditioned. The simplest, but sometimes restricted, strategy is to put each actuator as close as possible to their corresponding sensors, in an attempt to enlarge the magnitude of the diagonal entries of $\mathbf{A}$. However, the implementation in closed domains might require the placement of an actuator in a location that favors the excitation of cavity resonances, to which other sensors could have better observability. This, in turn would lead to large non-diagonal entries in $\mathbf{A}$, even when effort had been made in placing a sensor close to its corresponding actuator.
- Use of regularization parameter β : provided the definition of matrix β in Eq. 2.19, it is straightforward to see that this parameter does help enlarging the main diagonal of $\mathbf{A}$, in a pure-algorithmic way (cf. Eq. 2.22). This strategy is attractive, from the point of view of loosening the implementation guideline given in the previous paragraph, as the control designer would not have to cope with SAP placement issues. However, regularization indeed implies in constraining the individual cost functions stated in Eqs. 2.4 and 2.11, which will bring a degradation in the control performance, as it can be verified by plugging Eq. 2.22 into Eqs. 2.18a and 2.18b, once that, as $\beta \rightarrow 0$, $\mathbf{E}'[l] \rightarrow \mathbf{0}$ *if* $\mathbf{g} = \mathbf{0}$.

The stability of decentralized active sound profiling systems can then be discerned by detecting frequencies at which: (i) the control matrix is diagonally dominant; (ii) the control matrix is not diagonally dominant, but the real part of all the eigenvalues of $\mathbf{A}$ is positive; and (iii) any of the real parts of the eigenvalues of $\mathbf{A}$ is negative. Whilst low -or even null- interference amongst channels is expected from the implementation of multiple SISO control units operating at frequencies of the former sort, due to the negligible contribution of the coupling terms to a given sensor, some degree of cross-channel interference is expected when the decoupled array operates at frequencies where the coupling terms are noticeable. It is also worth noting that only the latter type of control matrix requires implementation of control output limitation, in order to get a stable system, at the expense of losing control performance.

Computational complexity

Table 2.1 summarizes the calculations each control unit should perform to execute an iteration of either the time- or the frequency-domain version of the decentralized control

scheme, developed in previous paragraphs. These calculations are sorted from the measurement of the error signals to the generation of the control signals.

The computational complexity of the calculations reported in Tables 2.1, 2.2, 2.3 and 2.4 has been worked out by assuming that:

- A complex multiplication takes 4 real-domain multiplications;
- A complex addition takes 2 real-domain additions;
- The computational complexity of a FIR filter amounts to L multiplications and $L - 1$ additions, where L is the order of the filter.
- The computational complexity of a discrete Fourier transform is equal to $K \log_2 K$ multiplications and $K \log_2 K$ additions, where K is the length of the transform.

Table 2.1: Computational complexity of time- (TD) and frequency-domain (FD) versions of the current decentralized multichannel control scheme, given in real-valued multiplications and additions, required to control O (TD) or $L/2 - 1$ (FD) harmonics. The **total** number of multiplications and additions is given for the entire system (M channels).

Version	Equation	Number of Mult. ($\times$)	Number of Add. (+)
TD	2.1	-	-
	2.3a	Q	Q
	2.3b	1	1
	2.8	Q	$Q - 1$
	2.7	$3L$	L
	2.9	L	$L - 1$
Total		$O[M(2Q + 4L + 1)]$	$O[M(2Q + 2L - 1)]$
FD	2.1	-	-
	2.3a	Q	Q
	2.12	$2L(\log_2 L + 2)$	$2L(L \log_2 L + 1)$
	2.8	Q	$Q - 1$
	2.15	$L \log_2 L$	$L \log_2 L$
	2.14	$12L$	$2L$
	(2.17) - 2.16	$L \log_2 L$	$L \log_2 L$
	2.9	L	$L - 1$
Total		$M(2Q + 17L + 4L \log_2 L)$	$M(2Q + 5L + 4L \log_2 L - 2)$

A comparison amongst the multichannel control schemes, with regard to the computational requirements, is provided in Section 2.5. In that comparison, it will be possible to verify that all the control schemes derived in this Section are the least demanding. The

additional computational cost that the proposed multichannel control schemes require will be worth, as they come along with the possibility of implementing independent active sound profiling tasks for a number of listeners.

Summary

In this section, the current state-of-the-art framework for implementing a number of LMS-based, SISO active sound profiling units has been derived, aiming at attaining local sound profiling goals. Although the derivation of both time- and frequency-domain multichannel decentralized systems was worked out for a single control unit, by deliberately neglecting the coupling amongst channels and by getting rid of other than the corresponding error signals to a given control unit, convergence and stability aspects were necessarily studied by explicitly accounting for the coupling amongst channels. This discussion provides the proper background for the following algorithms for multichannel active sound profiling with coupling compensation, which will be discussed in the following section.

2.3 Multichannel control schemes for amplitude-based active sound profiling

This section introduces two multichannel control schemes that are able to carry out amplitude-based, sound profiling tasks at a number of sensor locations, by means of *compensating* for cross-channel interferences. The operation of the proposed control schemes relies on exchanging data amongst the control units, so that each unit is able to calculate the signal that *compensates* other control signals reaching its corresponding sensor, at the time that the system accomplishes the control targets at the locations of interest. Whilst the first proposed control scheme is based on exchanging both adapted control weights and control signals, the second one only requires exchanging adapted control weights, which represents noticeable computation and communication savings, at the cost of reducing convergence speed. This novel decentralization framework makes no use of control output restrictions for avoiding cross-channel interferences, even when controlling tones that excite non-diagonally-dominant, but stable, control matrices. This allows the proposed multichannel schemes to attain effortful sound profiling goals at a number of locations, with no control performance degradation. Moreover, from the point of view of stability, the inclusion of β in the cost function (cf. Eq. 2.5) helps in getting the control system stable at problematic discrete frequencies, while still featuring the claimed ability of coupling compensation. However, as mentioned before, the performance of the proposed control schemes in this scenario could result affected, which depends on the amount of regularization needed.

Each control scheme is derived for time- and frequency-domain LMS algorithms, the latter ones featuring the ability to deal with multi-harmonic sounds, even with a single adaptive filter per control unit. The derivation of the algorithms follows the same organization as in the previous section, where time-domain control loops were first derived for single-frequency primary sounds; frequency-domain control loops were subsequently derived for tackling multi-frequency primary sounds; and their convergence/stability features were eventually examined from the point of view of the overall system operation.

2.3.1 Algorithm 1

Figure 2.2 illustrates the block diagrams of both time- and frequency-domain versions of the channel M of the first proposed $M \times M$ multichannel control array featuring the coupling compensation ability. Each control unit executes the same calculations, provided with internal representations of the corresponding secondary transfer paths.

Time-domain adaptive algorithm

The definition of the error signal follows what it was stated in Eq. 2.1, which takes into account all the control signals that reach the sensor placed at location m . Based on such a mathematical model of the linear superposition of primary and secondary signals, an expression for *accurately* estimating the primary sound is derived, which does account for the M control signals that reach location m , as follows:

$$\begin{aligned} d_m''[n] &= e_m[n] + \sum_{j=1}^M \hat{\mathbf{S}}_{(m,j)}^T[n] \{ \mathbf{w}_j^T[n] \mathbf{x}[n] \}, \\ &= e_m[n] + \sum_{j=1}^M \hat{\mathbf{S}}_{(m,j)}^T[n] \mathbf{u}_j[n], \end{aligned} \quad (2.23)$$

where $\mathbf{u}_j \in \mathbb{R}^{Q \times 1}$ is a buffer that contains Q time-domain samples of the convolution ($\mathbf{w}_j^T[n] \mathbf{x}[n]$); and $d_m'' \in \mathbb{C}$ is the *correct* estimate of the primary sound measured at location m . In this expression, it can be noticed that the m^{th} control unit must be aware of its own control signal $u_m[n]$, and the remaining $M - 1$ control signals $u_{(j=1:M, j \neq m)}[n]$. This, in turn, requires estimating the secondary paths $\hat{\mathbf{S}}_{(m,j)}[n]$ comprised between the sensor m and each of the $1 \dots M$ actuators in the array. Therefore, calculation of Eq. 2.23 requires *data exchange* amongst the control units.

A special mathematical entity is defined, by flipping the systems $\hat{\mathbf{S}}[n]$ and $\mathbf{w}[n]$ in Eq. 2.23, which leads to estimate the contribution of all the control signals on the m^{th}

Figure 2.2: Block diagrams of the multichannel control scheme 1: (a) time-domain version; (b) frequency-domain version.

Source: Mosquera-Sánchez et al. (2017b).

sensor, as follows:

$$\tilde{u}_m[n] \equiv \sum_{j=1}^M \mathbf{w}_j^T[n] \mathbf{x}'_{(m,j)}[n]; \quad (2.24a)$$

$$x'_{(m,j=1:M)}[n] \equiv \hat{\mathbf{S}}_{(m,j=1:M)}[n] \mathbf{x}[n], \quad (2.24b)$$

The flipping of $\hat{\mathbf{S}}[n]$ and $\mathbf{w}[n]$ follows the fact that the inherent *commutation error* of the IMC scheme can be corrected (LIAO; LIN, 2007; WU et al., 2015), in order to ensure the fastest convergence for each of the control units in the array.

The pseudoerror signal is then newly defined, by taking Eqs. 2.23, 2.24a, and 2.24b, which yields in:

$$e'_m[n] \equiv (1 - g_m) d''_m[n] - \tilde{u}_m[n], \quad (2.25)$$

wherein the gain factor $(1 - g_m)$ enables the control unit to implementing other than pure-reduction targets over $d_m[n]$, in a similar form as in Eq. 2.3, while still *compensating* for cross-channel interferences.

A LMS-based updating rule for the proposed control scheme is then derived, by substituting Eq. 2.25 into the time-domain, Lagrange function in Eq. 2.5, which already features a constraint on the control effort. Thus, by following calculations requested in Eqs. 2.5, and 2.6, it follows that:

$$\mathbf{w}_m[n+1] = \delta_m \mathbf{w}_m[n] + \alpha_m \left\{ \overline{\mathbf{x}'_{(m,m)}}[n] e'_m[n] \right\}, \quad (2.26)$$

where $\overline{\mathbf{x}'_{(m,m)}}[n]$ is the complex conjugate of the reference signal filtered by $\hat{\mathbf{S}}_{(m,m)}[n]$. Notice that Eq. 2.26 is similar to the obtained expression for the decentralized algorithm with no compensation mechanism in Eq. 2.7. This, in turn, means that the updating scheme for the proposed array does not require the reference signal filtered by other than the direct secondary path, and this comes from the fact that the proposed multichannel control scheme optimizes *independent* cost functions.

The control loop is eventually closed by making $M + 1$ copies of the adapted controller weights $\mathbf{w}_m[n+1]$ in Eq. 2.26, which are used as follows: (i) two copies within the m^{th} control unit for calculating Eq. 2.9 (actual control unit output $u_m[n]$) and Eq. 2.24a (estimated array control output $\tilde{u}_m[n]$); and (ii) the remaining $M - 1$ copies are sent to the other control units, for them to calculate Eq. 2.24a at next iteration. In addition, calculation of Eq. 2.23 into channel m requires the incoming time-domain, control signals from all the control units in the array, as well as the corresponding secondary paths (including cross-terms) within each of the M control units, for the next iteration. This time-domain control scheme is illustrated in Fig. 2.2(a) and summarized in Table 2.2.

Frequency-domain adaptive algorithm

Significant computational savings that are evident when controlling multifrequency sounds are achieved when deriving the above multichannel scheme, by using frequency-domain entities. Length- K , run-time discrete Fourier transforms on a set of L time-domain samples of $d''[n]$ in Eq. 2.23 should then be calculated, with $K = L$, once every LT s[s], as follows:

$$\mathbf{D}_m''[l] = \mathcal{F} \left\{ \left[\hat{d}_m[lL - 1] \ \dots \ \hat{d}_m[lL - L] \right]^T \right\}, \quad (2.27)$$

and on each time-domain convolution stated in Eq. 2.24b, as follows:

$$\begin{aligned} \mathbf{X}'_{(m,1)}[l] &= \mathcal{F} \left\{ \left[x'_{(m,1)}[lL - 1] \ \dots \ x'_{(m,1)}[lL - L] \right]^T \right\} \\ &\vdots \\ \mathbf{X}'_{(m,M)}[l] &= \mathcal{F} \left\{ \left[x'_{(m,M)}[lL - 1] \ \dots \ x'_{(m,M)}[lL - L] \right]^T \right\}, \end{aligned} \quad (2.28)$$

in order to define a frequency-domain version of the pseudoerror defined in Eq. 2.25.

The computation burden arising from the time-domain convolutions in Eq. 2.24a can be reduced to complex-domain multiplications, provided the adapted control weights $\mathbf{w}_{(j=1:M)}[n+1]$ are given in the frequency domain. With these frequency-domain control weights, the frequency-domain version of $\check{u}_m[n]$, is obtained, as follows:

$$\check{U}_{(k,m)}[l] = \sum_{j=1}^M W_{(k,j)}[l] X'_{(k,m,j)}[l], \quad (2.29)$$

where notation k is made explicit for highlighting that the calculation should be carried out for each Fourier bin, $k = 0 \ \dots \ K - 1$.

The frequency-domain version of the pseudoerror signal in Eq. 2.25 is eventually derived, by using Eqs. 2.27, 2.28, and 2.29, as follows:

$$E'_{(k,m)}[l] = (1 - g_{(k,m)}) D''_{(k,m)}[l] - \check{U}_{(k,m)}[l] \quad (2.30)$$

A frequency-domain LMS-based updating rule for the m^{th} control unit is derived, by substituting Eq. 2.30 in Eq. 2.13, and by calculating partial derivatives of the resulting equation, as Eq. 2.6 indicates:

$$W_{(k,m)}[l+1] = \delta_{(k,m)} W_{(k,m)}[l] + \alpha_{(k,m)} \left\{ \overline{X'_{(k,m)}}[l] E'_{(k,m)}[l] \right\} \quad (2.31)$$

As in the frequency-domain multichannel active sound profiling system derived in the previous Section, the calculation of the updating rule in Eq. 2.31 can just be carried

out for the first $(K/2 + 1)$ Fourier bins, as long as active sound profiling tasks are carried out upon real-valued signals (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b). Afterwards, the entire m^{th} frequency-domain, adapted controller $\mathbf{W}_m[l]$ is realized by following Eq. 2.17, otherwise $\mathbf{W}_m[l]$ is directly obtained by calculating Eq. 2.31.

In a similar fashion as in the time-domain version of this control loop, the proposed frequency-domain multichannel system makes $M + 1$ copies of $\mathbf{W}_m[l + 1]$ in Eq. 2.31, whereof one of them is used within the m^{th} control unit to calculate Eq. 2.29, and other copy is transformed into the time domain to realize the m^{th} control signal by following Eqs. 2.16, and 2.9. Yet, the remaining $M - 1$ copies of $\mathbf{W}_m[l + 1]$ are taken in the frequency domain to the other control units for them to calculate Eq. 2.29 at next iteration. The time-domain, control output $u_m[n]$ is also shared to the other control units, for them to calculate Eq. 2.23 at next iteration. This frequency-domain control scheme is illustrated in Fig. 2.3(b) and summarized in Table 2.2.

Convergence and stability

Since the derived LMS updating rules for both time- and frequency-domain versions of Algorithm 1 are similar to the ones obtained for the decentralized control scheme with no compensation (cf. comparison between Eqs. 2.7 and 2.26; and Eqs. 2.14 and 2.31), the derivations start by taking Eq. 2.19, which stands for the matrix form of the frequency-domain LMS control scheme in Eq. 2.14. The derivations below are worked out for a single Fourier bin k .

The frequency-domain, pseudoerror signal given in Eq. 2.30 is rewritten in matrix form, as follows:

$$\mathbf{E}'[l] = (\mathbf{I} - \mathbf{g}) \mathbf{D}''[l] - \check{\mathbf{U}}^H[l], \quad (2.32)$$

where $\mathbf{D}''[l] \in \mathbb{C}^{M \times 1}$ contains the frequency-domain representation of the correct estimated primary sound; and:

$$\begin{aligned} \check{\mathbf{U}}[l] &= \mathbf{W}^H[l] \left\{ \check{\mathbf{S}}^H X[l] \right\}, \\ &= \mathbf{W}^H[l] \mathbf{X}''^H[l] = (\mathbf{X}''[l] \mathbf{W}[l])^H, \end{aligned} \quad (2.33)$$

is the matrix form of Eq. 2.29, where $\check{\mathbf{S}} \in \mathbb{C}^{M \times M} \leftarrow \mathbf{S}(z)$ is the steady-state approximation that provides magnitude and phase information of the estimated, *full* control matrix that accounts for coupling terms. The term in curly brackets in Eq. 2.33, i.e. $\mathbf{X}''[l]$, is

accordingly defined as follows:

$$\mathbf{X}''[l] \equiv \mathcal{F} \left\{ \tilde{\mathbf{S}}^H[n] \mathbf{x}[n] \right\} = \begin{bmatrix} \mathcal{F} \left\{ \hat{\mathbf{S}}_{(1,1)}^H[n] \mathbf{x}[n] \right\} & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(1,2)}^H[n] \mathbf{x}[n] \right\} & \cdots & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(1,M)}^H[n] \mathbf{x}[n] \right\} \\ \mathcal{F} \left\{ \hat{\mathbf{S}}_{(2,1)}^H[n] \mathbf{x}[n] \right\} & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(2,2)}^H[n] \mathbf{x}[n] \right\} & \cdots & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(2,M)}^H[n] \mathbf{x}[n] \right\} \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{F} \left\{ \hat{\mathbf{S}}_{(M,1)}^H[n] \mathbf{x}[n] \right\} & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(M,2)}^H[n] \mathbf{x}[n] \right\} & \cdots & \mathcal{F} \left\{ \hat{\mathbf{S}}_{(M,M)}^H[n] \mathbf{x}[n] \right\} \end{bmatrix} \quad (2.34)$$

By substituting Eqs. 2.32 and 2.33 into Eq. 2.19, it follows that:

$$\mathbf{W}[l+1] = \mathbf{W}[l] + \alpha \left\{ -\beta \mathbf{W}[l] + \mathbf{X}'^H[l] (\mathbf{I} - \mathbf{g}) \mathbf{D}''[l] - \mathbf{X}'^H[l] \mathbf{X}''[l] \mathbf{W}[l+1] \right\}, \quad (2.35)$$

where $\mathbf{X}'[l]$ is as defined in Eq. 2.19.

By providing a suitable α , the term in curly brackets should vanish when $\mathbf{W}[l+1] = \mathbf{W}[l]$, which implies that:

$$\mathbf{W} = \left[\hat{\mathbf{S}}^H (\mathbf{I} - \mathbf{g}) \mathbf{D}'' \right] \left[\beta + \hat{\mathbf{S}}^H \tilde{\mathbf{S}} \right]^{-1} \quad (2.36)$$

Since the second term in brackets in both Eqs. 2.22 and 2.36 are similar between each other, it is said that Algorithm 1 inherits all the stability properties of the current decentralized multichannel active sound profiling system, derived in the previous Section. The difference between those equations lies in their first term in brackets, as $\hat{\mathbf{D}}[l]$ in Eq. 2.22 is never equal to $\mathbf{D}[l] \xrightarrow{\mathcal{F}^{-1}} \mathbf{d}[n]$, due to the incorrect definition given for such an entity in Eq. 2.3.

Computational complexity

Table 2.2 summarizes the calculations each control unit should perform to execute an iteration of either the time- or the frequency-domain version of the multichannel Algorithm 1 with coupling compensation. These calculations are sorted from the measurement of the error signals to the generation of the control signals. The computational complexity of the calculations reported on in Table 2.2 has been also worked out by taking into account the same assumptions as in Section 2.2.

The comparison amongst the multichannel control schemes with regard to the computational requirements in Section 2.5 will reveal that the multichannel Algorithm 1 is the most demanding one. While this Algorithm is the fastest one in delivering active sound profiling targets for multiple listeners, the computational requirements might hinder its implementation in low-power DSP boards. This is the motivation for searching a less demanding multichannel control scheme, which can still be able to

Table 2.2: Computational complexity of time- (TD) and frequency-domain (FD) versions of the multichannel Algorithm 1, given in real-valued multiplications and additions, required to control O (TD) or $L/2 - 1$ (FD) harmonics. The **total** number of multiplications and additions is given for the entire system (M channels).

Version	Equation	Number of Mult. ($\times$)	Number of Add. (+)
TD	2.1	-	-
	2.23	MQ	MQ
	2.24b	MQ	$M(Q - 1)$
	2.24a	ML	$M(L - 1)$
	2.25	1	2
	2.26	$3L$	L
	2.9	L	$L - 1$
Total		$O\{M[M(2Q + L) + 4L + 1]\}$	$O\{M[M(2Q + L - 2) + 2L + 1]\}$
FD	1	-	-
	2.23	MQ	MQ
	2.24b	MQ	$M(Q - 1)$
	2.27	$L\log_2 L$	$L\log_2 L$
	2.28	$ML\log_2 L$	$ML\log_2 L$
	2.29	$4ML$	$2L(M - 1)$
	2.30	$4L$	$3L$
	2.31	$12L$	$2L$
	(2.17) - 2.16	$L\log_2 L$	$L\log_2 L$
	2.9	L	$L - 1$
Total		$M\{M[2Q + L(\log_2 L + 4)] + L(2\log_2 L + 17)\}$	$M\{M[2Q + L(\log_2 L + 2) - 1] + 2L(\log_2 L + 2) - 1\}$

Source: Mosquera-Sánchez et al. (2017b).

attain active sound profiling targets for multiple listeners.

2.3.2 Algorithm 2

Figure 2.3 illustrates the block diagrams of both the time- and the frequency-domain versions of the channel M of the second $M \times M$ multichannel control scheme that also feature the compensation mechanism. The main difference with the previously derived scheme relies on the fact that only the calculation of $\check{u}[n]$ is required to perform free-of-interference multichannel active sound profiling. This will allow the calculation of $d''[n]$ to be discarded, which will notably reduce the computation burden, but at the cost of reducing the convergence speed.

Time-domain adaptive algorithm

By plugging Eq. 2.23 into Eq. 2.25, and by assuming that $\hat{\mathbf{S}}_{(m,j)}^H[n] \mathbf{w}_j^T[n+1] \mathbf{x}[n] \approx \mathbf{w}_j^T[n+1] \hat{\mathbf{S}}_{(m,j)}^H[n] \mathbf{x}[n]$, which implies in slowing down the convergence rate due to the system flipping, it follows that:

$$e'_m[n] = (1 - g_m) e_m[n] + g_m \check{u}_m[n] \quad (2.37)$$

This new definition for the pseudoerror signal in Eq. 2.37 does not depend on the estimation of the primary sound, which allows saving costly filtering operations required in Eq. 2.23.

Now, by substituting Eq. 2.37 into the Lagrange function in Eq. 2.5, and by following calculations in Eq. 2.6 required for deriving a LMS-based updating rule, the same expression as in Eqs. 2.7 and 2.26 is obtained.

The time-domain control loop of the Algorithm 2 is eventually closed by making $M + 1$ copies of $\mathbf{w}_m[n+1]$, wherein two of them are used into the m^{th} controller to calculate Eq. 2.9 and $\check{u}_m[n]$ in Eq. 2.24a, for the next iteration. The remaining copies are taken to the $M - 1$ control units for them to calculate Eq. 2.24a at next iteration. This time-domain control scheme is illustrated in Fig. 2.3(a) and summarized in Table 2.3.

Frequency-domain adaptive algorithm

The frequency-domain version of this control scheme can be straightforwardly derived by collecting a set of L points of the error signal, as measured at each of the M channels, and by calculating a discrete Fourier transform over such a buffer, as follows:

$$\mathbf{E}_m[l] = \mathcal{F} \left\{ [e_m[lL - 1] \ \dots \ e_m[lL - L]]^T \right\}, \quad (2.38)$$

Now, a frequency-domain version of the pseudoerror signal for this multichannel

Figure 2.3: Block diagrams of the proposed low-cost multichannel control schemes 2: (a) time-domain; (b) frequency-domain.

control scheme is defined, by using the definitions given in Eqs. 2.28, 2.29, and 2.38, as follows:

$$E'_{(k,m)}[l] = (1 - g_{(k,m)}) E_{(k,m)}[l] - g_{(k,m)} \check{U}_{(k,m)}[l] \quad (2.39)$$

The use of the Lagrange function enables deriving a LMS updating rule, by substituting Eq. 2.39 into Eq. 2.13, and by calculating the requested partial derivatives in Eq. 2.6. These operations yield in the same frequency-domain, LMS algorithm stated in Eq. 2.31.

The control loop is closed by making $M + 1$ copies of $\mathbf{W}_m[l + 1]$, whereof two of them are used into the m^{th} control unit to calculate the control output, by following Eqs. 2.17 (only for real-valued, error and reference signals), 2.16, and 2.9, and to calculate $\check{U}_m[l]$ in Eq. 2.29. The remaining copies are taken in the frequency domain to the $M - 1$ control units, for them to calculate Eq. 2.29. This frequency-domain control scheme is illustrated in Fig. 2.3(b) and summarized in Table 2.3.

Convergence and stability

Convergence and stability aspects of the second proposed multichannel control scheme with coupling compensation are examined in a similar form to that of Algorithm 1. The following derivations are carried out for a generic Fourier bin, thus requiring no explicit notation in equations.

The frequency-domain, pseudoerror signal in Eq. 2.39 is now rewritten in matrix form, as follows:

$$\mathbf{E}'[l] = (\mathbf{I} - \mathbf{g}) \mathbf{E}[l] - \mathbf{g} \check{\mathbf{U}}^H[l], \quad (2.40)$$

By substituting Eqs. 2.18b and 2.33 into Eq. 2.40, and the resulting expression into Eq. 2.19, it follows that:

$$\begin{aligned} \mathbf{W}[l + 1] = \mathbf{W}[l] + \alpha \{ & -\beta \mathbf{W}[l] + \mathbf{X}^H[l] (\mathbf{I} - \mathbf{g}) (\mathbf{D}[l] - \mathbf{S} \mathbf{W}[l + 1] X[l]) \\ & - \mathbf{g} \mathbf{X}^H[l] \mathbf{X}''[l] \mathbf{W}[l + 1] \} \end{aligned} \quad (2.41)$$

Convergence is attained when suitable values for α have been provided in Eq. 2.41, and when the term in curly braces has vanished, which implies that:

$$\mathbf{W} = \left[\hat{\mathbf{S}}^H (\mathbf{I} - \mathbf{g}) \mathbf{D} \right] \left[\beta + \hat{\mathbf{S}}^H \left((\mathbf{I} - \mathbf{g}) \mathbf{S} + \mathbf{g} \check{\mathbf{S}} \right) \right]^{-1} \quad (2.42)$$

As long as $\check{\mathbf{S}}(z) \rightarrow \mathbf{S}(z)$, it follows that:

$$\mathbf{W} = \left[\hat{\mathbf{S}}^H (\mathbf{I} - \mathbf{g}) \mathbf{D} \right] \left[\beta + \hat{\mathbf{S}}^H \mathbf{S} \right]^{-1}, \quad (2.43)$$

expression that is analogous to that of the Algorithm 1, stated in Eq. 2.36. Therefore,

while stability of Algorithm 2 is governed by the same statements described for both Algorithms 1 and the multichannel system with no coupling compensation scheme, the convergence of Algorithms 1 and 2 turned out to be similar between each other. In this form, the goal on deriving a cost-effective multichannel control scheme that still features the coupling compensation scheme has been accomplished.

Computational complexity

Table 2.3 summarizes the calculations each control unit should perform to execute an iteration of either the time- or the frequency-domain version of the multichannel Algorithm 2 with coupling compensation. These calculations are sorted from the measurement of the error signals to the generation of the control signals. The computational complexity of the calculations reported on in Table 2.3 has been also worked out by taking into account the same assumptions as in Section 2.2.

The comparison amongst the multichannel control schemes with regard to the computational requirements in Section 2.5 will reveal that the multichannel Algorithm 2 is indeed a cost-effective solution for multichannel active sound profiling tasks, since its computational requirements are less demanding than the ones for Algorithm 1. The elimination of the calculation for $d_m''[n]$ (Eq. 2.23) allows saving MQ multiplications and MQ additions, which, depending on the length Q of the FIR filters that represent the secondary paths, may represent a significant reduction of the computational requirement. However, since the compensation for the flipping between $S(z)$ and $w[n]$ is lost, due to the fact that the term $d''[n] = e[n] + \sum_M S(z)w[n]x[n]$ is eliminated by means of Eq. 2.37, the convergence rate turns out to be negatively affected. Even so, since the special mathematical entity $\tilde{u}[n]$, defined in Eq. 2.24a, is accounted for the derivation of Algorithm 2, the ability for counterbalancing cross-channel interferences is still present in this system.

2.4 Multichannel control scheme for amplitude- and relative-phase-based active sound profiling

The multichannel control scheme that will be derived in this section is based on the IMC strategy, discussed in Section 2.2. With the innovative strategy for compensating for cross-channel interferences, introduced in the previous section, time- and frequency-domain LMS-based updating rules have been newly derived for the IMC-based multichannel control scheme. As a result, the time-domain control scheme derived in this section is shown to carry out amplitude-based sound profiling tasks whereas the frequency-domain control scheme features the important ability to independently controlling the amplitude and the relative phase of $K/2 - 1$ equally-spaced tones in a

Table 2.3: Computational complexity of time- (TD) and frequency-domain (FD) versions of the multichannel Algorithm 2, given in real-valued multiplications and additions, required to control O (TD) or $L/2 - 1$ (FD) harmonics. The **total** number of multiplications and additions is given for the entire system (M channels).

Version	Equation	Number of Mult. ($\times$)	Number of Add. (+)
TD	2.1	-	-
	2.24b	MQ	$M(Q - 1)$
	2.24a	ML	$M(L - 1)$
	2.37	2	2
	2.26	$3L$	L
	2.9	L	$L - 1$
	Total	$O \{M [M(Q + L) + 4L + 2]\}$	$O \{M [M(Q + L - 2) + 2L + 1]\}$
FD	2.1	-	-
	2.24b	MQ	$M(Q - 1)$
	2.28	$ML \log_2 L$	$ML \log_2 L$
	2.29	$4ML$	$2L(M - 1)$
	2.38	$L \log_2 L$	$L \log_2 L$
	2.39	$8L$	$4L$
	2.31	$12L$	$2L$
	(2.17) - 2.16	$L \log_2 L$	$L \log_2 L$
	2.9	L	$L - 1$
	Total	$M \{M[Q + L(\log_2 L + 4)] + L(2 \log_2 L + 21)\}$	$M \{M[Q + L(\log_2 L + 2) - 1] + L(2 \log_2 L + 5) - 1\}$

Source: Mosquera-Sánchez et al. (2017b).

complex primary sound, for multiple listeners within a cavity. In this case, $K = L$ is the length of internally calculated discrete Fourier transforms, which also equals the order of the adaptive FIR filter that represents the adaptive controller into each channel.

2.4.1 Algorithm 3

Figure 2.3 illustrates block diagrams of both time- and frequency-domain versions of the channel M of the third $M \times M$ multichannel control scheme that features the compensation mechanism. The operation of the compensation strategy in this multichannel control scheme relies on the fact that $d''[n]$ correctly represents the primary sound, together with the control signals that reach the M^{th} error sensor.

Time-domain algorithm: amplitude control

The derivation of this control scheme directly starts from Eqs. 2.1 and 2.23, which represent both the error signal $e_m[n]$, as well as the *correctly estimated* primary sound, $d''_m[n]$. At this point, it has to be recalled that the accuracy of $d''_m[n] \rightarrow d_m[n]$ relies on the quality of the estimate of each j^{th} term, $\hat{S}_{(m,j)}(z)$, in Eq. 2.23.

The pseudoerror stated in Eq. 2.3b can be straightforwardly redefined, by using Eqs. 2.1 and 2.23, as follows:

$$c_m[n] = g_m^{(a)}(d''_m[n]) \quad (2.44a)$$

$$e'_m[n] \equiv e_m[n] - c_m[n], \quad (2.44b)$$

where $c_m[n]$ is the so-called *command signal* of the m^{th} channel (REES; ELLIOTT, 2006), and $g^{(a)} \in \mathbb{R}^{[0, 2]}$ is a gain factor for the amplitude of $d''_m[n]$.

A time-domain LMS updating rule can be obtained, by substituting Eq. 2.44b into Eqs. 2.5 and 2.6 that stand for the Langrange function and the complex-domain iterative algorithm, respectively. The resulting expression is equal to the one in Eq. 2.7, or Eq. 2.31, which in turn are similar between each other. Notice that, even when the derivation in Eqs. 2.44a and 2.44b accounted for the proper estimation of the primary sound, the resulting LMS updating rule is merely a function of the direct secondary path $\hat{S}_{(m,m)}(z)$. This result is similar to the one obtained when deriving Algorithms 1 and 2, which follows from the fact that independent cost functions at each error sensor location are proposed to be minimized.

The time-domain control loop of the channel m is closed by following the same expression as in the previously derived control schemes, namely Eq. 2.9.

Figure 2.4: Block diagram of the multichannel amplitude and relative-phase control scheme 3: (a) time-domain version; (b) frequency-domain version.

Source: Mosquera-Sánchez et al. (2017a).

Frequency-domain algorithm: amplitude and relative-phase control

Amplitude and relative-phase control of periodic noises containing a number of harmonics is tackled by using frequency-domain ASQC systems, mainly due to computational aspects, as well as to the possibility of retrieving the relative-phase data of the targeted tones (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b).

The pseudoerror signal in Eq. 2.44b is then transformed into the frequency domain, by means of length- K discrete Fourier transforms, to be calculated over buffers of L time-domain samples of both the estimated primary disturbance and the error signal, as stated in Eqs. 2.27 and 2.38, respectively.

Prior to calculate $\mathbf{E}'_m[l] \leftarrow e'_m[n]$, the frequency-domain version of the command signal $c_m[n]$ in Eq. 2.44a should be realized, by applying multiplicative ($g_{(k,m)}^{(a)} \in \mathbb{R}^{[0, 2]}$), and/or additive ($g_{(k,m)}^{(p)} \in \mathbb{R}^{[-1, 1]}$) factors at each Fourier bin k . This has the purpose of requesting the frequency-domain adaptive algorithm to converge to either *amplitude* or *relative-phase operation modes*, or to a combination of both, as follows (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b):

$$|C_{(k,m)}[l]| = g_{(k,m)}^{(a)} |D''_{(k,m)}[l]| = g_{(k,m)}^{(a)} \sqrt{\text{Re}(D''_{(k,m)}[l])^2 + \text{Im}(D''_{(k,m)}[l])^2} \quad (2.45a)$$

$$\angle C_{(k,m)}[l] = \text{mod} \left(\pi g_{(k,m)}^{(p)} + \angle D''_{(k,m)}[l], \pi \right) \quad (2.45b)$$

$$= \text{mod} \left[\pi g_{(k,m)}^{(p)} + \tan^{-1} \left(\frac{\text{Im}(D''_{(k,m)}[l])}{\text{Re}(D''_{(k,m)}[l])} \right), \pi \right],$$

$$C_{(k,m)}[l] = \{|C_{(k,m)}[l]| \cos(\angle C_{(k,m)}[l]), |C_{(k,m)}[l]| \sin(\angle C_{(k,m)}[l])\} \quad (2.45c)$$

$\mathbf{C}_m[l] \in \mathbb{C}^{(K \times 1)}$ should be returned in Cartesian coordinates, as indicated in Eq. 2.45c, so that the frequency-domain version of the subtraction in Eq. 2.58 can be carried out. Notice that the Fourier bin index k has been made explicit in Eqs. 2.45a, 2.45b and 2.45c, for highlighting that the application of amplitude and/or relative-phase factors should be carried out for each Fourier bin. When dealing with real-valued signals, only $K/2 + 1$ Fourier bins are requested to update the adaptive controller, then $\{\mathbf{E}_m[l], \hat{\mathbf{D}}_m[l]\} \in \mathbb{C}^{(K/2+1 \times 1)}$, and thus amplitude/relative-phase operations in Eqs. 2.45a and 2.45b can just be applied to $K/2 - 1$ Fourier bins, with $k = 1 : K/2$ being the bins at which primary sound harmonics are supposed to be falling into. In this way, $\mathbf{C}_m[l] \in \mathbb{C}^{(K/2+1 \times 1)}$.

At this point, the frequency-domain version of Eq. 2.44a can be calculated, as follows:

$$\mathbf{E}'_m[l] = \mathbf{E}_m[l] - \mathbf{C}_m[l] \quad (2.46)$$

The pseudoerror signal in Eq. 2.58 is substituted into Eq. 2.13, and the result is

eventually substituted in Eq. 2.14. In this form, the same frequency-domain LMS updating rule as in Eq. 2.14 is obtained. The resulting LMS updating rule is a function of the direct secondary path, in a similar form as in the time-domain counterpart of this multichannel control scheme.

The control loop is closed after performing an inverse Fourier transform on the adapted frequency-domain weights, in a similar form as in the frequency-domain multichannel systems previously derived. Therefore, Eq. 2.17 (only applicable if $\mathbf{W}_m[l] \in \mathbb{C}^{(K/2+1 \times 1)}$) and Eq. 2.16 can be followed to realize the time-domain controller, and Eq. 2.9 should be eventually used to close the loop with the generation of the m^{th} control signal, $u_m[n]$.

Convergence and Stability

To study convergence and stability aspects, the time-domain version of the multichannel Algorithm 3 will be used, once that the time- and frequency-domain updating rules are essentially the same, except from the time-domain block index, $l = nL Ts$.

Equation 2.7 is then rewritten in matrix form, as follows:

$$\mathbf{w}_{(n+1)}(z) = (\mathbf{I} - \alpha\beta) \mathbf{w}_{(n)}(z) + \alpha \mathbf{x}'^H[n] \mathbf{e}'[n], \quad (2.47)$$

where $\{\mathbf{e}'[n], \mathbf{w}_{(n)}(z), \mathbf{w}_{(n+1)}(z)\} \in \mathbb{C}^{M \times 1}$ are vectors containing M pseudoerror signals, and adaptive weights of the M control units at times n and $n + 1$, respectively; $\mathbf{I} \in \mathbb{1}^{M \times M}$ is the identity matrix; $\{\alpha, \beta\} \in \mathbb{R}^{M \times M}$ are diagonal matrices containing step-sizes and constraint values for the M control units, respectively; and $\mathbf{x}'[n] \in \mathbb{C}^{M \times M}$ is the matrix defined as:

$$\mathbf{x}' = \hat{\mathbf{S}}(z)x[n] \equiv \begin{bmatrix} \hat{\mathbf{S}}_{(1,1)}(z)x[n] & 0 & \cdots & 0 \\ 0 & \hat{\mathbf{S}}_{(2,2)}(z)x[n] & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{\mathbf{S}}_{(M,M)}(z)x[n] \end{bmatrix} \quad (2.48)$$

Equations 2.1, 2.23, and 2.44b are rewritten in matrix form, as follows:

$$\begin{aligned} \mathbf{e}[n] &= \mathbf{d}[n] - \mathbf{S}(z) \{\mathbf{w}_{(n+1)}(z)x[n]\}; \\ \mathbf{d}''[n] &= \mathbf{e}[n] + \check{\mathbf{S}}(z) \{\mathbf{w}_{(n+1)}(z)x[n]\}; \\ \mathbf{e}'[n] &= \mathbf{e}[n] - \mathbf{g}(\mathbf{d}''[n]), \end{aligned} \quad (2.49)$$

where $\mathbf{g} \in \mathbb{R}^{M \times M}$ is a diagonal matrix containing either amplitude or relative-phase (only for the frequency-domain control loop) gain factors for the M control units; $\check{\mathbf{S}}(z)$ is the estimate of the *full* control paths matrix that accounts for both diagonal and coupling terms; and $\{\mathbf{d}[n], \mathbf{d}''[n], \mathbf{e}[n]\} \in \mathbb{C}^{M \times 1}$ are vectors containing the actual primary sound,

the estimated primary sound and the error signals, respectively, as measured at the M locations.

The expressions in Eqs. 2.48 and 2.49 allows Eq. 2.47 being rewritten as follows:

$$\begin{aligned} \mathbf{w}_{(n+1)}(z) = \mathbf{w}_{(n)}(z) + \alpha \bigg\{ & -\beta \mathbf{w}_n(z) + \left(\hat{\mathbf{S}}(z)x[n] \right)^H \mathbf{d}[n] \\ & - \left(\hat{\mathbf{S}}(z)x[n] \right)^H \mathbf{g}(\mathbf{d}''[n]) - \left(\hat{\mathbf{S}}(z)x[n] \right)^H \mathbf{S}(z) \mathbf{w}_{(n+1)}(z)x[n] \bigg\} \end{aligned} \quad (2.50)$$

As long as suitable values have been provided for α , the convergence of the algorithm is attained, when $\mathbf{w}_{(n+1)}(z) = \mathbf{w}_{(n)}(z)$. Moreover, provided that $x[n]$ is an unitary-amplitude, zero-phase reference signal with frequency $\omega^{(x)}$, $\mathbf{S}(z)x[n]$ and $\hat{\mathbf{S}}(z)x[n]$ are nothing but $\mathbf{S}(z)$ and $\hat{\mathbf{S}}(z)$ themselves, as excited at $\omega^{(x)}$. Thus, the terms within curly braces in Eq. 2.50 can be rewritten as follows:

$$\mathbf{w}_n(z) = \left\{ \hat{\mathbf{S}}^H(z) [\mathbf{d}[n] - \mathbf{g}(\mathbf{d}''[n])] \right\} \left[\beta + \hat{\mathbf{S}}(z)^H \mathbf{S}(z) \right]^{-1}, \quad (2.51)$$

Equation 2.51 provides the set of adaptive weights that makes the multichannel array to attain the desired sound profiling targets, as given by $\mathbf{g}$ in terms of either amplitude or relative-phase modes, or both, provided that the matrix in brackets has all of its eigenvalues with positive, real parts (BOUCHER et al., 1991; ELLIOTT; BOUCHER, 1994). As soon as $\mathbf{d}''[n] = \mathbf{d}[n]$, the expression given by Eq. 2.51 becomes analogous to that of the Algorithms 1 and 2, for which some remarks have been already drawn.

Computational complexity

Table 2.4 summarizes the calculations each control unit should perform to execute an iteration of either the time- or the frequency-domain version of the multichannel Algorithm 3 with coupling compensation. These calculations are sorted from the measurement of the error signals to the generation of the control signals. The computational complexity of the calculations reported on in the Table has been worked out by taking into consideration the same assumptions as in Section 2.2, as well as the following ones for the amplitude and relative-phase calculations:

- The number of bins at which harmonics of the primary sound are falling into is $K/2 - 1 = L/2 - 1$. This makes the calculations in Eqs. 2.45a, 2.45b and 2.45c to be realized $L/2 - 1$ times during a single iteration.
- The computational complexity of a square root equals to 5 real-valued multiplications and 2 real-valued additions (MULLER, 2006);
- The computational complexity of a division is comparable to that of a multiplication, regardless of whether the operands are real- or complex-valued.

- The computational complexity of the $\tan^{-1}$ function amounts to 9 real-valued multiplications and 2 real-valued additions, as long as a 7th-order, Chebyshev polynomial is used to approximate such a function (MATHWORKS., 2016b);
- The computational complexity of the $\text{mod}()$ function is 2 real-valued multiplications and 1 real-valued addition;
- The conversion from polar to Cartesian coordinates takes 9 real-valued multiplications and 4 real-valued additions, by assuming that a 7th-order, Taylor series is used (MATHWORKS., 2016b).

The comparison amongst the multichannel control schemes with regard to the computational requirements in Section 2.5 reveals that the multichannel Algorithm 3 is comparable to the cost-effective Algorithm 2.

2.5 Discussion on the proposed control schemes

Three multichannel active periodic sound profiling systems have been derived in this chapter, which feature an innovative scheme for compensating for cross-channel interferences. The main concept behind the proposed strategy relies on the fact that the acoustic coupling terms, which have been deliberately neglected from the pure-decentralized multichannel formulation due to computational cost reasons, should be taken into account for multichannel active sound profiling tasks. While the acoustic coupling amongst channels is indeed taken into account in the centralized multichannel formulation, the proposed schemes account for the coupling, in such a form that *independent-zone* active sound profiling becomes feasible. The fact that the proposed control schemes minimize a number of cost functions associated to each error sensor, instead of minimizing a *centralized* cost function that associates all the sensors in the array, allows accomplishing such a goal.

The major difference amongst the centralized, decentralized and the proposed multichannel control schemes, relies on the processing of both the error and pseudoerror signals. While the adaptive algorithm in the centralized scheme should be aware of all the error signals, which also requires the reference signal to be filtered by both the direct and coupling terms of the secondary paths matrix, the adaptive algorithm in the decentralized control scheme is only aware of a reduced set of error signals, with the corresponding direct terms of $\mathbf{S}$. Thus, the calculations proposed for counterbalancing for the cross-channel interferences can be regarded as a means of *improving the information sensed by a single error sensor*, by adding up informations acquired by the remaining sensors. Hence, the pseudoerror signal that is fed through the m^{th} adaptive algorithm in the proposed control schemes is indeed an improved one that contains data from both the direct and coupling terms.

Table 2.4: Computational complexity of time- (TD) and frequency-domain (FD) versions of the multichannel Algorithm 3, given in real-valued multiplications and additions, required to control O (TD) or $L/2 - 1$ (FD) harmonics. The **total** number of multiplications and additions is given for the entire system (M channels).

Version	Equation	Number of Mult. ($\times$)	Number of Add. (+)
TD	2.1	-	-
	2.23	MQ	MQ
	2.44a	1	0
	2.44b	0	1
	2.8	Q	$Q - 1$
	2.7	$3L$	L
	2.9	L	$L - 1$
Total		$O \{M [(M + 1)Q + 4L + 1]\}$	$O \{M [(M + 1)Q + 2L - 1]\}$
FD	2.1	-	-
	2.23	MQ	MQ
	2.27	$L \log_2 L$	$L \log_2 L$
	2.45a	$3(L - 2)$	$L - 2$
	2.45b	$13(L/2 - 1)$	$L - 2$
	2.45c	$9(L/2 - 1)$	$2(L - 2)$
	2.38	$L \log_2 L$	$L \log_2 L$
	2.58	0	L
	2.8	Q	$Q - 1$
	2.15	$L \log_2 L$	$L \log_2 L$
	2.14	$12L$	$2L$
	(2.17) - 2.16	$L \log_2 L$	$L \log_2 L$
	2.9	L	$L - 1$
Total		$M \{(M + 1)Q - 28 + L(4 \log_2 L + 27)\}$	$M \{(M + 1)Q - 10 + 4L(\log_2 L + 2)\}$

Source: Mosquera-Sánchez et al. (2017a).

The possibilities in which the pseudoerror signal can be improved have led to the proposition of the three control schemes already discussed, as follows:

- Algorithm 1: the pseudoerror signal is improved by sharing the time-domain control signals, $u[n]$, and time- or frequency-domain adapted weights, $w[n]$ or $W[l]$, in order to calculate an entity, $\check{u}[n]$ or $\check{U}[l]$, which in turn allows estimating all the control output signals that reach a given sensor location.

- Algorithm 2: the pseudoerror signal is improved by just sharing the time- or frequency-domain adapted weights, $w[n]$ or $W[l]$, in order to calculate either $\tilde{u}[n]$ or $\tilde{U}[l]$.
- Algorithm 3: the pseudoerror signal is improved by sharing the time-domain control signals, $u[n]$, in order to properly calculate the signal $d''[n]$, which contains both primary sound and control signals that reach a given sensor location.

All the explored possibilities rely on the fact that the *overall array control output* should be estimated, being it directly ($\tilde{u}[n]$), or indirectly ($d''[n]$). At that point, it has to be recalled that the operation of these multichannel systems strongly relies on: (i) the proper estimation of the secondary paths from the m^{th} error sensor to each of the M actuators; and (ii) the *interchange* of the data amongst the channels of the system.

As an example of the operation of the cross-coupling compensation scheme, let a control signal generated by Channel 1, $u_1[n]$ in Figs. 2.2, 2.3, or 2.4, be copied to the Channel M , by means of the internal representation of the dynamics between actuator 1 and sensor M , namely $S_{(M,1)}(z)$. This will enable Channel M to estimate the incoming signal from Channel 1, which reaches its corresponding sensor M . Then, according to Eq. 2.1, the cross-channel interference caused by the Channel 1 at Channel M can be modeled as follows:

$$e_M[n] = d_M[n] - S_{(M,1)}(z) \{w_1[n]x[n]\} \quad (2.52)$$

If the inactive, or *preservation* operation mode, i.e. $\{g_M^{(a)}, g_M^{(p)}\} = \{1, 0\}$, is targeted at location M , the control unit M should then minimize the pseudoerror given by:

$$e'_M[n] = -S_{(M,1)}(z) \{w_1[n]x[n]\} - \hat{S}_{(M,M)}(z) \{w_M[n]x[n]\}, \quad (2.53)$$

i.e. the cross-channel interference *and* the corresponding control signal for location M , respectively. At the very beginning of the operation, it follows that:

$$\hat{S}_{(M,M)}(z) \{w_M[n]x[n]\} = 0, \quad (2.54)$$

since no control action is requested for control unit M . Moreover, after convergence, i.e. when the pseudoerror is minimized, it follows that:

$$w_M[n \rightarrow \infty] = -S_{(M,1)}(z)w_1[n]\hat{S}_{(M,M)}(z)^{-1}, \quad (2.55)$$

i.e. the adaptive controller M converges to the counterbalance of the interference coming from Channel 1, provided that the inverse of the direct secondary path exists, which is the case in physical multichannel arrays that have their sensors properly associated

to corresponding actuators. Moreover, as soon as Channel M starts sending counterbalance signals, these should be also exchanged with Channel 1 in order to perform the same calculations described before, so that both adaptive controllers $w_{(j=\{1,M\})}[n]$ are simultaneously adjusted, while its coefficients (only for Algorithms 1 and 2) are also interchanged during uptime.

In the actual acoustic plant, counterbalancing the cross-channel interferences at location M implies in physically sending signals that compensate for the control signals coming from Channel 1. In addition, Channel 1 that implement the requested actions should also carry out calculations for accounting for the cross-channel interference from location M , so as to first obtain the compensated pseudoerror signal, and to converge to the adaptive filter that implements the desired action. Hence, the proposed *distributed multichannel control schemes* do incur in additional energy requirement, as compared with current decentralization schemes, but they bring the benefit of canceling out cross-channel interferences that (i) prevent the right attainment of sound profiling tasks for multiple listeners, and that (ii) may deteriorate the auditory qualities of sounds at locations of interest within a cavity.

The ability of the frequency-domain versions of the multichannel systems in controlling either the amplitude or the relative-phase function, or both, of $K/2 - 1$ harmonics in a multi-harmonic sound, where $K = L$ is the length of the Fourier transform that equals the order of the adaptive filter per control unit, should make the proposed control schemes to be the definitive choice for performing active sound profiling of periodic disturbances for multiple listeners. Provided the matrix given by $\mathbf{A} = \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ only shows eigenvalues with positive real parts, the proposed control targets can be attained with no control effort constraints. Otherwise, the stabilization of the multichannel control schemes via control effort constraints reduces the performance of the controllers, as given in terms of both attainment of control targets and rejection of cross-channel interferences. Even so, this stabilization strategy has been shown to not hinder the operation of the counterbalancing scheme, and this will be verified through both computer simulations and experiments with the proposed multichannel systems.

Finally, it is worth noticing that each control unit in the Algorithm 2 consists of a novel IMC control scheme, which eliminates the need for estimating $d[n]$ (cf. Eq. 2.3). This, in turn, results in less computational cost than the time-domain IMC-based multichannel Algorithm 0, which is the pure-decentralized multichannel control scheme, as well as Algorithm 3, which is the multichannel amplitude- and relative-phase-based control scheme with coupling compensation. Moreover, each control unit in the Algorithm 1 is indeed the modified filtered-X control scheme, which is known for featuring the fastest convergence, being its adaptive controller updated by either LMS or recursive-least-squares (RLS) algorithms (OPHEM; BERKHOF, 2015). Hence, while the Algorithm 1 is the fastest solution to perform free-of-interference multichannel active sound pro-

filing, the Algorithm 2 can be regarded as a cost-effective solution, intended for less powerful DSP boards, but still able to deliver active sound profiling solutions for multiple listeners. Furthermore, the additional computation cost that has to be incurred by using Algorithm 3, as compared to Algorithm 2, is worth when delivering amplitude- and relative-phase-based active sound profiling for multiple listeners. These operation modes enable the specialist to control SQ metrics such as Roughness and others that are sensitive to both amplitude and relative-phase spectral functions of periodic sounds.

Computational demands of the proposed control schemes

Figure 2.5 illustrates the number of multiplications and additions Algorithms 0, 1, 2 and 3 require to complete an iteration, as a function of the number of control units implemented in a system. A fixed order of $Q = 584$ weights has been defined for the FIR filter that represents any of the direct and coupling terms of the secondary paths. This filter length matches that of the Experiments 1, 2, 3, and 4, cf. Chapter 5. For the calculation of that Figure, it has also been assumed that a periodic sound with $O = 10$ harmonics is to be controlled. Hence, while the computational cost of the frequency-domain control loops has been calculated by making $L = 22$, which allows controlling $L/2 - 1 = 10$ harmonics, the order of the adaptive filters in the time-domain control schemes has been assumed as $L = 2$, once that this is the minimum length that still allows controlling narrowband disturbances.

Figure 2.5(a) evidences that, while the time-domain Algorithm 0, i.e. the pure-decentralized one, requires a minimum of multiplications and additions to complete one iteration, the Algorithm 1 does require a large amount of resources for providing free-of-interference active sound profiling, at a speed that is only comparable to that of the computationally decoupled Algorithm 0. Moreover, the computational needs of both the time-domain Algorithms 2 and 3 are comparable to each other, being that Algorithm 2, which has been claimed as a new form of IMC scheme, slightly outperforms Algorithm 3 in this aspect. The elimination of the calculation for $d''[n]$ has helped in accomplishing that computational saving. Even so, since the time-domain Algorithms 2 and 3 are only able to deliver amplitude-based active sound profiling tasks, the preferred choice in this case should then be the Algorithm 2, which still operates at a reasonable convergence rate, as compared with the fastest Algorithm 1.

When it comes to comparing the frequency-domain versions of the multichannel Algorithms, Fig. 2.5(b) again unveils that, while the decoupled Algorithm 0 is the lightest one, the Algorithm 1 is the heaviest one. However, it is worth noticing in this Figure that the computational demands of Algorithm 2 become larger than the ones of the Algorithm 3, as the number of control units grows. This comes from the fact that, while the calculation of the pseudoerror in Algorithm 2 directly considers all the

Figure 2.5: Computational complexity of the multichannel Algorithms 0, 1, 2 and 3, as a function of the number of SAPs: (a) time-domain versions; (b) frequency-domain versions. Parameters: $O = 10$; $Q = 584$; $L_{TD} = 2$; $L_{FD} = 22$.

K Fourier bins, the calculation of the pseudoerror in Algorithm 3 has been mainly focused on the obtainment of the *command signal* $c[n] \rightarrow C[l]$, which is only concerned with the Fourier bins $k = 1 : K/2$, i.e. with the functional $K/2 - 1$ bins in which the narrowband components of the primary sound are falling into. This small saving in the computation of Algorithm 3 becomes critical as the amount of control locations grows, to such an extent that its computation requirement becomes more affordable than the one of Algorithm 2.

Therefore, even when it has been acknowledged that Algorithm 3 owns an important advantage over Algorithms 1 and 2 in controlling both amplitude and relative-phase functions of periodic sounds, the fact that this Algorithm also requires less computation resources should make it the preferred choice for delivering independent-zone active sound profiling for multiple listeners. However, when multichannel amplitude-based active sound profiling is of concern, either the Algorithm 1 should be chosen if the convergence speed is of concern, at the cost of a high computational demand, or the Algorithm 2 if only a low-power DSP hardware is available for the real-time implementation.

2.6 Computer simulations

This section provides results from computer simulations, which are intended to give insights on the influence of the SAP placement, the system damping and plant magnitude variations on the tuning performance of the proposed multichannel control schemes. Their performance is also compared with the one of the pure-decentralized and the centralized control schemes.

2.6.1 Numerical model of the plant

An arbitrary lumped parameter mechanical system, composed of eight DoFs is considered. This model has been simplified for the sake of the quick verification of the proposed control schemes, while keeping resemblances with the actual workbench cavity acoustics, e.g. similar resonance frequencies. The DoFs, each of which is 0.125 kg in mass, are restricted to move along the x axis. A global stiffness value of $Kk = 2.5e^{05}$ N.m⁻¹ is given to the system, from which each of the springs along the x axis have been defined as $Kk/0.6$ N.m⁻¹, each of the springs along the y axis is $Kk/0.8$ N.m⁻¹, and each of the ones along the z axis is $Kk/1.2$ N.m⁻¹. A proportional damping matrix is used, as well. Since a number of damping conditions are to be tested in Section 2.6.4, these coefficients will be provided and discussed in that subsection.

A number of SAP combinations can be obtained, by varying the DoFs at which the inputs/outputs are placed/sensed. To do this, the 2nd-order mass-stiffness-damping representation of the system, with mass, $\mathcal{M}$, and stiffness, $\mathcal{K}$, given by:

$$\mathcal{M} = 0.13 (\mathbf{I}) Kg;$$

$$\mathcal{K} = \begin{bmatrix} 1.35 & -0.21 & 0.00 & -0.31 & -0.42 & 0.00 & 0.00 & 0.00 \\ -0.21 & 1.35 & -0.31 & 0.00 & 0.00 & -0.42 & 0.00 & 0.00 \\ 0.00 & -0.31 & 1.35 & -0.21 & 0.00 & 0.00 & -0.42 & 0.00 \\ -0.31 & 0.00 & -0.21 & 1.35 & 0.00 & 0.00 & 0.00 & -0.42 \\ -0.42 & 0.00 & 0.00 & 0.00 & 0.94 & -0.21 & 0.00 & -0.31 \\ 0.00 & -0.42 & 0.00 & 0.00 & -0.21 & 0.94 & -0.31 & 0.00 \\ 0.00 & 0.00 & -0.42 & 0.00 & 0.00 & -0.31 & 0.94 & -0.21 \\ 0.00 & 0.00 & 0.00 & -0.42 & -0.31 & 0.00 & -0.21 & 0.94 \end{bmatrix} \times 10^6 N/m,$$

where $\mathbf{I} \in \mathbb{R}^{8 \times 8}$ is the identity matrix, and the proportional damping matrix is given by $\mathcal{D} = \gamma_{\mathcal{M}} (\mathcal{M}) + \gamma_{\mathcal{K}} (\mathcal{K})$, where both coefficients of mass and stiffness proportionality take five different values (cf. Section 2.6.4) for comparisons, is rewritten in the state space form, with state matrix $\mathcal{A}$, input matrix $\mathcal{B}$, output matrix $\mathcal{C}$ and feedthrough matrix $\mathcal{G}$ given by:

$$\mathcal{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathcal{K}.\mathcal{M}^{-1} & -\mathcal{C}.\mathcal{M}^{-1} \end{bmatrix}; \quad \mathcal{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{b}.\mathcal{M}^{-1} \end{bmatrix}$$

$$\mathcal{C} = [\mathbf{c} \quad \mathbf{0}]; \quad \mathcal{G} = 0,$$

where $\mathbf{b} = \mathbf{I}$ and $\mathbf{c} = \mathbf{I}$, from which two different SAP setups have been extracted for comparisons. While in both SAP setups the primary input is plugged to DoF #5, the sensors and actuators have been placed in either collocated or non-collocated fashions, as follows:

- SAP setup #1 has both of its sensors and actuators placed at DoFs #5, 6, 7 and 8.
- SAP setup #2 has its sensors placed at DoFs #5, 6, 7 and 8, whereas the actuators have been placed at DoFs #1, 2, 3 and 4. In this setup, the sensor/actuator correspondence has been defined as 5/1, 6/2, 7/3 and 8/4. This is the non-collocated SAP setup.

Figure 2.6: *Sketch of the numerical model of the mechanical system used for simulations.*

Source: Adapted from Mosquera-Sánchez et al. (2017b).

Figure 2.6 illustrates the numerical model investigated in this section. The dark-gray masses are the DoFs in which the inputs are placed. While in the SAP setup #1 the outputs are also sensed at the same input DoFs (5, 6, 7, and 8), the SAP setup #2 has its outputs sensed at DoFs 1, 2, 3, and 4.

2.6.2 Implementation

The mass and stiffness matrices of the structural system have been assembled in MATLAB. The system is then rewritten in the state space, from which two sub-systems are extracted, for each SAP setup: (i) the first sub-system with one input and four outputs, which represents the primary input paths, and (ii) the second one with four inputs and four outputs at the same locations of the outputs of the primary input paths, which represents the secondary paths. The impulse responses extracted from each actuator to each sensor are eventually programmed in the form of FIR filters.

The scripts for the control schemes have been written as C-S functions for Simulink. The Simulink implementation of the secondary paths follows the block diagrams squared by using dashed lines and labeled as "system", in any of Figs. 2.1, 2.2, 2.3

or 2.4. The control units execute their operations in a serial form, i.e. the generation of the control outputs should wait until the communication flow from Channels 1 - 4 has been carried out.

Since the multichannel centralized controller has the purpose of minimizing the primary disturbance at all locations, this control scheme has been adapted in an attempt to make its results comparable with the ones of the pure-decentralized system, as well as of the Algorithms 1, 2 and 3. Then, the calculations given in Eq. 2.3b have been appended to the flow of the m^{th} error signal towards the centralized LMS algorithm, in order to provide, or at least emulate, the equalization ability of the above cited control schemes. The remaining $M - 1$ error signals $e_{(j=1:M; j \neq m)}[n]$ are routed to the LMS algorithm with no additional calculations, as described by Elliott et al. (1987) and González et al. (2006). Figure 2.7 illustrates the adaptations made on the decentralized IMC-based control scheme described in this paragraph. The adopted sampling rate for all the simulations is 1600 Hz.

Figure 2.7: Block diagram of the modified time-domain multichannel centralized control scheme.

2.6.3 Influence of the SAP positioning

The visual comparison between the magnitude of the frequency response function (FRF) of the SAP Setups #1 and #2, cf. Fig. 2.8(a) and Fig. 2.9(a), reveals some important differences. While in Setup #2 the overall magnitude levels are smaller than the observed ones in Setup #1, due to the actuator locations, the level of the crossed paths in Setup #2

(dash-dot and dotted lines in Fig. 2.9(a)) becomes larger than the one of the direct paths (continuous lines in the same Figure) at some bandwidths, e.g. the one between 550 Hz and 650 Hz.

The fact that the level of any of the crossed paths is larger than the one of the direct paths has an influence on the stability of any of the decentralized/distributed multichannel control schemes. In general, when any of the off-diagonal entries of $|\mathbf{S}(z)|$ is larger than the corresponding diagonal entry at the m^{th} row, the matrix $\mathbf{A} = \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ will exhibit, at least, one of its eigenvalues with its real part negative. This situation will demand the use of the control output constraint, β , in order to make $\mathbf{A} = \beta \mathbf{I} + \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ to show all its eigenvalues with positive, real parts.

Figures 2.8(b) and 2.9(b) that illustrate the norm-2 condition number of matrix $\mathbf{A}(z)$ as a function of the frequency, also highlight, in dark points, the frequencies at which an eigenvalue with negative real part has been found. In these Figures, it is shown that some instability occurrences into the bandwidth comprised between 500 Hz and 700 Hz vanish from Setup #2 to Setup #1, as a result of having the level of the crossed paths smaller than the one of the direct paths. Since the difference between Setups #1 and #2 rely on the location of the actuators, it can be stated that the placement of the sensor/actuator pairs does have an influence on the stability of the multichannel systems along the operation bandwidth. It is still possible, however, to find matrices that exhibit eigenvalues with negative real parts, even when all the off-diagonal entries at the m^{th} row are smaller than the corresponding diagonal entry. Setup #2 offers some examples of such unusual cases, e.g. the matrices comprised between 400 Hz and 440 Hz, cf. Fig. 2.9(a).

Since the spread of the magnitude levels of Setup #1 is smaller than the one of Setup #2, cf. Figs. 2.8(a) and 2.9(a), the norm-2 condition number functions plotted in Figs. 2.8(b) and 2.9(b) reflect such a condition. The fact that the LMS algorithm is sensitive to the condition of the system of linear equations will have an influence on the convergence speed of the proposed multichannel control schemes. As the control matrix becomes more ill-conditioned, the LMS algorithms at each control unit will need to take more iterations to either converge or diverge, which depends on whether the persistently excited control matrix meets or not the stability condition discussed in the previous paragraphs.

2.6.4 Influence of the system damping

Figure 2.10 illustrates the influence on both the magnitude and the norm-2 condition number functions of five different proportional damping coefficients tested on the SAP Setup #1. The damping matrix has been obtained by making $\mathbf{D} = \gamma_{\mathcal{M}}(\mathbf{M}) + \gamma_{\mathcal{K}}(\mathbf{K})$, where $\gamma_{\mathcal{M}} = \gamma_{\mathcal{K}} = \{0.25, 0.44, 0.63, 0.81, 1.0\} \times 10^{-05}$. In the mentioned Figure, the

Figure 2.8: Setup #1: (a) magnitude of the FRF; (b) norm-2 condition number.

Source: Mosquera-Sánchez et al. (2017b).

system plotted by dark lines is the most similar to the one that is found in most of the automotive applications, where the floor, roof and walls are typically covered by acoustically-absorbent material. As soon as the magnitude values become more uniform, i.e. their spread is reduced, the conditioning of the system gets improved, as it can be verified by examining Fig. 2.10(b). In this Figure, it is also possible to notice that the less damped system shows a large number of instability occurrences, highlighted in light-gray star markers. Some of those instabilities vanish by the effect of the added passive damping, thus giving rise to control matrices that allow the proposed control

Figure 2.9: Setup #2: (a) magnitude of the FRF; (b) norm-2 condition number.

Source: Mosquera-Sánchez et al. (2017b).

schemes to perform with no output constraints.

2.6.5 Assessment of the tuning performance

Simulations with five time-domain, multichannel control schemes, namely the centralized, pure-decentralized (Algorithm 0) and the proposed Algorithms 1, 2 and 3, are presented in this subsection, which provide deep insights on the particularities of each multichannel system. The test system is the one that was plotted in Fig. 2.8(a), in other words, the collocated, most damped system that was also plotted in Fig. 2.10(a). Plant

Figure 2.10: Setup #1 under different damping conditions: (a) magnitude of the FRFs; (b) norm-2 condition number.

Source: Mosquera-Sánchez et al. (2017b).

magnitude variations in the form of $\hat{\mathbf{S}}(z) = a\mathbf{S}(z)$ (REES; ELLIOTT, 2006), where a has been allowed for taking five different values, have been deliberately introduced to verify the robustness of the control schemes.

Parameters calculations

At the frequencies in which the off-line analysis showed instability, the constraints were calculated by making:

$$\delta = 2diag \left(\left| \hat{\mathbf{S}}(z) \right| \right) L, \quad (2.56)$$

where $L = 10$ was adopted as the order of the time-domain adaptive controller.

The step sizes for the Algorithm 1 were found by calculating the following, adapted expression (VICENTE; MASGRAU, 2006):

$$\mu_j = \frac{1.0}{LB_j O (2\Delta_j + 1)}, \quad (2.57)$$

where μ is given for each $j = 1 : M$ control unit, as a function of the length of the adaptive filter $L = 10$; the number of tones being controlled $O = 1$; the power of the reference signal related to a given sensor B and the minimum phase delay Δ between a given sensor and the actuators, which in turn have been calculated as follows:

$$B_j = \sqrt{\sum_{j=1}^M |\hat{\mathbf{S}}_{(m,j)}(z)|^2}; \quad \Delta_j = \min \left(-\frac{\phi_{(m,j=1:M)}}{\Omega} \right), \quad (2.58)$$

where $\phi_{(m,j=1:M)}$ is the absolute phase of the secondary paths related to sensor m , and Ω is the frequency vector at which the secondary paths have been identified. The step-sizes for Algorithm 2 were taken as half the ones for Algorithm 1, and the ones for Algorithm 3 that still ensure fast and stable operation were found as being a quarter the ones for Algorithm 1. The step-sizes for the centralized control scheme were found in a trial-and-error basis.

Table 2.5 summarizes the parameters for the four multichannel systems being compared. Notice that, since the centralized control scheme is inherently stable, no effort constraints were needed, even when dealing with the case of the primary sound that excited a unstable matrix $\mathbf{A}(z)$, i.e. the mono-frequency primary sound at 400 Hz. Moreover, the Algorithm 3 was stabilized by using a smaller constraint value than the required one for Algorithms 1 and 2. This has allowed Algorithm 3 performing better in this situation, as it will be observed in the following paragraphs.

In this Table, the step sizes have been sorted by starting from the Centralized control scheme to Algorithm 3, for each disturbance.

Simulations: centralized scheme and Algorithms 0, 1 and 2

Two different pure sinusoids are selected as the primary disturbance, in order to evaluate the SAP Setup #1. The first disturbance, which consists of a 500 Hz tone, excites a control matrix that meets the stability condition. The second disturbance, which is a 400 Hz tone, excites an unstable control matrix. Since the two disturbances excite different matrix conditions, two timeframes have been allowed for the controllers to attain the requested target: (i) for the disturbance at 500 Hz the allowed timeframe is 5 s, and (ii) for the 400 tone the allowed timeframe is 15 s. Then, all the operation modes, namely cancellation, reduction, amplification and inactive modes, are tested in the following

Table 2.5: The smallest real part of any of the eigenvalues, and norm-2 condition number, of matrix $A = \text{diag}(\hat{S}(z))^H S(z)$ during simulations, together with the parameters for the LMS adaptive algorithm in multichannel Algorithm 1, for each control unit. Algorithms 0, 1 and 2 use the same constraint value (δ). Algorithms 0 and 2 use half the μ values in this Table.

Freq. Hz	$Re(\lambda_{(A(z))})$	CN.	Position 1		Position 2		Position 3		Position 4	
			δ	μ	δ	μ	δ	μ	δ	μ
400	$-8.00e^{-04}$	154.98	0.00	$3.50e^{-02}$	0.00	$3.50e^{-02}$	0.00	$3.50e^{-02}$	0.00	$3.50e^{-02}$
				$1.75e^{-02}$		$1.75e^{-02}$		$1.75e^{-02}$		$1.75e^{-02}$
			$4.33e^{-03}$	0.70	$4.33e^{-03}$	0.70	$4.33e^{-03}$	0.70	$4.33e^{-03}$	0.70
				0.35		0.35		0.35		0.35
			$2.60e^{-03}$	0.18	$2.60e^{-03}$	0.18	$2.60e^{-03}$	0.18	$2.60e^{-03}$	0.18
				0.23		0.23		0.23		0.23
500	$1.29e^{-04}$	69.59		1.17		1.17		1.17		1.17
			0.00	4.70	0.00	4.70	0.00	4.70	0.00	4.70
				2.35		2.35		2.35		2.35
				0.59		0.59		0.59		0.59

Source: Mosquera-Sánchez et al. (2017b).

fashion:

- The control scheme under test is left at inactive mode during the first timeframe.
- The following timeframe is intended to test the cancellation mode.
- Next, the control scheme is set up as $g = \{0.5, 1.5, 2.0\}$, which are amplitude factors that belong to the reduction and amplification modes. Each mode is verified during one single timeframe.
- The control scheme under test is eventually driven to the mode $g = 1$, i.e. the inactive mode.

To verify the cross-channel interference, only Channels 1 and 3 (DoFs 5 and 7) are requested to follow the aforementioned schedule, while Channels 2 and 4 are requested to keep on at inactive mode, i.e. $g = 1.0$. Therefore, DoFs 6 and 8 (Channels 2 and 4) should present the unaltered primary disturbance.

The results of the multichannel systems, when controlling both disturbances, are displayed in Figs. 2.11, 2.12 and 2.13, by means of their Hilbert transforms. Bold, continuous lines show the controller results when the secondary paths are assumed to be perfectly identified. Gray dashed and dash-dot lines show the results of a given control scheme that undergoes plant variations. The results of the Algorithm 3 have been left for the following subsection, merely due to page format reasons. The following

statements on the results of the centralized control scheme, as well as on the Algorithms 0, 1 and 2, can be asserted:

- *Simulation by exciting an array-stable control matrix at 500 Hz:*
  1. Figure 2.11(a) illustrates the results of the centralized control scheme. While the adaptations made to this system seemed to succeed in tricking the LMS algorithm to provide other than pure-reduction targets, it unfortunately attempted to provide the same result at all channels. This follows from the fact that the centralized scheme relies on a cost function that minimizes all the error signals. Hence, this control scheme is found as the worst one in providing active sound profiling, as none of the intended operation modes could be attained. The requirement for Channels 2 and 4 to be "shielded" from the cross-channel influences coming from Channels 1 and 3 was not accomplished. Even so, this multichannel system seemed to be more robust to plant magnitude variations than the Algorithms 0, 1 and 2, as it is demonstrated by the discontinuous lines that remained bounded, even when the plant representation was 90% wrong in amplitude ($\hat{S}(z)/S = 0.1$).
  2. The pure-decentralized control scheme also failed in accomplishing the designed active sound profiling tasks, as it can be observed in Fig. 2.11(b). While this multichannel system was robust to amplitude overestimation of 40% on the plant model, which was not accomplished by none of the other control schemes, it went unstable when the plant was underestimated by only 10%. When facing the latter condition, the implementation of the operation mode $g = 2.0$ led to system instability. However, the system managed to recover as soon as the operation mode was reset to $g = 1.0$. This multichannel system also failed at keeping Channels 2 and 4 out of interferences, which follows from the fact that its control units are not aware of what is happening at the remaining control locations.
  3. Figures 2.11(c) and (d) show the results of the proposed fast and low-cost multichannel Algorithms 1 and 2, respectively. In these Figures, it can be noticed that, provided that the plant has been accurately identified, the intended active sound profiling tasks can be successfully attained by any of these control schemes. Furthermore, both control schemes are shown to accurately isolate Channels 2 and 4 from the interferences coming from Channels 1 and 3. Only when a large difference between $\hat{S}(z)$ and $S(z)$ exists, i.e. the plant representation has errors larger than 50%, did the proposed multichannel control schemes lose this ability. Moreover, while the convergence speed of Algorithm 1 is almost insensitive to plant model errors, the convergence speed of Algorithm 2 turned out to be strongly affected by this condition.

While Algorithm 1 attained 45 dB reduction in 5 s at Channels 1 and 3, regardless of the plant model errors, Algorithm 2 only delivered 3 dB reduction in the same timeframe, when facing plant magnitude errors of 20%.

Figure 2.11: Simulation results: time histories per channel of the controlled disturbance that excites an array-stable control matrix (500 Hz), subject to plant magnitude variations: (a) centralized; (b) pure-decentralized; (c) Algorithm 1; (d) Algorithm 2.

From these numerical exercises, it can be observed that: (i) the proposed control

Source: Mosquera-Sánchez et al. (2017b).

schemes own a good level of robustness face to plant magnitude variations, in which the convergence process of the Algorithm 1 seemed to be more robust than the one of Algorithm 2; (ii) the proposed scheme for compensating for cross-channel interferences is quite robust to plant magnitude misestimates; (iii) the accuracy in delivering the desired amplification or reduction is somewhat lost, under extreme plant variation conditions.

- *Simulation by exciting an array-unstable control matrix at 400 Hz:*

1. Figure 2.12 illustrates the results of the centralized control scheme. It is worth recalling that this multichannel system does not require regularization, once that its operation is inherently stable. As expected, this control scheme attempted to provide the same result at all the channels, as it can be seen in Fig. 2.12(a). The centralized control scheme was again successful in facing the same plant misestimate conditions, as in the previous example. However, since neither the active sound profiling operation was attained, nor Channels 2 and 4 were shielded against cross-channel interferences, it is said that the centralized control scheme is unable to deliver active sound profiling for multiple listeners.
2. Likewise, the Algorithm 0 was not able to accurately accomplish the desired active sound profiling targets, cf. Fig. 2.12(b). Even when this control scheme was provided with control effort constraints, it run into instability during the test of the amplification mode $g = 2.0$, as soon as the plant model error reached 5% error. When the plant model error reached 10%, none of the operation modes were operated under stable conditions.
3. Unlike the results observed when dealing with the stable control matrix, the results of Algorithms 1 and 2 in Figs. 2.12(c) and (d), respectively, are shown to be inaccurate but stable. The desired amplification or reduction amplitude values were not properly attained, even when the internal plant model representation was perfect. Still in this condition, Algorithms 1 and 2 outperformed Algorithm 0. As predicted, the lost performance due to the use of constraint values resulted in more cross-channel interference. Again, the most sensitive operation mode to plant variations is $g = 2.0$, in which Algorithm 1 fell into instability when facing a 50% plant magnitude error.
4. With regard to the isolation of Channels 2 and 4 while facing plant magnitude errors, the Algorithm 0 provided unbounded values in between -11 dB and ∞ dB, due to instability. This result was substantially improved by Algorithm 2, which delivered bounded amplitude values in between -13 dB and -5 dB. At this point, it has to be recalled that the expected value at both Channels 2 and 4 is -9 dB.

Simulations: Algorithm 3

The results for the Algorithm 3 will only be compared with the ones of the Algorithms 1 and 2, since this is the only set capable of accomplishing multichannel ANE with minimum cross-channel interference.

Figure 2.12: Simulation results: time histories per channel of the controlled disturbance that excites an array-unstable control matrix (400 Hz), subject to plant magnitude variations: (a) centralized; (b) pure-decentralized; (c) Algorithm 1; (d) Algorithm 2.

- *Simulation by exciting an array-stable control matrix at 500 Hz:* Figure 2.13(a) illustrates the time histories of the controlled primary disturbance, when dealing with a control matrix that does not require control effort constraints for the multichannel system to operate stably. When operating under a perfectly identified plant,

Source: Mosquera-Sánchez et al. (2017b).

Algorithm 3 accurately delivers the targeted operation modes while properly solving cross-channel interferences. However, it should be noticed that Algorithm 3 was not able to deliver the same reduction levels as the Algorithms 1 and 2, mainly due to its lower convergence rate. Whereas Algorithms 1 and 2 reached up to 50 dB reduction in 5 s, Algorithm 3 did 40 dB. However, the trend in Fig. 2.13(a) indicates that if a longer timeframe had been allowed, this Algorithm would

eventually have the same performance. Moreover, Algorithm 3 is shown not to be as robust as Algorithms 1 and 2, since it has only shown robustness against plant variations as small as 2% above and 50% below the actual magnitude value, as compared with plant variations between +20% and -50% that Algorithms 1 and 2 could manage. Moreover, the level of inaccuracy of Algorithm 3, when facing plant magnitude errors, is comparable with that of Algorithms 1 and 2.

- *Simulation by exciting an array-unstable control matrix at 400 Hz:* Figure 2.13(b) illustrates the time histories of the controlled primary disturbance, when dealing with a control matrix that does require control effort constraints for the multichannel system to operate stably. In this aspect, the Algorithm 3 shows to slightly overcome Algorithms 1 and 2, as it allows for a smaller constraint factor that in turn enabled a better performance. This result can be seen at both the noise equalization and cross-channel interference avoidance. When operating under a perfectly identified plant condition, Algorithms 1 and 2 delivered reductions of 7 dB and 9 dB at Channels 1 and 2, respectively (cf. Fig. 2.12(c) and (d) whereas Algorithm 3 delivered reductions of 10 dB and 11 dB respectively, as a consequence of using a smaller constraint value. Even so, the operation of the Algorithm 3 did show a noticeable oscillation after attaining convergence, which was not observed in Algorithms 1 and 2. This observation suggests that both the step-sizes and constraint parameters have to be set up concurrently. Hence, since the performance of Algorithm 3 was not affected by large constraint values, the accuracy in attaining the amplitude operation modes was shown to be better than the one of Algorithms 1 and 2. The oscillatory pattern of the Algorithm 3 in mode $g = 2.0$ has again been seen when facing a large plant variation, i.e. $a = 0.4$.

2.7 Conclusions

This chapter has been concerned with the development of multichannel active sound profiling control schemes for multiple listeners within cavities. Cross-channel interferences have been pointed out as the main cause for the current decentralized multichannel control algorithm to fail in delivering multichannel active sound profiling. Then, the current strategy of placing error sensors at the locations of interest for independently minimizing the so-called pseudoerror signals has been improved by means of sharing data amongst the control units. The innovative forms in which the data acquired by each single control unit are handled have given rise to three multichannel control schemes that feature the ability of counterbalancing for cross-channel interferences.

Operation aspects of the proposed multichannel control schemes, related to the tuning performance, robustness against magnitude plant variations, and choice of the

Figure 2.13: Simulation results: time histories per channel of the Algorithm 3 when facing plant magnitude variations: (a) control of a disturbance that excites an array-stable control matrix (500 Hz); (b) control of a disturbance that excites an array-unstable control matrix (400 Hz).

controllers parameters, have been verified in this chapter through computer simulations on a simple structural system, which consisted of 8 DoFs and 4 inputs/4 outputs. The influence of both the SAP positioning and the system damping on the stability of the proposed algorithms have also been examined. Chapter 5 will present the experimental

validation of these numerical exercises.

Through numerically benchmarking the performance of the centralized, pure-decentralized and the proposed multichannel distributed Algorithms, it can be asserted that:

- Provided that the matrix $\mathbf{A}$ being persistently excited shows all of its eigenvalues with positive, real parts, the proposed algorithms with coupling compensation are the only ones that accurately deliver the desired amplification, reduction or cancellation values of the primary disturbance at the locations of interest. On the contrary, while the centralized algorithm always attempts to deliver the same control target at all the sensor locations, which is inappropriate for active sound profiling, the pure-decentralized algorithm does try to deliver amplitude values close to the targeted ones. However, the fact that the latter is not provided with the proposed compensation scheme makes the pure-decentralized algorithm to fail in delivering accurate active sound profiling for multiple listeners.
- When plant magnitude variations had to be faced, none of the tested algorithms was able to accurately deliver the desired amplitude values, as requested by the operation modes $g = \{0.5, 1.5, 2.0\}$. Nevertheless, the proposed multichannel Algorithms 1, 2 and 3 were able to keep the targeted channels out of cross-interferences, even when moderate plant variations are present. It has to be remarked that, when the magnitude of the internal model of the plant exceeds bounds between $\pm 20\%$ of the actual plant, it should be updated in order to match the actual one. Further numerical studies are envisaged at this point, in order to assess the robustness of the control schemes face to realistic plant magnitude variations.
- The realization of bandwidths that exhibit stable control matrices, as well as the realization of good conditioning of the control matrices, depend on both the SAP placement and the existing passive damping. While the rearrangement of the SAPs may help in treating unstable control matrices, passive damping has been shown as a means for improving the conditioning of the control matrices. In this form, it is stated that the proposed multichannel algorithms are promising in applications where passive damping is present.
- When dealing with primary disturbances that excite array-unstable matrices, the use of constraints in the LMS algorithm for stabilization purposes was seen to not hinder the operation of the coupling compensation mechanism. However, the performance of the algorithms in both equalizing and avoiding cross-channel interferences is reduced.

Table 2.6 summarizes the features of the multichannel algorithms discussed in this chapter. In order to come up with a single score, different attributes have been given weights, according to the Author's judgment. Thus, attributes such as the accuracy

in delivering the requested operation modes, stability and cross-channel coupling compensation, have been given more preponderance. With regard to the accuracy, it can be said that, for instance, if the user is willing to reduce the primary noise by a half, this reduction should be as close as possible to -3 dB_{SPL} , once that this action might be linked to some specific SQ target. Stability is also an important feature, as the control action should never degrade the original SQ condition beyond that of the primary disturbance itself. With regard to this attribute, it is recalled that, while the centralized algorithm is considered unconditionally stable, the Algorithms 0, 1, 2 and 3 must account for both SAP placement and uncertainties in the plant model estimate. Even so, it was always shown to be possible to stabilize these Algorithms by restricting the control output, but at the expense of losing performance. Finally, the compensation feature, being as the ability to manage cross-channel interferences, is strongly related to the accuracy of multichannel algorithms in delivering the requested amplitude and/or relative-phase control targets. Compensation has therefore been given a high weight, once that the control action at one or several channels cannot degrade the SQ at other relevant locations.

Table 2.6: Summary of features of multichannel algorithms. Scale: 3 - good; 2 - fair; 1 - poor.

Feature	Weight	Centralized	Alg. 0	Alg. 1	Alg. 2	Alg. 3
Accuracy	3	1	1	3	3	3
Stability		3	2	2	2	2
Compensation		1	1	3	3	3
Relative phase	2	1	3	1	1	3
Convergence speed		1	3	3	2	1
Robustness	1	3	2	2	3	2
Computational cost		1	3	1	2	2
Mean score		1.53	1.93	2.33	2.33	2.40

The ability for controlling the relative phase, as well as the convergence speed, have been given a secondary role, since Roughness is the only SQ metric that is sensitive to relative-phase shifts and, to the best of our knowledge, there is no consensus on whether active control tasks should be provided quickly or smoothly, from the point of view of the psychoacoustical perception of temporal changes in sounds. The remaining two aspects, namely the robustness and computational costs, can be regarded in a third place, since, as soon as the internal representation of the plant is updated, the robustness aspect is alleviated, and the computational costs could no longer represent a concern when high-power DSP boards are available.

Thus, according to the scores given to each multichannel algorithm in Table 2.6,

the multichannel Algorithm 3 is found as the best option for performing multichannel amplitude- *and* relative-phase-based active sound profiling tasks. On the contrary, the least suitable option is the multichannel centralized algorithm.

The experimental verification of the theories and algorithms discussed in this chapter will be presented in Chapter 5, in which the multi-objective SQ optimization, to be presented in the following chapters, will be merged into the proposed methodology for controlling the SQ of the powertrain noise in HEVs.

Chapter 3

Sound quality models and algorithms

FROM the theory of product quality management (GILMORE, 1974; GARVIN, 1984), current approaches for the design and analysis of the sound quality of a product can be framed into two lines of thought, as follows: (i) the manufacturing-based approach, which deals with *the degree to which a product conforms to a design or specification*; or (ii) the user-based approach, which is concerned with *the degree to which a product satisfies the wants of a specific consumer*. While most of the research done on NVH aspects in passenger vehicles points to comply product standards and directives, recent papers have put forward on the need for innovative vehicle design procedures that, besides meeting these standards, truly aims at satisfying the expectations of -specific- customers. It is at that point where the basic psycho-acoustic quantities (FASTL, 2005) come into play to offer the NVH specialist a set of tools for objectively estimating the customer judgments. To this regard, psycho-acoustic models of Loudness (FASTL; ZWICKER, 2007; HASTINGS, 2004), Roughness (DANIEL; WEBER, 1997; FASTL; ZWICKER, 2007; WANG et al., 2013), Sharpness (FASTL; ZWICKER, 2007) and Tonality (ZHANG; SHRESTHA, 2003; SHIN et al., 2009; SHIN et al., 2014), have been proposed for objectively estimating the psycho-acoustic constructions of such sound qualities.

The goal that is pursued in this research relies on how these basic auditory perceptions should be handled, such that the resulting soundscape induced by the powertrain within the passenger cavity of HEVs truly meets a set of prescribed objective metrics. Hence, it is important to review the underlying theory and concepts behind these mathematical models. To this regard, this Chapter discusses two approaches for calculating psycho-acoustic models that quantify Loudness, Roughness, Sharpness and Tonality. While the standard time-domain models rely on the time history of the acoustic pressure signal as the main input, the frequency-domain ones just use the amplitude, frequency and relative-phase data of the relevant tones in the primary sound. Common calculations, notation and formulae for the models are introduced. Since the calculation of a given metric via either time- or frequency-domain algorithms may show differences between each other, due to the spectral leakage that is often present in the time-domain

models, a method for *calibrating the models* is also introduced and discussed. Thus, the frequency-domain algorithms are provided with *calibration weights*, which should resemble the accuracy and meaning of the time-domain models while being more computationally efficient. In this way, the frequency-domain versions of those algorithms are able to be used for optimization routines. Computer validations of each frequency-domain model are appended at the end of this chapter, through comparisons with the time-domain algorithms. Like so, this chapter serves as a detailed introduction for the multi-objective SQ cost function, which is treated in Chapter 4.

3.1 Introduction

This section describes common calculations for the SQ algorithms. A brief discussion of spectral leakage is also presented, which leads to the calibration issue, such that the frequency-domain SQ models remain equivalent to the time-domain ones in terms of both accuracy and meaning. One of the requirements for a signal to fit into the frequency-domain SQ algorithms is to be a periodic signal with a limited number of tonal components. Since the focus of this research is to tackle stationary motor noise (either ICE or electric), it seems worth investing in such alternative methods.

3.1.1 Influence of spectral leakage in determining SQ scores

As far as rotating machines at stationary regimes are of concern, long measurements of their acoustic emissions can be regarded as if they were *periodic extensions* of a single cycle. Thus, all the psycho-acoustic information could just be inferred from one signal cycle, as long as the fundamental period of the noise remains constant during uptime. This suggests that *frequency-domain psycho-acoustic models* could be a feasible and computationally efficient way to assess the SQ of such sounds.

However, when comparing the SQ metrics values via either time- or frequency-domain models, some differences may arise, which have been attributed due to the spectral leakage of time-domain data. For the sake of illustration, let us take a 0.2 s time history of the definition signal of Roughness, which states that 1 asper is the psycho-acoustic perception raised by the 60 dB_{SPL}, 1 kHz tone that is 100% amplitude-modulated (AM) by a pure sinusoid at 70 Hz (FASTL; ZWICKER, 2007). Equation 3.1 shows the discrete time series that represent such signal, given in Pa:

$$d[n] = 2.31e^{-02} \cos [2 (1000) \pi n] \{1 + \cos [2 (70) \pi n]\}, \quad (3.1)$$

where $d \in \mathbb{R}$ denotes the sound pressure at the discrete time $n \in \mathbb{N}$.

Figure 3.1 illustrates the spectrum of the signal in Eq. 3.1. The time history of the signal has been sampled at 44.1 kHz, and preprocessed by using three windowing

functions, namely the rectangular, Hamming and Blackman. It can be seen that, regardless of the windowing function, the spectral leakage is noticeable in both magnitude and relative-phase functions. Although the rectangular window causes larger relative-phase artifacts than the other window functions, it does keep the RMS value into the frequency-domain. Furthermore, it is also shown that the three window functions do keep the relative-phase value of the relevant harmonics at zero radians, which agrees with the definition for the Roughness of 1 asper. Moreover, while both Hamming and Blackman windows effectively solve relative-phase artifacts found with the rectangular window, the Blackman window, which is the function that should be calculated into the Roughness algorithm (DANIEL; WEBER, 1997; FASTL; ZWICKER, 2007; WANG et al., 2013), allows a better magnitude estimation. Still, the spectrum that results from the Blackman window gives peak values of $\{47.7, 53.7, 47.7\}$ dB_{SPL}, while the theoretical ideal values would be $\{55.2, 61.3, 55.2\}$ dB_{SPL}. This difference in amplitude estimation gives rise to a difference in the final Roughness value of 0.65 asper, i.e. an error of 57.5% above the theoretical ideal value, which should be 1 asper.

Figure 3.1: Frequency-domain representation of the Roughness definition signal: (a) magnitude function; (b) relative-phase function.

Whilst the time-domain Roughness algorithm uses the entire frequency-domain magnitude and relative-phase data, which depending on the resolution of the Fourier transform might amount to thousands of values (that will eventually be discarded from the calculations), the frequency-domain algorithms can just focus on the data for the three relevant frequencies of the signal, i.e. for the harmonics at 930, 1000 and 1070 Hz. It is, therefore, evident that the frequency-domain approach for calculating Roughness, and even other SQ metrics that can be fitted into a similar approach, is computationally efficient.

To alleviate for those discrepancies between time- and frequency-domain SQ algo-

rithms, the following non-linear curve-fitting problem is proposed:

$$\min_{\mathbf{X}} \sum_{j=1}^M \left(F_j^{time} - F_j^{freq}(\mathbf{a}, \mathbf{f}, \boldsymbol{\theta}, \mathbf{X}) \right)^2, \quad (3.2)$$

where $\mathbf{X}$ is a vector of calibration weights that is specifically defined for each SQ perception; F_j^{time} is the SQ score calculated by using the corresponding time-domain model; and F_j^{freq} is the calculated SQ score by using the frequency-domain model, which is a function of the amplitudes $\mathbf{a}$, frequencies $\mathbf{f}$ and relative phases $\boldsymbol{\theta}$ of the primary sound under test. It is worth recalling that, while the Roughness model is sensitive to both magnitude and relative-phase spectral functions, Loudness, Sharpness and Tonality models are just functions of the magnitude of the spectrum of $d[n]$.

Nonlinear programming solvers, e.g. the Sequential Quadratic Programming (SQP) algorithm, are envisaged for solving the optimization problem proposed in Eq. 3.2. It is worth recalling that the proposed calibration routine has only been tested with stationary periodic disturbances, which are sampled at sampling rates that hold the Nyquist sampling theorem. Since it was observed through simulations that the proposed calibration procedure is sensitive to the starting point, especially when $\mathbf{X}$ is a vector of two calibration weights, it is highly advisable to run the solver by testing different starting points. Nevertheless, sets of calibrated weights have always been found for Loudness, Roughness, Sharpness and Tonality algorithms, by optimizing Eq. 3.2 with the SQP algorithm, as long as the design variables (calibration weights) are bounded. These bounds are particular to each SQ model (BISMARK, 1974; GUIRAO; GARAVILLA, 1976; DANIEL; WEBER, 1997; HOELDRICH; PFLUEGER, 1999; PRESSNITZER; MCADAMS, 1999; HASTINGS, 2004; BAENE et al., 2004; KOHLRAUSCH et al., 2005; FASTL; ZWICKER, 2007; JANSSENS et al., 2007; WANG et al., 2013), and they will be presented in the corresponding subsequent sections.

3.1.2 Standard procedures

The calculations listed below are common for all the SQ metrics that will be described in the following sections. These have the purpose of determining the Excitation Levels per Critical Band produced by a given primary sound, as well as to determine equivalences between Hertz and Bark frequency scales.

- **Determination of the amplitudes, frequencies and relative-phases of the primary sound:** On the one hand, the calculations of the time-domain SQ metrics start with a measurement of the time-domain acoustic pressure signal, given in Pa. Windowing procedures, as well as a splitting of the input time history into a number of short buffers is carried out at this stage for accounting for the perception of the duration of sounds (FASTL; ZWICKER, 2007; WANG et al., 2013). On the

other hand, the frequency-domain algorithms directly start from the amplitude and relative-phase data from each relevant tone in the sound. Naturally, these frequency-domain models do not account for any perception that involves duration of sounds, once that the underlying premise of these models is that the sound remains stationary during uptime.

While the relative-phase data is typically given in radians, as a wrapped function between $\pm\pi$ rad, the magnitude function should be transformed into the decibel scale with reference to $p_{ref} = 20\mu Pa$, by using:

$$L_P = 20\log_{10}(p/p_{ref}), \quad (3.3)$$

where L_P is the sound pressure level (SPL) of the primary noise in a logarithmic scale; p is the measurement of $d[n]$ after converting the electric signal coming from a microphone into Pascal scale by using $p = v[n]s$, with the sensitivity s given in $Pa.V^{-1}$; and p_{ref} is regarded as the minimum pressure difference related to the environment pressure, which still causes the auditory perception of sound, provided that the frequency of $d[n]$ lies into 20 Hz - 20 kHz.

- **Correction of the magnitude function:** As suggested by Wang et al. (2013), the outcome from the stage above should be corrected for accounting for both free-or-diffuse acoustic propagation condition (a_{pf}) and for peripheral auditory system influences (a_{pa}). Figure 3.2 illustrates both sets of coefficients, obtained from Fastl & Zwicker (2007). These correction values, which are given in dB_{SPL} , are just applied on the magnitude function of the frequency-domain data of the measurement.

Figure 3.2: Coefficients for corrections: (a) free to diffuse acoustic field (a_{pf}); (b) peripheral auditory correction (a_{pa}) in both free and diffuse acoustic fields.

Source: Fastl & Zwicker (2007).

- **Conversion of frequency values in either Hertz or Bark scales:** The Schröder's formulae (SCHROEDER et al., 1979) are implemented for transforming frequency values in Hertz into the Bark scale and vice versa, as this Hz-to-Bark formulation holds close resemblances with the widely used Zwicker's one (FASTL; ZWICKER, 2007), and that also has a closed-form inverse:

$$\mathcal{Z} = 7 \sinh^{-1} \left(\frac{f}{650} \right) \quad (3.4)$$

$$f = 650 \sinh \left(\frac{\mathcal{Z}}{7} \right), \quad (3.5)$$

where $f \in [20, 20000]$ Hz is the frequency range of human hearing; and $\mathcal{Z} \approx [0.22, 28.84]$ Bark is the corresponding auditory range in the Bark scale. Figure 3.3 reveals that a strong similarity between the commonly used Zwicker's formula:

$$\mathcal{Z} = 13 \tan^{-1} \left(\frac{0.76f}{1000} \right) + 3.5 \tan^{-1} \left(\frac{f}{7500} \right)^2, \quad (3.6)$$

and the Schröder's one in Eq. 3.4 exists up to 4 kHz. Notice that Eq. 3.6 does not have a closed-form inverse.

Figure 3.3: Hertz-to-Bark scale conversions.

Source: Schroeder et al. (1979).

- **Absolute threshold of human hearing:** The absolute threshold of hearing L_{ETQ} is calculated by using the following formula:

$$L_{ETQ}(f) = 3.64 \left(\frac{f}{1e03} \right)^{-0.8} - 6.5e^{-0.6[(f/1e03)-3.3]^2} + 1e^{-03} \left(\frac{f}{1e03} \right)^4 \quad (3.7)$$

Figure 3.4 illustrates L_{ETQ} as a function of the frequency in Hz.

Figure 3.4: Absolute threshold of hearing L_{ETQ} .

- **Excitation level:** The Excitation Level, L_E , produced by the -corrected- magnitude function, L_P or L_C , is calculated as a function of the frequency in Hz, by using the following set of slopes (WANG et al., 2013):

$$\begin{aligned} SL^{(1)}(f) &= -27 \\ SL^{(2)}(f) &= -24 - 230/f + 0.2L, \end{aligned} \quad (3.8)$$

where $L \leftarrow L_P$ or $L \leftarrow L_C$. Figure 3.5 illustrates some critical bands that are obtained when filtering white noise falling into a bandwidth comprised between 20 Hz - 20 kHz.

3.2 Loudness

Psycho-acoustic Loudness is the model that characterizes the auditory perception of the *sound intensity* or volume. Two definitions for this metric are found along the literature, as follows:

- The Loudness level, quantified in *phon*, is defined as the sensation elucidated by a 1 kHz signal that propagates as a plane wave, and whose angle of incidence is 0° . One *phon* is defined as the sensation elucidated by the 1 kHz, 1 dB_{SPL} signal.
- The so-called *Zwicker-Loudness* model (FASTL; ZWICKER, 2007), which accounts for individual contributions to the total spectrum that are discriminated by *critical*

Figure 3.5: *Magnitude function of some critical bands.*

bands. This model also assess *auditory masking* effects. One *sone* is the sensation elucidated by the 1 kHz, 40 dB_{SPL} signal, i.e. by a 40 phon signal.

The Loudness algorithm reported on by Hastings (2004) that implements the ISO532b/DIN45631 standard (FASTL et al., 2009) has been studied in detail. Some computational improvements for speeding up calculations have been worked out. Figure 3.6 shows a block diagram that summarizes both time- and frequency-domain Loudness models.

Time- and Frequency-domain Loudness models

Initial calculations

The time-domain Loudness model starts from carrying out time-to-frequency-domain transforms. As discussed in Section 3.1.2, the metric can be calculated for either a long time series or short time buffers. Typically, the short buffers are 0.2 s long (HASTINGS, 2004; FASTL et al., 2009). A Hamming window is used to filter the time data, prior to the Fourier transform. At this point, it is worth to recall that all these calculations are needless in the frequency-domain model, since it starts directly from the magnitude and relative-phase functions of the sound.

Filtering of the frequency-domain data

An one-third-octave-band filtering that complies with the ANSI S1.11-1986 standard (ASA, 1986) is carried out upon the resulting frequency-domain data, through the MATLAB script by Couvreur (1997). The central frequencies of the filterbank ranges from 25 Hz to 12.5 kHz, thus giving rise to 28 3rd-order, one-third-octave passband filters. To synthesize the filterbank, a sampling rate of $F_s = 48000$ Hz is adopted. In

Figure 3.6: Block diagrams of time- and frequency-domain Loudness models.

Source: Adapted from Mosquera-Sánchez et al. (2017a).

order to obtain unitary-gain filters, the first eleven filters are synthesized by assuming slower sampling rates: the first five bands with central frequencies at 25, 31.5, 40, 50 and 63 Hz are synthesized with $F_s/8$ Hz, the second three bands with central frequencies at 80, 100 and 125 Hz are synthesized with $F_s/4$ Hz, and the following three bands with central frequencies at 160, 200 and 250 Hz are synthesized with $F_s/2$ Hz. The remaining one-third-octave bands assume a sampling rate of $F_s = 48$ kHz. A *calibration weight*, $X_N(2) \in \mathbb{R}^+$, is eventually implemented in the form of a *gain* at the output of the filterbank, as suggested in the Hastings (2004) algorithm. This has the purpose of improving the calibration of both time- and frequency-domain Loudness models.

Calculation of the excitation level, L_E

The excitation level, L_E , is now calculated by using the outputs of the one-third-octave-band filterbank. The Hastings (2004) algorithm proposes some corrections for the outputs of the low-frequency filterbanks, i.e. the ones that are centered at the frequencies from 25 to 250 Hz, due to the fact that L_E will be calculated from filtered data. Then, the first three critical bands that compose L_E are calculated by simply adding up the outputs of the corrected filtered values, as follows:

- First critical band, which is composed of the summation of the first corrected six low-frequency, one-third-octave-band filter outputs.

- Second critical band, which is composed of the summation of the following three low-frequency, one-third-octave-band filter outputs.
- Third critical band, which is composed of the summation of the following two low-frequency, one-third-octave-band filter outputs.

The remaining 17 critical bands are made to equal each of the outputs of the remaining non-corrected, one-third-octave bands.

Corrections for accounting for the propagation field and auditory system artifacts

Corrections for accounting for the acoustic field of propagation, a_{pf} , as well as for the peripheral auditory system artifacts, a_{pa} (cf. Section 3.1.2), are now carried out upon the resulting excitation level, L_E . As suggested in the Hastings (2004) algorithm, an additional correction factor, cf , should also be included for accounting for the use of one-third-octave-band levels. Therefore, the corrected L_E at the j^{th} critical band remains as follows:

$$L_{Ej} = L_{Ej} - a_{pfj} - a_{pa j} - cf_j \quad (3.9)$$

Details on the correction values, cf , can be found in the original Loudness algorithm (HASTINGS, 2004).

Calculation of the specific Loudness

The following procedure consists on the calculation of the Specific Loudness. According to the ISO532b/DIN45631 standard (FASTL et al., 2009), this calculation should also account for the human auditory threshold, cf. Section 3.1.2. The Specific Loudness is then calculated as follows:

$$\mathcal{N}'_j = 0.064 \cdot 10^{0.025 L_{ETQj}} \left\{ \left[1 + 0.25 \cdot 10^{0.1(L_{Ej} - L_{ETQj})} \right]^{0.25} - 1 \right\}, \quad (3.10)$$

where $\mathcal{N}'_j$ is the Specific Loudness, given in sone/bark; L_{ETQj} is the auditory threshold of the j^{th} critical band; and L_{Ej} is the corrected excitation level in Eq. 3.9 of the j^{th} critical band.

After calculating Eq. 3.10, an additional correction value, cv , is still necessary for the lowest critical band. This is calculated as follows:

$$cv = 0.4 + 0.32 (\mathcal{N}'_1)^{0.2} \quad (3.11)$$

If $cv > 1$, cv is made equal to 1. Then, it follows that:

$$\mathcal{N}'_1 = cv (\mathcal{N}'_1), \quad (3.12)$$

is the corrected Specific Loudness of the lowest critical band.

At this point, any $\mathcal{N}'_i$ that is found to be less than zero can eventually be zeroed.

Calculation of the total Loudness (Zwicker-Loudness)

The calculation of the total Loudness (FASTL; ZWICKER, 2007, Ch. 8) follows:

$$\mathcal{N} = X_{\mathcal{N}}(1) \int_0^{24\text{Bark}} \mathcal{N}' d\mathcal{Z} \approx \sum_{j=0}^{24} \mathcal{N}'_j \Delta\mathcal{Z}, \quad (3.13)$$

where $\mathcal{N}'$ is the specific Loudness; $X_{\mathcal{N}}(1) \in \mathbb{R}^+$ is defined as a *calibration weight* for the output of the algorithm; and $\mathcal{N}$ is the total Loudness given in *some*, is carried out by approximating the integrand in Eq. 3.13, by making $d\mathcal{Z} \approx \Delta\mathcal{Z} = 0.1$ Bark.

The calculation of $\mathcal{N}$ is dictated by the assessment of the masking effects at each critical band. When the specific Loudness is "masked" by the total Loudness being accumulated from the low-frequency critical bands, some specific calculations should be followed. Otherwise, the calculation of Eq. 3.13 can be carried out in a relatively straightforward way. Below is a list of steps that should be followed for accomplishing this calculation:

- The Hastings algorithm assumes the quantity $\mathcal{N}$ as a computer accumulator.
- $\Delta\mathcal{Z}$ is increased by 0.1 Bark for each iteration, unless the following condition holds:

If $\mathcal{N} > \mathcal{N}'_j$, i.e. the specific Loudness at the j^{th} critical band is "masked", then $\mathcal{N}'$ should be compared with predefined specific Loudness ranges given by the function SLR . This has the purpose of determining the steepness of the specific Loudness pattern, given by the function SLS , which should be applied in the calculation, as follows:

- This enforces the calculation of a modified $\Delta\mathcal{Z} \leftarrow \Delta\mathcal{Z}^* = (\mathcal{N} - SLR)/SLS$.
- The quantity called *accessory Loudness*, i.e. $\mathcal{N}_{acc} \leftarrow \Delta\mathcal{Z}^* (\mathcal{N}' + SLR)/2$, can now be calculated.
- The total Loudness is now accumulated as:

$$\mathcal{N} \leftarrow \mathcal{N} + \mathcal{N}_{acc} \quad (3.14)$$

- At that time, the specific Loudness is also corrected by making:

$$\mathcal{N}' = \mathcal{N} - \Delta\mathcal{Z} (SLS). \quad (3.15)$$

- If $\mathcal{N} \leq \mathcal{N}'_j$, i.e. the masker (total Loudness) is less than or equal to the specific Loudness at the j^{th} critical band, the total Loudness is calculated as follows:

$$\mathcal{N} \leftarrow \mathcal{N} + \mathcal{N}'_j \Delta \mathcal{Z}, \quad (3.16)$$

and the specific Loudness is made equal to its own value, with no further amendments.

Details on the functions SLR and SLS can be found in the original Loudness algorithm (HASTINGS, 2004).

The final Loudness value is corrected for round-to-integer purposes, as follows:

- If $\mathcal{N} \leq 0$, then $\mathcal{N} = 0$.
- If $\mathcal{N} \leq 16$, then $\mathcal{N} = X_{\mathcal{N}}(1) (\lfloor 1000\mathcal{N} + 0.5 \rfloor / 1000)$
- If $\mathcal{N} > 16$, then $\mathcal{N} = X_{\mathcal{N}}(1) (\lfloor 100\mathcal{N} + 0.5 \rfloor / 100)$,

where $\text{floor} \equiv \lfloor \cdot \rfloor$ is the round down function.

Discussion

The Loudness model is composed of involved calculations that hinder a straightforward interpretation of the input/output relationship. In particular, the calculation of the specific Loudness in Eq. 3.10, which is an intricate function of the excitation level per critical band, adds up a degree of complexity to the model. This, in turn, pose challenges for optimization solvers, when attempting to search for improved Loudness scores. Unlike the Specific Loudness calculation, all the remaining ones are linear relationships amongst the variables, which optimization solvers can face with less difficulty.

The calculations of the Loudness algorithm described in this section have mostly been preserved in their original form. Some procedures related to the calculation of the one-third-octave-band filterbank have been changed, in order to ensure similarities between the time- and frequency-domain approaches. Two calibration weights have been included into the Hastings (2004) algorithm. The main output of the algorithm, as well as the outputs of the filterbank, are adjusted by tuning parameters, namely $X_{\mathcal{N}}(1)$ and $X_{\mathcal{N}}(2)$, respectively. According to the Hastings (2004) algorithm, $X_{\mathcal{N}}(1) = 1.0$ and $X_{\mathcal{N}}(2) \approx 0.95$. Moreover, with the new definitions given for the one-third-octave-band filterbank, it has been found that by making $\{X_{\mathcal{N}}(1), X_{\mathcal{N}}(2)\} = \{1.05, 1.0\}$, the time-domain Loudness algorithm still provides an output of 1 sone, when a 1 kHz, 40 dB_{SPL} signal sampled at 44.1 kHz is used as the input. Furthermore, after carrying out the calibration procedure proposed in Eq. 3.2, it has been found that the calibration weights that make both time- and frequency-domain to match between each other, when using the same input as described before, are $\{X_{\mathcal{N}}(1), X_{\mathcal{N}}(2)\} = \{0.77, 1.0\}$.

A further improvement to the algorithm has been proposed, in an attempt to accelerate calculations along a number of iterations. On the basis that Loudness is only sensitive to magnitude changes, a number of variables can be saved into memory. Provided that the frequencies of the primary sound remain constant along a number of repetitions, variables such as the one-third-octave filterbank response, windowing function, correction functions, among others, can be calculated only once. This will have a dramatic effect on reducing both computational cost and time.

3.3 Sharpness

According to Fastl & Zwicker (2007, Ch. 9), psycho-acoustic Sharpness is the model that describes the auditory sensation related to the *sound density*. Although this metric has not been standardized yet, it has largely been used for assessing the SQ of technical sounds with high-frequency content (GONZÁLEZ et al., 2003). Sharpness is measured in *acum*. One "acum" is defined as the perception elucidated by the noise filtered within a 1-critical-band-wide filter, centered at 1 kHz, and whose RMS value equals 80 dB_{SPL}.

Since psycho-acoustic Sharpness is a model derived from that of Loudness, the corresponding calculations are quite straightforward to describe. Fig. 3.7 shows block diagrams of both the time- and the frequency-domain algorithms for calculating this metric.

Figure 3.7: Block diagrams of time- and frequency-domain Sharpness models.

Time- and Frequency-domain Sharpness models

The calculations for the Sharpness model start directly from taking the specific Loudness, $\mathcal{N}'_i$, in Eq. 3.15, which has already been corrected by virtue of the masking effects.

Sharpness is defined as follows (FASTL; ZWICKER, 2007, Ch. 9):

$$\mathcal{S} = X_S(1) \left(\frac{\int_0^{24\text{Bark}} \mathcal{N}'_i h(\mathcal{Z}) \mathcal{Z} d\mathcal{Z}}{\int_0^{24\text{Bark}} \mathcal{N}'_i d\mathcal{Z}} \right) \approx X_S(1) \left(\frac{\sum_{j=1}^{24} \mathcal{N}'_j h(\mathcal{Z}) \mathcal{Z} \Delta \mathcal{Z}}{\mathcal{N}} \right), \quad (3.17)$$

where $\mathcal{S}$ is the total Sharpness given in *acum*; $X_S(1) \in \mathbb{R}^+$ is a *calibration weight*; and $h(z)$ is a weighting function that has been defined by some researchers as follows:

- Von Bismark (BISMARCK, 1974):

$$h(\mathcal{Z}) = \begin{cases} 1, & \mathcal{Z} \leq 14 \\ 1.2e^{-04} \mathcal{Z}^4 - 5.6e^{-03} \mathcal{Z}^3 + 0.1 \mathcal{Z}^2 - 0.81 \mathcal{Z} + 3.51, & \mathcal{Z} > 14, \end{cases} \quad (3.18)$$

- Zwicker (FASTL; ZWICKER, 2007, Ch. 9):

$$h(\mathcal{Z}) = \begin{cases} 1, & \mathcal{Z} \leq 16 \\ 6.6e^{-02} e^{0.171 \mathcal{Z}}, & \mathcal{Z} > 16, \end{cases} \quad (3.19)$$

These sets of weights can be visually contrasted in Fig. 3.8.

Figure 3.8: Sharpness weights, according to Bismark (1974) and to Fastl & Zwicker (2007).

The calibration weight, $X_S(1) \in \mathbb{R}^+$, is defined as $X_S(1) = 0.11$ in the original time-domain Sharpness model. This value is turned into a design parameter, i.e. calibration weight, for the curve-fitting procedure between the time- and frequency-domain models.

The integral at the numerator of Eq. 3.17 should be approximated by using $dZ \approx \Delta Z = 0.1$, which follows from using the specific Loudness calculations from the model introduced in Section 3.2.

Discussion

As stated earlier, the Sharpness metric consists of a straightforward weighting of the specific Loudness function. At its turn, the specific Loudness was already shown as an intricate function of the excitation level of the sound under analysis, discriminated by critical bands. It is worth recalling that, whilst the Von Bismark weights are a 4th-order function of the frequency, the Zwicker ones are a less complicated, exponential function of the frequency. This has an obvious influence on the computational complexity of the Sharpness algorithm. Since the Zwicker function is a good fitting of the more complex Von Bismark one, cf. Fig. 3.8, the Zwicker weights can be safely adopted for the Sharpness calculations. Furthermore, as long as a number of repetitions of this algorithm are needed, these weights can be calculated only once and stored into memory, in order to save computation.

When the definition signal is used as the input, the time-domain algorithm described above yields 1 acum. The calibration weight, $X_Z(1)$, which adjusts the frequency-domain algorithm to provide the same value as its time-domain counterpart, has been determined as 0.12.

3.4 Tonality

Psycho-acoustic Tonality is the model that extracts the *tonal* characteristic of a sound. Tonality is strongly related to the *pitch* of sounds. The mathematical model proposed by Terhardt has been studied by some researchers, e.g. Zhang & Shrestha (2003), Shin et al. (2009), Shin et al. (2014). This psycho-acoustic model has been adapted for meeting specific soundscapes: internal combustion (IC) engine noises, laser printer noises, among others. Similar to Sharpness, this metric has not been standardized yet. Moreover, it has not been possible to find a definition for this metric along the specialized literature, which makes use of a single scalar value, or even an acknowledged unit. To the best of our knowledge, the only effort made for defining Tonality in such a way is that of Shin et al. (2009), whose adjusted the so-called *spectral pitch strength* of a 1 kHz, 80 dB_{SPL} pure-sinusoid signal, to have unit value. In the present research, this "unit" has been adopted as the *spectral pitch*, SP, as defined through the same definition signal proposed by those authors.

Tonality theories and algorithms can be clustered in two approaches, as follows:

- Place theory: this approach assumes that the human auditory system discriminates

sounds by frequencies, in which they are assumed to excite fixed locations along the basilar membrane within the inner ear of the auditory system. Models based on this theory rely on the identification of the spectral components of the sound, for subsequently evaluating the excitation level in the light of masking effects, background noise and the auditory threshold. The identified "tones" are eventually classified according to their *aural relevance* (aural weight), based on the excitation level calculations. This theory gives rise to the so-called *weighted spectral pitch*, wSP (SHIN et al., 2009).

- Temporal/frequency theory: this approach is an extension of the place theory, which also states that the time pattern of the primary excitation should be accounted for when assessing its pitch (DRAGONETTI et al., 2017).

Since temporal effects of sounds can be better described by metrics such as Roughness (SHIN et al., 2009), the place theory for approaching the pitch perception seems to suffice for the task of characterizing the Tonality of periodic sounds. Thus, the adopted approach in the present research is that of the place theory, for which existing models have been already discussed and validated by using human jury. Fig. 3.9 shows the calculation flows of the time- and frequency-domain Tonality algorithms.

Time- and Frequency-domain Tonality models

Initial calculations

The time-domain Tonality model starts from carrying out time-to-frequency-domain transforms. As discussed in Section 3.1.2, the metric can be calculated for either a long time series or short time buffers. Typically, these short buffers are 0.2 s long (HASTINGS, 2004; FASTL et al., 2009). A Hamming windowing function is used to preprocess the time series.

Corrections for accounting for the propagation field and auditory system artifacts

The magnitude function obtained after performing a discrete Fourier transform is converted from linear Pa to dB_{SPL} by following Eq. 3.3. Then, the corrected magnitude function, L_C , can be expressed as follows:

$$L_C = L_P - a_{pf} - a_{pa}, \quad (3.20)$$

where the correction terms a_{pf} and a_{pa} have already been defined in Section 3.1.2.

Figure 3.9: Block diagrams of time- and frequency-domain Tonality models.

Identification of tonal components

The procedure for identifying the possible tonal candidates consists on "visually" identifying peaks in the magnitude function. A harmonic component that meets the following two conditions can be regarded as a possible tonal candidate: (i) its peak amplitude is larger than the amplitude of the surrounding frequency bins, which can be regarded as a "coarse search"; and (ii) a difference of 7 dB_{SPL} between the current bin and the three bins that precedes and the three that proceeds it, can be verified, which can be regarded as a "fine discrimination" of the candidate.

In contrast, for the frequency-domain algorithm it is assumed that *all* the harmonics, whose corrected amplitude values are greater than zero, are considered as possible tonal components, as long as their minimum distance between the closest harmonics is 5 Hz (SHIN et al., 2009). To this regard, it is important to recall that the just-noticeable difference (JND) in frequency has been demonstrated to be lower than 4 Hz, for the bandwidth below 700 Hz (FASTL; ZWICKER, 2007). This JND in frequency has been also found to increase at a rate of 0.7% above that frequency (FASTL, 2005). However, Shin et al. (2009) have established that the booming sensation elucidated by ICE noises can be assessed by setting up this JND at 5 Hz. This value seems to be suitable for discriminating harmonics very close between each other, while alleviating for more demanding search procedures that would be necessary if the JND were settled lower than 4 Hz, as Fastl & Zwicker (2007) suggest.

Calculation of the SPL excess, L_X

The sound pressure level excess, L_X , is now calculated for each tonal candidate, in order to determine its effective participation in the Tonality perception, as follows:

$$L_{Xi} = L_{Ci} - 10 \log_{10} \left[\left(\sum_{\substack{j=1 \\ j \neq i}}^V 10^{L_{Ej}(f_i)/20} \right)^2 + Y_i + 10^{L_{ETQ}(f_i)/10} \right], \quad (3.21)$$

where i is redefined in this section as an index for the L_X of the i^{th} tonal candidate; V is the number of identified *tonal candidates*, and:

1. *Excitation level, L_{Ei}* : the excitation level caused by other than the i^{th} tonal candidate is calculated by using the slopes reported on in Eq. 3.8. The application of such slopes should be carried out as follows:

$$\begin{aligned} L_{Ej}(f_i) &= L_{Cj} - 27 (Z_j - Z_i), \quad f_j < f_i; \\ L_{Ej}(f_i) &= L_{Cj} - [-24 - 230/Z_j + 0.2L_{Cj}] (Z_j - Z_i), \quad f_j > f_i \end{aligned} \quad (3.22)$$

where Z_i is the frequency in the Bark scale, and f_i is the frequency in the Hertz scale, of the i^{th} tonal candidate.

2. *Background noise Y_i* : the procedure for calculating the background noise is different from the time- to the frequency-domain algorithms, as detailed below:
  - **Time-domain algorithm**: the background noise surrounding the i^{th} tonal candidate has been proposed by Zhang & Shrestha (2003) to be extracted by adding up the corrected linear pressure levels given in Pa, $p_C \leftarrow L_C$, within an one-critical-band-wide area, centered at the frequency of the i^{th} tonal candidate, but by excluding the level of the five central frequency bins, which are the ones where the energy of the tonal candidate is supposed to be located. Figure 3.10 illustrates the corrected magnitude content, L_C , of the 1 kHz, 80 dB_{SPL} signal, sampled at 44.1 kHz, which falls into an one-critical-band-wide region. Three datatips have been included into the Figure, to show the extreme frequencies of the one-critical-band-wide region, as well as the corrected SPL of the Tonality test signal. The L_C of interest has been drawn by using a continuous dark line whereas the "background noise" that surrounds the tonal candidate is highlighted by using a continuous light-gray line. The background noise should then be transformed into linear Pa and subsequently added up, in order to obtain the term Y_i in Eq. 3.23.

Figure 3.10: Background noise of the corrected SPL, L_C , of a 1 kHz, 80 dB_{SPL} signal, sampled at 44.1 kHz.

- **Frequency-domain algorithm**: if one-third-octave-band data related to the background noise is available, then the procedure for calculating Y_i merely

consists on finding the band at which the i^{th} tonal candidate is falling into, in order to determine the corresponding level of background noise. This value should be given in linear Pa. If no background noise data is available, then Y_i can be assumed as equal to p_{ref} Pa.

3. *Auditory threshold, L_{ETQ}* : the auditory threshold in quiet is determined for the i^{th} tonal candidate, by using Eq. 3.7. Since L_{ETQ} in that equation is given in dB_{SPL} , it should be transformed into linear Pa for being integrated into Eq. 3.23.

Calculation of the weighted spectral pitch, WS

Tonality calculations conclude in the weighting of the tonal components whose $L_X > 0$. The Aures' spectral-pitch weighting formula:

$$WS_j = \left[1 - e^{\left(\frac{-L_{Xj}}{15}\right)} \right] \left[1 + 0.07 \left(\frac{f_j}{700} - \frac{700}{f_j} \right)^2 \right]^{-1/2}, \quad (3.23)$$

or the Shin et al. (2009) spectral-pitch weighting formula:

$$WS_j = \frac{1}{100} [25 + 1.2L_{Xj}] \left[1 + 0.09 \left(\frac{f_j}{1200} - \frac{1200}{f_j} \right)^2 \right]^{-1/2} \quad (3.24)$$

can be used for obtaining the *strength* of the tonal components in the primary sound. Whilst Aures' equation is claimed as a general-purpose weighting formula, the Shin et al. (2009) one is specially derived for describing the booming sensation evoked by ICEs in passenger vehicles.

The Weighted Spectrum, WS , is a set of tonal strengths extracted from the primary sound. However, for the sake of the calculations in the subsequent optimization and active control steps, it is of the utmost importance to define the outcome of this SQ metric through a single scalar value. Accordingly, the following definition is proposed:

Definition 1. *If the disturbance contains harmonic components such that $WS_j > 0$, then Tonality is defined as the mean value of the weighted spectral-pitch pattern, as follows:*

$$\mathcal{T} = X_{\mathcal{T}}(1) \left(\frac{1}{\mathbb{W}} \sum_{j=1}^{\mathbb{W}} WS_j \right), \quad (3.25)$$

where $\mathbb{W}$ is the number of tonal components; $X_{\mathcal{T}}(1) \in \mathbb{R}^+$ is a calibration weight for tuning purposes; and WS is as defined in either Eq. 3.23 or Eq. 3.24. Thus, 1 SP (unit termed from the acronym Spectral Pitch) is the Tonality elucidated by the 1 kHz, 80 dB_{SPL} pure-sinusoid signal that propagates in a free-field condition.

Discussion

While the weighted spectral-pitch pattern provides the tonal content of the disturbance discriminated by tones, by Def. 1 it follows that $\mathcal{T} : \mathbb{R}^{\mathbb{W}} \rightarrow \mathbb{R}$ is a scalar value that describes the *average tonal content* of the disturbance, in between the analyzed time range. For the time-domain algorithm, this timeframe can be either the entire signal, or a short buffer, being that the latter one might enable the analysis of signals whose frequency content change *slowly*, along uptime. The condition for the rate of the frequency change would be that the instantaneous frequency of the signal remains fairly constant during each single analysis buffer, such that Def. 1 is still valid. Moreover, since the frequency-domain approach assumes that the data represent a infinite measurement of a periodic disturbance, the interpretation of the model outcome will be exactly that of its constant, average tonal content.

Tonality metric consists on some involved calculations. In particular, the calculation of L_X demands Hertz-to-Bark and Bark-to-Hertz calculations, as well as SPL-to-Pa and Pa-to-SPL ones, which take some computational cost to be carried out. Even so, the relationship amongst variables is kept at a low complexity level. However, the complexity of the model can increase, depending on the chosen weighting function, WS . While the Aures' weighting function is an exponential function of L_X , the Shin's one is instead linear, therefore computationally less demanding. Whereas the influence of the choice of the WS calculation method on the computation burden is obvious, Section 3.6, which illustrates comparisons between the time- and frequency-domain algorithms, will unveil the approaches result better fitted, as long as the Shin's method is implemented.

When using the 1 kHz, 80 dB_{SPL} signal sampled at 44.1 Hz as the input of the time-domain algorithm, an output of 1 SP is obtained by using $X_{\mathcal{T}}(1) = 1.03$, for the Aures' weighting function, and by using $X_{\mathcal{T}}(1) = 0.89$, for the Shin's one.

3.5 Roughness

Psycho-acoustic Roughness is the model that quantify the perception of amplitude fluctuations in the range of 20 - 200 Hz (BAENE et al., 2004). The semantic interpretations that some authors have conferred to this psycho-acoustic phenomenon are, in some sense, contradictory. On the one hand, Baene et al. (2004) denote auditory Roughness as an *impure* or *unpleasant* sound quality. Daniel & Weber (1997) argue that Roughness in sounds reduces its *sensory pleasantness*. Wang et al. (2013) coin terms such as *rattle* and *creak* to auditory stimuli that elucidate Roughness. On the other hand, NVH specialists in the automotive industry do take advantage of this -unpleasant- perception for inducing, or even enhancing, sensations like *sportiveness* or *powerfulness* of ICE noises

perceived at the interior of passenger cars (GONZÁLEZ et al., 2003; JAY, 2007; LEE, 2008; OLIVEIRA et al., 2009; OLIVEIRA et al., 2010; MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b).

Time-domain Roughness models proposed by Daniel & Weber (1997), Hoeldrich & Pflueger (1999) and Wang et al. (2013) have been studied in detail. The incorporation of relative-phase influences, reported on by Pressnitzer & McAdams (1999), confirmed by Kohlrausch et al. (2005), have also been taken into account. The Wang et al. (2013) model also accounts for the acoustic field of propagation, as well as for the peripheral auditory system artifacts. Moreover, a computationally-optimized algorithm for calculating Roughness in ICE noise auditory stimuli, proposed by Janssens et al. (2007), has been also studied in detail, once that this is the first frequency-domain SQ metric that has been reported on in the specialized literature (OLIVEIRA et al., 2009). Fig. 3.11 illustrates both time- and frequency-domain approaches for calculating Roughness.

As mentioned before, auditory Roughness is quantified in *asper*, where 1 asper is the perception elucidated by the 1 kHz, 60 dB_{SPL} sound that is 100% amplitude-modulated by a pure-sinusoid signal whose frequency is 70 Hz (FASTL; ZWICKER, 2007).

Time- and Frequency-domain Roughness models

Initial calculations

The initial calculations of the time-domain Roughness algorithm are focused on obtaining both amplitude and relative-phase functions. To this regard, either the entire time history, or short buffers of the stimulus, can be analyzed. While Daniel & Weber (1997) propose splitting the signal into a number of 0.2 s long buffers, Wang et al. (2013) propose using shorter buffers of 0.05 s long. Since the auditory stimuli of interest to this research are stationary, 0.2 s long buffers suffice this requirement. The resulting time series is preprocessed by using the Blackman windowing function, as indicated by Daniel & Weber (1997) and Wang et al. (2013). A discrete Fourier transform is then calculated over the windowed time history, in order to determine the spectral functions of the sound.

Corrections for accounting for the propagation field and auditory system artifacts

The magnitude function given in dB_{SPL} is corrected for accounting for both acoustic propagation conditions a_{pf} and peripheral auditory system artifacts a_{pa} , as recommended by Wang et al. (2013). To this regard, Eq. 3.20 can be followed. At this point, it is worth noticing that the relative-phase data are not corrected, but saved into memory for subsequent operations.

Figure 3.11: Block diagrams of time- and frequency-domain Roughness models.

Source: Adapted from Mosquera-Sánchez et al. (2017a).

Critical band filtering

A critical-band filtering takes place by using one-critical-band-wide overlapping filters. The masking slopes given in Eq. 3.8 are used for accomplishing this calculation. For a given j^{th} critical band, L_E should be calculated as follows:

$$L_{Ej} = \begin{cases} L_C(\mathcal{Z}) + SL^{(2)}(\mathcal{Z}) [(\mathcal{Z}_j - 0.5) - \mathcal{Z}] & \mathcal{Z} \in [0, \mathcal{Z}_j - 0.5], \\ L_C(\mathcal{Z}) & \mathcal{Z} \in [\mathcal{Z}_j - 0.5, \mathcal{Z}_j + 0.5], \\ L_C(\mathcal{Z}) + SL^{(1)}[\mathcal{Z} - (\mathcal{Z}_j + 0.5)] & \mathcal{Z} \in (\mathcal{Z}_j + 0.5, \mathcal{Z}_{max}], \end{cases} \quad (3.26)$$

where $\mathcal{Z}_{max} = \mathcal{Z}(Fs/2)$ is the maximum allowed number of critical bands. Unlike the Daniel & Weber (1997) and Wang et al. (2013) models, which fix $\mathcal{Z}_{max}$ at 24 critical bands, this research proposes that $\mathcal{Z}_{max}$ be a function of the sampling rate. This adaptation follows from the fact that this algorithm may be required for input signals sampled at rates other than the usual 44.1 kHz. For instance, an input signal sampled at 4 kHz would just require Eq. 3.26 to be calculated until $\mathcal{Z}_{max} = \lfloor \mathcal{Z}(2000) \rfloor$, i.e. $\mathcal{Z}_{max} = 12$ Bark, or $f_{max} = 1746.10$ Hz.

Calculation of modulation indices

The calculation of the modulation indices per critical band is a cumbersome procedure. Costly computations, such as the Hilbert transform, are needed to calculate the modulation index per critical band, mi . However, not all the sounds have spectral content along the entire bandwidth that contribute to the overall Roughness level. This condition can be verified by calculating a time series at the j^{th} critical band, through an inverse discrete Fourier transform over L_{Ej} , i.e. $d'_j[n] \xleftarrow{\mathcal{F}^{-1}} L_{Ej}$, to subsequently calculating its RMS value and comparing it with the corresponding auditory threshold. If the RMS value falls under the auditory threshold at the j^{th} critical band, its contribution to the Roughness perception can be disregarded.

To obtain $d'[n]$, an inverse discrete Fourier transform should be calculated at each critical band, by using the relative-phase extracted at the initial calculations, with the magnitude function given by L_{Ej} from Eq. 3.26. Then, if $d'_{RMSj}[n] \leq L_{ETQj}$ (cf. Eq. 3.7) at the j^{th} critical band, then mi_j is made equal to zero. Otherwise, the following set of calculations, which are particular to either the time- or the frequency-domain algorithm, should be performed:

- *Time-domain algorithm:*

1. Calculation of the envelope, $env_j[n]$, at the j^{th} critical band: a Hilbert transform is performed over $d'_j[n]$, and its modulus function is taken, i.e. $env_j[n] \xleftarrow{|\cdot|} d'_j[n]$. Subsequently, the magnitude and the relative-phase functions of $env_j[n]$ are extracted by using a DFT.

2. Correction of the envelope magnitude: the weighting coefficients illustrated in Fig. 3.12 are applied on the magnitude function of the envelope that was calculated in the previous step. These coefficients account for the human perception of the Roughness. This is the reason why the magnitude of those coefficients is large in frequencies around 70 Hz. The sets of weighting coefficients at the j^{th} critical band are as follows: if $0 \leq \mathcal{Z} \leq 2$, the corresponding set is that of $\mathcal{Z} = 1$; if $2 < \mathcal{Z} \leq 8$, the corresponding set is that of $\mathcal{Z} = 5$; if $8 < \mathcal{Z} \leq 10$, the corresponding set is that of $\mathcal{Z} = 10$; if $10 < \mathcal{Z} \leq 21$, the corresponding set is that of $\mathcal{Z} = 15$; otherwise the corresponding set is that of $\mathcal{Z} = 30$, in Fig. 3.12.

Figure 3.12: *Weighting coefficients as a function of the modulation frequency.*

It is worth recalling that the relative-phase data extracted in the previous step are just saved into memory for the following calculations.

3. Reconstruction of a new time series, $d_j''[n]$, with the corrected magnitude function: the corrected magnitude function obtained from the previous step is used for reconstructing a new time series, $d_j''[n]$, with the help of the relative-phase data retrieved at Step 1. This procedure is accomplished by using an inverse DFT.
4. Calculation of the modulation index, mi :

$$mi_j = \frac{RMS(d_j''[n])}{RMS(d_j'[n])}, \quad (3.27)$$

- *Frequency-domain algorithm:* the costly procedure of calculating the envelope,

$env_i[n]$, via Hilbert transform in the time-domain algorithm, is replaced by the one proposed by Janssens et al. (2007):

$$env_i[n] = \sqrt{DC + \sum_{j=1}^{R-1} AC_j}, \quad (3.28)$$

where:

$$DC = \sum_{r=1}^R (AC_r)^2, \quad (3.29)$$

$$AC_j = 2 \sum_{r=j}^{R-1} a_r a_{r-1} \cos [2\pi (f_r - f_{r-1}) [n] + (\theta_r - \theta_{r-1})], \quad (3.30)$$

where i has been redefined for this section as a index for critical bands; $\{a, f\}$ are the amplitude and frequency of the r^{th} tone in the disturbance, respectively, after the critical-band-filtering procedure; $\theta \in [-\pi, \pi]$ is the *original* relative-phase of the r^{th} tone, i.e. without critical-band filtering; and $\{DC, AC_j\}$ are terms proportional to the DC and AC components of the filtered time-domain series, $env_i[n]$, stated in Eq. 3.26. Notice that $env_i[n]$ requires a time vector for its calculation, for which a small time series of 0.2 s, sampled at 650 Hz, will suffice, due to the fact that the largest modulation frequency (f_{mod}) that is assessed by the original Roughness model matches this sampling rate.

Having synthesized $env_i[n]$, steps 2, 3, and 4, listed for the time-domain algorithm, can be performed for calculating the modulation indices for each critical band.

Cross-correlation between contiguous critical bands

Since the temporal interactions between adjacent critical bands might affect the Roughness perception, some authors have proposed to estimate these influences through the calculation of cross-correlations, b_j . Although not being a computationally demanding operation, these calculations might also be saved, as long as $mi_j = 0$ for a given j^{th} critical band.

The calculation of the cross-correlations should be carried out as follows:

- If $mi_j = 0$, then $b_j^{(L)} = 1$ and $b_j^{(R)} = 1$, so $b_j = 1$.
- If $mi_{j-1} = 0$, then $b_j^{(L)} = 1$ and $b_j^{(R)}$ should be calculated as $b_j^{(R)} = d_j''[n] \star d_{j+1}''[n]$, where $d''[n]$ is the reconstructed time series from step 3 of the calculations for mi_j ; and the operator $(\star)$ denotes time-domain correlation.
- If $mi_{j+1} = 0$, then $b_j^{(R)} = 1$ and $b_j^{(L)} = d_{j-1}''[n] \star d_j''[n]$.

- If neither $mi_{j-1} = 0$ nor $mi_{j+1} = 0$, then $b_j^{(L)} = d_{j-1}''[n] \star d_j''[n]$ and $b_j^{(R)} = d_j''[n] \star d_{j+1}''[n]$,

where the superscripts L , and R stand for left-side and right-side cross-correlations.

Specific Roughness

After correcting for the modulation frequency at each critical band in the previous steps, an additional correction on the carrier frequency should be implemented. Then, the specific Roughness, given in asper/Bark, is calculated, as follows:

$$\mathcal{R}'_j = q(\mathcal{Z}) (mi_j b_j)^{X_{\mathcal{R}}(2)}, \quad (3.31)$$

where $X_{\mathcal{R}}(2) \in [1.4, 2.2]$ is a *calibration weight* that define the order of dependence of the Roughness on the corrected modulation index mi , and $q(\mathcal{Z})$ is the correction function for the carrier frequency, which is given in Fig. 3.13.

Figure 3.13: Weighting coefficients as a function of the carrier frequency.

Source: Data extracted from Wang et al. (2013).

A number of authors have discussed the level of dependency of Roughness on the modulation index. Guirao & Garavilla (1976) demonstrated that for AM noises, $X_{\mathcal{R}}(2)$ can be as low as 1.4. Daniel & Weber (1997) and Wang et al. (2013) stated that the dependency is quadratic, i.e. $X_{\mathcal{R}}(2) = 2$. Hoeldrich & Pflueger (1999) state that $X_{\mathcal{R}}(2)$ can be allowed to take values in between 1.5 - 2.0. Fastl & Zwicker (2007) proposed that $X_{\mathcal{R}}(2) = 1.6$. In view of such discrepancy, it has been allowed for the frequency-domain algorithm to be adjusted in between 1.4 - 2.0, according to the stationary periodic disturbance under study.

Total Roughness

The total Roughness, $\mathcal{R}$, is eventually calculated as the summation of all the specific Roughness values obtained at the previous step. Roughness is then calculated as follows:

$$\mathcal{R} = X_{\mathcal{R}}(1) \sum_j \mathcal{R}'_j, \quad (3.32)$$

where $X_{\mathcal{R}}(1) \in \mathbb{R}^+$ is a *calibration weight* that intends to tune the model for predetermined outputs. For instance, when the definition signal is used as the input, the Daniel & Weber (1997) and Wang et al. (2013) models state that $X_{\mathcal{R}}(1) = 0.25$ makes the output to be equal to 1 asper. The time-domain algorithm implemented in the present research provides an output of 1.03 asper, by using the definition signal sampled at 44.1 kHz. The calibration weights used are, therefore $\{X_{\mathcal{R}}(1), X_{\mathcal{R}}(2)\} = \{0.62, 2.08\}$.

Discussion

Auditory Roughness is a largely studied psycho-acoustic metric. However, no general consensus exists on a generalized model that quantifies this perception. From the point of view of the computational needs, it has been shown that the time-domain approach requires a great deal of computation, due to the required time-to-frequency transforms. This computation cost could hinder the use of exhaustive search algorithms for investigating tone magnitude patterns that would enhance Roughness. At that point, the frequency-domain model comes into play and allows for this metric to be included in the multi-objective optimization.

The fact that Auditory Roughness is a function of the corrected modulation index per critical band prevents a straightforward relation to the time/frequency pattern of the sound. This level of complexity still reaches a higher level, when one considers the intricate relationship amongst variables and the dependency of Roughness on the modulation index to be non-linear.

3.6 Comparisons between time- and frequency-domain SQ models

The purpose of this section is to validate the frequency-domain methods to be used in the following stages of this research. In order to do so, simple stimuli, such as pure sinusoids and narrowband noises, will be used with both time- and frequency-domains models and the results will be compared and contrasted.

The methodology followed to carry out the comparisons is described below:

- The time-histories used for each SQ metric are 1 s long time series of the *definition*

signals, sampled at 44.1 kHz, whose acoustic propagation is assumed as in free-field:

- Loudness: 1 sone = 1 kHz, 40 dB_{SPL} signal.
  - Roughness: 1 asper = 1 kHz, 60 dB_{SPL} sinusoid that is 100% AM with a 70 Hz sinusoid.
  - Sharpness: 1 acum = noise filtered with an one-critical-band-wide filtered, centered at 1 kHz, whose RMS value is 80 dB_{SPL}.
  - Tonality: 1 SP (spectral pitch) = 1 kHz, 80 dB_{SPL} signal.
- The calibration procedure is executed by using the time- and frequency-domain data of the test signals described above, as well as the tuning weights determined from the literature for the time-domain algorithms. In this way, the calibration weights for the frequency-domain algorithms are determined.
  - The same set of calibration weights is tested for a number of different test signals, in a form particular for each metric. The results from both time- and frequency-domain algorithms are then plotted and compared with each other
  - The execution time is also measured for each calculation of either the time- or the frequency-domain model. The measurements are briefly described, in order to report on the most computationally economic approach for calculating each metric.

3.6.1 Loudness

The Loudness algorithms are tested as a function of both the level and frequency of pure-sinusoid signals. Regarding the level, one sinusoid with fixed frequency at 1000 Hz has been used. Its amplitude level is varied from 0 to 120 dB_{SPL}, with 10 dB_{SPL} steps. Figure 3.14(a) shows the comparison between the results of the time- and frequency-domain methods, as well as the coefficient of determination, R^2 , for the data fit. As it can be seen, there is a perfect match between the two methods. To verify the frequency-domain method for different frequencies, a fixed-level at 60 dB_{SPL} has been predefined. The frequency of the fixed-level signal is discretely varied by using the central frequencies of the one-third-octave-band filterbank (ASA, 1986). Figure 3.14(b) shows, again, a comparison of time- and frequency-domain methods, with a perfect match. From that, it can be stated that both time- and frequency-domain Loudness algorithms correlate well, even when the calibration weights were obtained just for the definition signal. In other words, there is no need for running the calibration procedure, every time the input signal is changed.

Finally, both algorithms have been tested for computational time, by repeating the calculations for a number of iterations, and averaging the elapsed time. As expected, the frequency-domain method outperforms its time-domain counterpart, running up to 30 times faster and, therefore, it is selected as the preferred method.

Figure 3.14: Comparisons between time- and frequency-domain Loudness models: (a) fixed-frequency, pure-sinusoid signals as a function of their SPL; (b) fixed-SPL, pure-sinusoid signals as a function of their frequency.

3.6.2 Sharpness

The Sharpness algorithms are tested as a function of both the level and frequency of Gaussian noises filtered with one-critical-band-wide filters. Both of the weighting functions for Sharpness have been tested, namely the Von Bismark's and Zwicker's ones.

Regarding the level, a Gaussian noise filtered with an one-critical-band-wide filter centered at 1000 Hz has been used. Its amplitude level is varied from 0 to 120 dB_{SPL} RMS with 10 dB_{SPL} steps. Figure 3.15(a) shows the comparison between the results from the time- and frequency-domain methods, as well as the coefficient of determination, R^2 , for the data fit. As it can be seen, there is a perfect match between the two methods. To verify the frequency-domain method for different frequencies, a Gaussian noise is filtered by using an one-critical-band-wide filter, whose central frequency is varied by using the central frequencies of the one-third-octave-band filterbank (ASA, 1986). Figure 3.15(b) shows, again, a comparison of time- and frequency-domain methods, with a perfect match. From that, it can be stated that both time- and frequency-domain Sharpness algorithms correlate well, even when the calibration weights were obtained just for the definition signal.

Finally, both algorithms have been tested for computational time, by repeating the calculations for a number of iterations and averaging the elapsed time. On the one hand,

Figure 3.15: Comparisons between time- and frequency-domain Sharpness models: (a) pure-sinusoid signals as a function of their SPL; (b) pure-sinusoid signals as a function of their frequency.

when subjected to SPL changes, the time-domain, Zwicker-weighted Sharpness function seemed to take slightly longer than the Von Bismark-weighted one. With regard to the frequency-domain algorithms in the same experiment, no appreciable differences were found when comparing both weighting functions. On the other hand, when subjected to frequency changes, it has been observed that, while the time-domain algorithms showed no differences in processing time, the frequency-domain Zwicker-weighted algorithm slightly overcome the Von Bismark's one. As expected, by avoiding the steps such as the DFT, the frequency-domain method outperforms its time-domain counterpart, running up to 60 times faster and, therefore, it is selected as the preferred method.

3.6.3 Tonality

The Tonality algorithms are tested as a function of both the level and frequency of pure-sinusoid signals. Regarding the level, one sinusoid with fixed frequency at 1000 Hz has been used. Its amplitude level is varied from 0 to 120 dB_{SPL} with 10 dB_{SPL} steps. Figure 3.16(a) shows the comparison between the results from the time- and frequency-domain methods, as well as the coefficient of determination, R^2 , for the data fit. While the Tonality weighted by the Shin's formula showed a perfect correlation between the two methods, the Tonality weighted by the Aures' formula showed results slightly inferior to those provided by the Shin's formula. To verify the frequency-domain method for different frequencies, a fixed-level at 80 dB_{SPL} has been predefined. The frequency of the fixed-level signal is discretely varied by using the central frequencies of the one-third-octave-band filterbank (ASA, 1986). Figure 3.16(b) shows, again, a comparison of the time- and frequency-domain methods, with a perfect match, regardless of the

weighting formula that is used. From that, it can be stated that both time- and frequency-domain Tonality algorithms correlate well, even when the calibration weights were obtained just for the definition signal.

Finally, both algorithms have been tested for computational time, by repeating the calculations for a number of iterations and averaging the elapsed time. As expected, by avoiding the steps such as the DFT, the frequency-domain method outperforms its time-domain counterpart, running up to 5 times faster and, therefore, it is selected as the preferred method.

Figure 3.16: Comparisons between time- and frequency-domain Tonality models: (a) pure-sinusoid signals as a function of their SPL; (b) pure-sinusoid signals as a function of their frequency.

3.6.4 Roughness

Since the Roughness metric is a function of the corrected modulation index per critical band, cf. Eqs. 3.31 and 3.32, both the time- and the frequency-domain algorithms have been first tested by using fixed pure-sinusoid signals that are 100% amplitude modulated by a variety of modulation signals. Figure 3.17(a) shows the comparison between the results from the time- and frequency-domain Roughness algorithms in this situation. The outcomes have been split into four subplots, in the same fashion as presented by Daniel & Weber (1997). Seven pure-sinusoid signals with fixed central frequencies 125, 250, 500, 1000, 2000, 4000 and 8000 Hz have been tested. The frequency of the modulation signal is varied from 0 Hz, i.e. no modulation, to 160 Hz, by using steps of 8 Hz. The results in Fig. 3.17(a) were calculated by using the calibration weights determined by just using the *definition signal* for Roughness. It is possible to notice, however, that rather low coefficients of determination were attained, which indicates a poor fit between time- and frequency-domain algorithms. In special, it is shown that when a pure-sinusoid with central frequency at 125 Hz is subjected to diverse

modulation frequencies, the accuracy of the frequency-domain Roughness model just amounts to 77%. Moreover, when modulating the 1 kHz tone, the frequency-domain Roughness model attains an accuracy of 95%. However, those values are low, as related to the obtained ones when assessing Loudness, Sharpness and Tonality algorithms.

This situation has enforced to carry out the calibration routine, before each single calculation with the frequency-domain algorithm to take place. The new results are shown in Fig. 3.17(b), which reveals that both algorithms do agree well, provided that the frequency-domain algorithm is calibrated before changing the input signal.

Figure 3.18(a) shows the comparison between the results from the time- and frequency-domain Roughness algorithms as a function of the modulation depth. The test signal is that of the definition one, but its modulation depth is gradually increased from 0% to 260%, according to the Daniel & Weber (1997) research, with steps of 13%. Without recalibration, the frequency-domain algorithm is already shown to match well the changes in the modulation depth. After running calibration before each single measurement, the data fit turned out to be perfect, as it can be seen in Fig. 3.18(b).

Finally, both algorithms have been tested for the computation time, by repeating the calculations for a number of iterations, and averaging the elapsed time. As expected, by avoiding the steps such as the DFT, the frequency-domain method outperforms its time-domain counterpart, running up to 25 times faster and, therefore, it is selected as the preferred method.

3.7 Conclusions

This chapter has described computational procedures for calculating four psycho-acoustic models, which are widely used in diagnosing the SQ of technical sounds, namely Loudness, Roughness, Sharpness and Tonality. Since this research focuses on stationary periodic noise, frequency-domain SQ algorithms have been derived. This approach is useful, mainly when an optimization step is foreseen, such that frequency-domain data from the original disturbance can be extracted only once and used along a number of iterations of the optimization procedure, thus saving computational time. The frequency-domain methods have been calibrated and validated by benchmarking against time-domain methods under diverse conditions. In this way, the frequency-domain SQ models are chosen for driving the subsequent stages of the proposed methodology. At this point, it is worth recalling that the Sharpness model will be calculated with the Zwicker weights, as well as the Tonality model will be calculated with the Shin weights. Moreover, since the time- and frequency-domain Roughness models need to be adjusted for each sound tested, the calibration procedure will be executed before each single algorithm run.

Although the computational complexity of the models is expected to grow, as the

Figure 3.17: Comparisons between time- and frequency-domain Roughness models: (a) AM signals with fixed central frequency as a function of the modulation frequency - no calibration; (b) AM signals with fixed central frequency as a function of the modulation frequency - calibrated.

number of tones present in the input signal grows, the analyses carried out with single-sinusoid signals presented in this chapter still serve as an indicative of the computational needs of each algorithm. The following chapter will then pose with a multi-objective

Figure 3.18: [cont'] Comparisons between time- and frequency-domain Roughness models: (a) pure-sinusoid signal as a function of the modulation depth - no calibration; (b) pure-sinusoid signal as a function of the modulation depth - calibrated.

optimization problem that aims at searching for optimized frequency parameters of a given primary sound, such that its SQ is enhanced, on the basis of the psycho-acoustic models and algorithms discussed in this chapter.

Chapter 4

Multi-objective sound quality optimization of periodic disturbances

MOST of the noise, vibration and harshness studies in passenger cars are oriented towards reducing disturbance levels. In that sense, the decision on whether actions must be taken is often based on predetermined thresholds (DRAGONETTI et al., 2017). Although intuitively the reduction of noise and/or vibration levels should always be perceived as good, human related perceptions might result negatively affected, once that psycho-acoustic issues, e.g. masking, pitch, equalization, etc. are not foreseen in this noise control approach. Hence, NVH refinement can only be achieved if, besides the mere level reduction, all the relevant psycho-acoustic features are taken into account. The question that arises at this point is related to the correlation between the modifications to the powertrain emitted tonal components and the enhancement of its sound qualities.

This Chapter introduces a framework for guiding active control actions towards the enhancement of the sound qualities of the noise emitted by the powertrain in HEVs. The chapter starts with a literature survey on existing approaches to the SQ of technical noises, which can be seized in the goal being pursued. After exploring their strengths and weaknesses, a multi-objective optimization (MOO) formulation is posed, which features the relevant SQ metrics to the noise of concern, namely Loudness, Roughness, Sharpness and Tonality. These psycho-acoustic models are arranged in a vector form, and their concurrent optimization is examined via two multi-objective evolutionary solvers such as the Non-dominated Sorting Genetic Algorithm, NSGA-II (DEB et al., 2002), and the Strength Pareto Evolutionary Algorithm, SPEA2 (ZITZLER et al., 2001). This Chapter also shows that the multi-objective SQ optimization formulation is computationally feasible, not only for the hybrid electric powertrain noise, but also for a variety of noises with similar spectral features, as long as a reduced set of tones can be found, and that can be proven as the cause for large variations in the output of the associated SQ dimensions. To this concern, a set of sensitivity analyses is proposed

for searching, amongst the large number of tones that compose the powertrain noise in HEVs, for the one(s) that truly drive(s) each single SQ metric to substantial changes. The most valuable benefit of optimizing the SQ of technical noises in a multi-objective fashion is that of obtaining a set of diverse optimum solutions in a single solver run. This will allow the NVH specialist to closely meet the auditory expectation of specific users, by simply selecting, amongst the variety of obtained optimum solutions, the one that better fits the requirements.

Two computer simulations are appended at the end of this Chapter to demonstrate the proposed framework for optimizing the SQ of periodic disturbances. On the one hand, the optimization of a simple periodic disturbance, composed of just six tones, allows for an intuitive assessment of the relationship between the tones levels (design space) and the SQ metrics (performance space) associated with the MOO. On the other hand, the optimization of a sound synthesized from a real hybrid electric powertrain noise serves as a demonstration of the effectiveness of the proposed framework.

This Chapter is mainly devoted to demonstrate the proposed steps of the MOO, oriented for single listeners, leaving for the following Chapter the experimental results, as well as the extension of the method for multichannel control scenarios.

4.1 Vector optimization of SQ metrics

A number of studies can be found in the literature, which attempt to describe and predict the sound quality of a noise through a single scalar value. A variety of mathematical relationships amongst the so-called *elementary perceptions* have been proposed, which are determined for each sort of technical noise. Their level of complexity ranges from straightforwardly linear formulations, e.g. weighted sum of metrics and linear regressions, to complex non-linear ones, e.g. neural network-based formulations. In the light of the variety of opinions that is encountered on how a given machine or system should sound, the qualification of its byproduct noise through a single scalar value, or an adjective (*good, pleasant, smooth, sporty*, among others), might be imprecise and rather difficult to reproduce.

When it comes to searching for better SQ conditions for a noise, the sort of mathematical formulation that maps a number of variables into a single scalar offer a valuable starting point, since its minimization or maximization can be directly associated to the physical variables that resulted in such SQ score. Further insight could be gained by analyzing individually each of the elementary perceptions that resulted in the SQ score enhancement.

The mathematical formulations that are found in the literature for quantifying and predicting the SQ of sounds can be roughly clustered in three groups, namely (i) the single *Sensory pleasantness* model (FASTL; ZWICKER, 2007), (ii) the -weighted- sum

of metrics (GONZÁLEZ et al., 2003; JEON et al., 2007; SHIN et al., 2009; LEITE et al., 2009; NYKÄNEN; SIRKKA, 2009; SHIN; CHEONG, 2010; LEE et al., 2010; CHO et al., 2011; BRIZON; MEDEIROS, 2012; JEONG et al., 2015), and (iii) neural network-based models (WANG et al., 2007; LEE, 2008; PIETILA; LIM, 2012; LIU et al., 2015; XING et al., 2016; HUANG et al., 2017; WANG et al., 2017). Whilst both of the Sensory Pleasantness model and the weighted sum of metrics explicitly take the SQ models into the formulations, neural network-based SQ approaches attempt to first emulate the psycho-acoustic models, so the relationship between the SQ of a sound and its magnitude function turns out to be inferred from the "model of a model", i.e. from meta-models. Moreover, while the Sensory Pleasantness, as well as the weighted sum of metrics, are models that map a number of SQ dimensions into a single scalar value, the neural network-based SQ approaches own the capability of mapping the associated SQ dimensions into more than a single scalar value.

Recalling that the main objective of this research is to propose active control systems that enables the SQ enhancement of HEV noise, the purpose of this MOO problem is to provide such systems with a target, based on the physical properties of the disturbance. Therefore, a mapping of such physical quantities (e.g. tone levels) and the SQ perceptions becomes necessary. In this manner, the arrangement of the elementary perceptions in a vector form is proposed, and its optimization is worked out in a multi-objective fashion. This formulation, mostly based on the weighted sum of metrics, first eliminates the intermediary mapping of the SQ variables into a single scalar, required in single-objective formulations, which results in a single-mapping function of the form $f : \mathbb{R}^R \rightarrow \mathbb{R}^Q$, similar to that of the neural network-based SQ models, where R is the amount of tones in the primary sound, and Q is the amount of SQ metrics being associated to the MOO. The vector optimization of the SQ metrics requires neither weight vectors nor reference values, often necessary in other approaches (such as Sensory Pleasantness and neural network-based metrics), which simplifies the present implementation for stimuli to which no *a priori* data is available.

The multi-objective SQ optimization problem for periodic disturbances is posed as follows:

$$\begin{aligned} \min_{\mathbf{a}} \mathbf{Y} &= \min (\mathbf{F}_j(\mathbf{a})); & j &= 1, \dots, Q; \\ \text{subject to} & : a_r^{(Lo)} \leq a_r \leq a_r^{(Up)}; & r &= 1, \dots, \mathcal{V}; \quad \mathcal{V} \leq R \end{aligned} \quad (4.1)$$

where $\mathbf{a} \in \mathbb{R}^{\mathcal{V}}$ is the vector composed of the amplitude values of the tones that belong to the *decision space*, with $\mathcal{V} \leq R$ is the amount of tones, out from the R tones, which compose the noise under study; each of the $\mathbf{F}_j \rightarrow \mathbf{Y} \in \mathbb{R}^Q$ functions are the associated SQ dimensions to the noise of concern, which belong to the *feature* (LIU et al., 2015) or *objective space*; and superscripts $\{Lo, Up\}$ stand for the lower and upper bounds of the r^{th} decision variable.

Equation 4.1 describes a constrained optimization problem of a set of SQ metrics. The computational burden related to the complexity of the MOO solver is the first aspect to be taken into account, when optimizing Eq. 4.1. This aspect is at its turn dependent on both the amount of SQ dimensions and the number of tones present in the noise under study. As discussed before, the SQ space that is commonly associated with periodic disturbances is composed of four dimensions, namely: Loudness, Roughness, Sharpness, and Tonality, each of them with its own computational cost. When it comes to the decision space, the powertrain noise in HEVs has been shown to contain a large amount of tones, which might jeopardize any attempt on assessing combinations of possible solutions. Therefore, it seems reasonable to work with a reduced set of tones, both in this stage and during the practical implementation of the ASQC. The underlying hypothesis behind this statement is that one can find a reduced set of tones, which most drastically affect each SQ perception. For instance, Loudness issues can easily be targeted to a few high level tones; Roughness ones can be regarded as a result of up to three tones with a certain frequency and amplitude relation that cause modulation; Tonality, by definition, is caused by tones that excite a certain threshold, while Sharpness can be assessed by targeting high high-frequency tones. Hence, a sensitivity analysis over the sound becomes an essential step, in order to render the optimization stage feasible.

Sensitivity analyses

One of the main features in human perception that leads to the conclusion that not all narrowband components of a sound are relevant to noise control, is that of masking. This mechanism depends on both the relative level and frequency gap between two (or more) tones, which may result in the dominant one to act as a masker, i.e. to actually block the aural contribution of the neighboring sound. In this way, any reduction of the masked orders, although may show as SPL reduction, will have no effect on the perception of the sound. This feature alone, which affects at least Loudness and Sharpness, advocates for the sensitivity analysis, yet other psycho-acoustic phenomena could be listed, such as the filtering of the peripheral auditory system that happens in the outer, middle and inner ear; the weighting of tonal components that happens into the central auditory system; particularities observed when exposed to modulated disturbances, among others. In this way, each of the selected SQ metrics will undergo a *sensitivity analysis* that will highlight the spectral components that truly drive the sound to noticeable changes in perception.

A method called One Factor at a Time (OAT) has previously been used to run these sensitivity analyses, which consists of perturbing a given input variable while keeping the other ones fixed, and assessing the corresponding output levels (MOSQUERA-SÁNCHEZ, 2012). This method has the advantage of owing a low computation cost

(neglecting the intrinsic cost of the function under study), which, connected with the straightforwardness of unambiguously associating model output changes to each input variable, make this an interesting choice. However, the OAT method is not good in assessing interactions between variables and clearly assumes linearity between perturbations in the input variables and the model outputs. In order to cope with that, the so-called Elementary Effects (EE) method has been studied, which relies on OAT-based input variations to provide two sensitivity measures: (i) the measure μ that describes the relevance of the inputs, and (ii) the measure σ that relates to non-linear effects and/or interactions amongst variables (CAMPOLONGO et al., 2007). These measures are determined as follows:

$$\mu_j = \frac{1}{R} \sum_{r=1}^R d_j(a_r), \quad (4.2)$$

$$\sigma_j = \sqrt{\frac{1}{R-1} \sum_{r=1}^R [d_j(a_r) - \mu_j]^2}, \quad (4.3)$$

where:

$$d_j(\mathbf{a}) = \frac{F_i(a_1, \dots, a_{j-1}, a_j + \psi, a_{j+1}, \dots, a_R) - F_i(\mathbf{a})}{\psi} \quad (4.4)$$

is the so-called *elementary effect* the j^{th} input variable, i.e. the j^{th} tone, causes on the i^{th} cost function, i.e. the i^{th} SQ metric, by keeping all the other variables at their nominal amplitude values. Each of the input variables is assumed to vary across y levels in the decision space. In Eq. 4.4, $F_i(\mathbf{a})$ in Eq. 4.4 stands for the nominal value of F_i , i.e. the function value at the original condition of the amplitudes of the primary sound, $\mathbf{a}$.

Campolongo et al. (2007) suggest that the number of levels, y , should be chosen as an even number, and that ψ should be made equal to $y/[2(y-1)]$. Although this choice assures that the inputs are "symmetrically treated", the large amount of function evaluations that arises from such strategy can be reduced by a half, as soon as $\psi = 1/(y-1)$, with no restriction on y other than being a positive integer. Moreover, since each of the input variables is mapped into an uniform distribution in $[0, 1]$, the obtained ψ in the hypercube must be mapped back into the actual distribution of the amplitudes, in order to conform the *region of experimentation*, given in the amplitude units (either Pa or dB_{SPL}). This should be carried out for each tone in the sound, in order to compute all the elementary effects caused by the R input variables. Finally, although Campolongo et al. (2007) suggest that R can be made smaller than the number of input variables itself, in this implementation all the sound tones are taken into account. By doing so, it is possible to determine all the effects on each SQ model, together with possible interactions amongst them.

Figure 4.1 illustrates the EE method when mapping the sensitivity of 3 tones to a

certain SQ metric. The range in the EE method targeting noise control would only consider values between the nominal amplitude and a lower bound (e.g. maximum noise reduction). However, the present implementation foresees active noise equalizations with four modes of operation: *cancellation*, *reduction*, *preservation* and *amplification*, hence the used range is $[0, a_r + 6.02]$ dB_{SPL}, or $[20e^{-06}, 2a_r]$ Pa. The amplification mode offers the masked components the "opportunity" to become relevant, as their amplitude could reach up to twice their original level.

Figure 4.1: Method of mapping amplitude values into hypercubes.

With these bounds for each variable, the amplitudes of the tones in the sound are mapped into a hypercube, and ψ is computed by defining a number of levels, which reads $y = 5$ for the example plotted in Fig. 4.1. It also illustrates the augmented cube that would result, if just three tones were taken into account. Nevertheless, it is recalled that all the tones in the sound under study should be considered. Each of the ψ values are brought back to the amplitude domain for calculating the trajectory, i.e. the amplitude vector, of each variable. Next, Eq. 4.4 is calculated at each increment of ψ . As soon as this procedure is repeated for the R tones, the measures μ and δ can be obtained.

The objective space: association of SQ metrics and evolutionary solvers

As seen early through the literature survey, Loudness, Roughness, Sharpness and Tonality metrics are associated with a wide sort of technical noises. While Loudness and Roughness are good SQ descriptors for low- and mid-frequency noise, Loudness, Sharpness and Tonality have been used for sounds with high-frequency content. Then, it seems reasonable to quantify the SQ of the hybrid electric powertrain noise by using

these metrics, once this sort of sounds spread into a wide bandwidth (cf. Chapter 1). This leads to rewrite $\mathbf{Y}$ in Eq. 4.1 as $\mathbf{F} = [\mathcal{N}(\mathbf{a}), \mathcal{R}(\mathbf{a}), \mathcal{S}(\mathbf{a}), \mathcal{T}(\mathbf{a})]^T$. In other words, the SQ vector that describes the hybrid electric powertrain noise conforms a fourth-dimensional objective space, with $\mathcal{V} = 4$ in Eq. 4.1.

The task of optimizing vectors is currently approached by using evolutionary algorithms, since they implement special strategies for handling the cost function into multi-dimensional objective spaces (MARLER; ARORA, 2004). Moreover, as long as the functions arranged in a vector are *conflicting*, i.e. the improvement of one single objective comes at the expense of the remaining ones, it is expected that *a set of diverse solutions*, rather than a single one, is obtained from the concurrent optimization (DEB, 2001). This set of diverse solutions is called *Pareto front*, or *compromise frontier*.

The optimization of multi-objective problems should accomplish two goals (DEB, 2001), namely: (i) to find a set of solutions such that they conform the *optimum* Pareto front, and (ii) to find a set of solutions such that they cover *properly* the entire -optimum- Pareto front. Whilst the first goal refers to convergence aspects, the second one is related to the distribution of the attained solutions along the compromise frontier. To these concerns, two evolutionary algorithms have been studied, namely the Non-dominated Sorting Genetic Algorithm (NSGA-II) (DEB et al., 2002) and the Strength Pareto Genetic Algorithm (SPEA2) (ZITZLER; THIELE, 1999; ZITZLER et al., 2001), which are widely acknowledged for being effective in accomplishing such objectives. The operation of these solvers is summarized in four main steps, as follows:

1. **Encoding:** Depending on whether the decision space is continuous or discrete, either real- or binary-domain genetic algorithms should be chosen. Since the amplitude values of the decision tones linked to the SQ optimization problem are allowed to take real values that satisfy imposed bounds, both the decision variables and the objective functions can be encoded in the real-valued domain.
2. **Definition of population size and number of generations:** A *chromosome* can be roughly interpreted as being a vector in $\mathbb{R}^{\mathcal{V}}$, in which each of its elements is allowed to take -real-domain- values that satisfy the imposed bounds. In this step, the initial population of chromosomes is generated, to which a variety of creation functions is reported in the literature. In special, the Uniform function can be used (MATHWORKS., 2016a), which creates a random initial population with a uniform distribution and also accounts for existing bounds for each decision variable. This population is *expected to evolve* along a number of allowed iterations, or *generations*. In multi-objective optimization problems, it is a common practice to set up a finite number of generations as a stop criterion.
3. **Evaluation of the fitness function:** This step deals with the evaluation of the population into the *fitness function*, at the current generation. It is at that point

where NSGA-II and SPEA2 differ from one another. The specificities of each multi-objective solver are described below:

- *Non-dominated sorting genetic algorithm (NSGA-II)*: this approach relies on sorting solutions according to the position that they had reached in the objective space. The evaluation of the position in the objective space is based on *dominance/non-dominance* relationships amongst solutions. It is said that a solution $\mathbf{Y}^{(1)}$ *dominates* solution $\mathbf{Y}^{(2)}$, if the following two statements hold (DEB, 2001):
  - $\mathbf{Y}^{(1)}$ is not worse than $\mathbf{Y}^{(2)}$ for all the objectives in $\mathbf{Y}$,
  - $\mathbf{Y}^{(1)}$ is strictly better than $\mathbf{Y}^{(2)}$ in, at least, one of the objectives in $\mathbf{Y}$.

From these statements, it is clear that the dominant set of solutions is the one that conforms the optimum Pareto front.

A formal definition for the optimum Pareto front can now be stated, as follows: "If for any $\mathbf{a} \in \mathbb{R}^V$ there is no $\mathbf{Y} \in \mathbb{R}^R$ that dominates any other solution, then the set of solutions belonging to $\mathbf{Y}$ conforms the optimum Pareto front" (DEB, 2001). As it follows, the members in the current generation that dominate the remaining solutions are the ones that have reached better positions in the objective space. These solutions are granted with a better *rank* than the one for the dominated individuals, such that, iteratively, the further generations will converge to the Pareto frontier.

In order to avoid losing of good chromosomes after subsequent genetic operators, the NSGA-II solver features a mechanism for saving the best individuals at the current generation, which is referred to as *elitism* (ZITZLER; THIELE, 1999). Elitism is a strategy that treats "elitist" chromosomes as normal individuals, so their fitness is assessed, and they are also applied genetic operators. At the generation in which a certain individual outperforms an elitist chromosome, the latter can be either replaced or eliminated from the elitist pool. Moreover, an issue related to overcrowding, common in the first version of NSGA, was fixed by means of implementing distance measures in the objective space. The so-called *crowding distance* measure has improved NSGA in the attainment of well-covered optimum Pareto fronts (DEB et al., 2002). These improvements have eventually given rise to the NSGA-II evolutionary solver.

- *Strength-Pareto evolutionary algorithm (SPEA2)*: The Strength-Pareto Evolutionary Algorithm (SPEA) was the first multi-objective solver in featuring Elitism. The underlying idea behind SPEA is that of *strength solutions*, which are the ones that dominate *large amounts of solutions*. This multi-objective solver also feature a strategy to ensure properly covered Pareto fronts, which is

based in gathering solutions within clusters. After determining the stronger solutions at a given generation, based on dominance/non-dominance relationships, they are clustered, the centroid of each single cluster is calculated and Euclidean distances between each solution and the centroid are calculated. While solutions with short distances from their corresponding centroid are qualified as overcrowded, the ones that show larger distances are kept for further genetic operations. It is worth recalling that the best individuals at the current iteration are given the highest *strength value*, whereas the remaining ones are sorted in descending strength values.

The high computational cost associated with the original SPEA mechanism, for assuring properly covered Pareto fronts, was replaced by that of *density estimates*, which is based on the k^{th} nearest neighbor method (ZITZLER et al., 2001). These improvements have eventually given rise to the SPEA2 evolutionary solver.

4. **Genetic operators:** The first genetic operation to be carried out is selection, or reproduction. The goal of this operator is to preserve the best chromosomes, while eliminating the remaining ones. Both the NSGA-II and SPEA2 solvers make use of the *tournament selection* operator, which compares the fitness values amongst a predefined number of chromosomes and selects the best ones. While NSGA-II uses the *rank* values, SPEA2 uses the *strength values*, for comparisons.

While all the individuals at the current generation should participate in the tournament selection operator, the user can decide how many individuals undergo to crossover and mutation, operations that are common in genetic algorithms and are useful to avoid solutions to get stuck at local minima. The simulated binary crossover (SBX) emulates that of the binary crossover (DEB, 2001) and is implemented in both NSGA-II and SPEA2 multi-objective solvers. As far as mutation is concerned, both solvers use the polynomial mutation (DEB, 2001).

All the steps listed above are summarized in the block diagram illustrated in Fig. 4.2. In the Figure, it can be observed that, provided that a reduced set of tones in the primary sound has been defined for driving the MOO, the size of the population turns out to be computationally affordable. Moreover, the block diagram in the cited Figure clearly illustrates that each assessment of the SQ vector takes into account the entire vectors of amplitudes and relative-phases that correspond to each tone in the primary sound. Then, the computational routine just needs to load into memory the *indices* of the targeted tones, as well as the original frequency-domain data of the primary sound, and the amplitude values retrieved from each individual along iterations are replaced into the entire vector of amplitudes, in order to evaluate the SQ vector along generations.

Figure 4.2: Block diagram of the proposed multi-objective SQ optimization.

Remarks

This section has introduced a multi-objective optimization problem, especially designed for investigating for better equalizations of the magnitude function of a given periodic disturbance, such that the associated SQ perceptions are enhanced. The literature survey on existing formulations for quantifying and predicting the SQ of a variety of sounds has led to associate four dimensions to the noise emitted by the powertrain in HEVs, namely Loudness, Roughness, Sharpness and Tonality. Moreover, since this sort of noise has a large number of tones that spread into wide bandwidths, sensitivity analyses based on the elementary effects method have been proposed, in an attempt for reducing the level of complexity of the design space. Multi-objective evolutionary algorithms such as the NSGA-II and the SPEA2 have been used for searching for the optimum Pareto fronts, which will eventually provide a set of amplitude values for each of the decision variables, such that the four SQ perceptions are driven towards optimal scores. Since no analytical solution is known for the optimization problem at hand, the verification of the attainment of the true Pareto fronts is proposed to be carried out through comparison amongst the outcomes from both evolutionary solvers. The next section will illustrate two examples aimed at clarifying all of the theory and procedures described so far, applied especially on a realistic hybrid electric powertrain noise.

4.2 Numerical examples

This section illustrates each of the steps that compose the proposed framework for optimizing the SQ of periodic disturbances. Two periodic stimuli are approached

by using the proposed method. On the one hand, the disturbance called **D1** has been created in such a way that a given single tone, or set of tones in the noise, is responsible for large output variations on each of the associated SQ metrics. On the other hand, the disturbance called **D2** has been synthesized by using the magnitude and relative-phase data extracted from a stationary periodic noise emitted by a real hybrid electric powertrain. Whereas the aspects related to the composition of the set of decision variables are thoroughly examined by using **D1**, the disturbance **D2** is directly optimized by following the steps proposed before.

The methodology for generating the results shown in this section is summarized below:

1. The initial step consists on identifying the magnitude, frequency and relative-phase of each tone that compose either D1 or D2.
2. The corresponding time history is synthesized by using the frequency-domain data of the previous step, at a compatible sampling rate.
3. The SQ scores of either D1 or D2 are determined by using the time-domain SQ metrics.
4. The frequency-domain SQ algorithms are calibrated at that point, by using the SQ scores obtained from the previous step (cf. Eq. 3.2, cf. Chapter 3).
5. Sensitivity analyses are used to identify the set of tones that will drive the MOO.
6. An exhaustive search of the objective space is carried out, before the multi-objective SQ optimization to take place, which aims at comparing the size and bounds of the *feasible space* with the results of the vector optimization. It is meant by *feasible space* the entire set of SQ scores that can be generated by each single combination of the amplitudes of the set of tones obtained from the previous step, subject to the amplitude bounds, i.e. from 0 dB_{SPL}, to twice their nominal value. Notice that this step has been carried out just for demonstration purposes. Once validated, only the MOO will suffice.
7. The MOO problem posed in Eq. 4.1 takes place, by using the set of decision variables obtained from Step 5. Both solvers, NSGA-II and SPEA2, have been used to minimize, as well as to maximize, the associated SQ metrics. Hence, two Pareto frontiers are found: one that shows the lower bound, and another one that shows the upper bound for the SQ space.

The following is the list of the parameter setup for both multi-objective solvers:

- Population size: 150.

- Number of generations: 100.
- Probability of an individual to undergo genetic crossover: 0.1. Therefore, mutation probability is $1 - 0.1 = 0.9$, which helps avoiding getting stuck at local minima.
- Crossover - SBX distribution index, η_c : 10.
- Mutation - distribution index, η_m : 10.

The results of this procedure are illustrated by using scatter-plot matrices, which help visualizing the resulting 4D SQ objective space. This method arranges and plots the SQ dimensions by pairs (cf. Figs. 4.5, 4.7, 4.8, 4.9 or 4.12). Since there are four SQ metrics associated to the SQ MOO, the resulting figures will show 4×4 scatter-plot matrices, wherein both maximization and minimization results from the NSGA-II solver are plotted on top of the main diagonal of the scatter-plot matrix, whereas the ones from the SPEA2 solver are plotted below the main diagonal. The results from the exhaustive search are included (in light-gray dots), in order to compare the Pareto fronts with the full feasible space. The SQ scores of the original disturbance, determined at Step 3, are also highlighted in the scatter-plot matrices, in order to illustrate the location of the original SQ scores of the disturbance under study. It is then expected that, while the Pareto front obtained from the concurrent minimization covers the lower edge of the feasible space, the one from the concurrent maximization covers the upper edge. Moreover, the inclusion of the original SQ scores in the scatter-plot matrices helps visualizing the extent at which these scores can be driven by the equalization of the most sensitive tones.

8. For the disturbance D2, a single MOO run is executed for each single solver, from which ten individual solutions have been extracted and compared. These solutions have been chosen by following two criteria, as follows:
  - Extreme values of the Pareto fronts, which gives rise to four solutions from minimization, i.e. maximum values for Loudness, Roughness, Sharpness and Tonality, as well as four from maximization, i.e. minimum values for Loudness, Roughness, Sharpness and Tonality;
  - Compromise global minimum and maximum, which give rise to two more solutions.

Figure 4.3 provides an example of a non-convex, continuous Pareto front that results from minimizing the Fonseca's three-variable, two-objective MOO (DEB,

2001), posed as follows:

$$f_1(x) = 1 - \exp\left(-\sum_{j=1}^3\left(x_j - \frac{1}{\sqrt{3}}\right)^2\right); \quad f_2(x) = 1 - \exp\left(-\sum_{j=1}^3\left(x_j + \frac{1}{\sqrt{3}}\right)^2\right),$$

For this example, the decision variables, $\mathbf{x}$, are allowed to take values in between $[-4, 4]$. Following the criteria listed above, three optimal solutions are extracted. These solutions have been pointed out in the mentioned Figure by placing datatips at the *extrema*, as well as at the *Global Minimum* solution, of the Pareto front. These datatips reveal that the *maximum values* for both $f_1(x)$ and $f_2(x)$ are extracted from the *minimization* of the MOO. Conversely, if the MOO were *maximized*, then the extrema of the resulting Pareto front will represent the *minimum values*.

Figure 4.3: Pareto front obtained from minimizing the Fonseca's MOO (DEB, 2001).

Moreover, the *Global minimum*, or the *Global maximum* solution, is found by calculating the Euclidean distance of all the solutions w.r.t. the origin of the coordinates, as follows:

$$\text{Global } \mathbf{F} = \min/\max(\mathbf{Y}) = \min/\max([\mathcal{E}_1, \mathcal{E}_2, \dots, \mathcal{E}_{\mathcal{P}}]^T);$$

$$\mathcal{E}_p = \sqrt{\sum_{j=1}^Q (\mathbf{F}_j - \mathbf{0})^2},$$

where $\mathcal{E}_p$ with $p = 1 \dots \mathcal{P}$ is the Euclidean distance of the p^{th} solution $\mathbf{F}_p$ w.r.t. the origin of the coordinates, which is given by the null vector $\mathbf{0} \in \mathbb{R}^Q$ with $j = 1 \dots Q$ that is compatible with the dimension of the objective space, Q , and finding the minimum or maximum value in the vector of Euclidean distances given by $\mathbf{Y}$. Following this procedure, the global Minimum of the Pareto front in Fig. 4.3 is

found to be $[f_1(x), f_2(x)] = [0.58, 0.68]$.

9. The attained optima for D2 are verified in two ways:

- By re-synthesizing of the noise with the optimized *amplitude values* for each tone in the decision variables set.
- By implementing the single-channel, SF-cFxLMS control scheme (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b), oriented by the optimized *amplitude gains* for each tone in the decision variables set.

It is expected that both approaches will give the same result, regardless of whether the implemented solution comes from the NSGA-II or the SPEA2 solver. The goal of this step is to give insights on the feasibility of attaining the prescribed tone amplitude values by an active controller.

10. The resulting time histories from both methods in the previous step are assessed by time-domain SQ algorithms. The average of the last seconds (after convergence of the active controller) is taken, for each of the SQ metrics. The resulting single scalar values are directly compared with those provided by the multi-objective optimization procedure, which was carried out by using frequency-domain SQ models. The comparison between the optimized and attained SQ scores on the noise will eventually allow the verification of the so-called *success percentage*, which is the metric that will quantify the success of the whole design/control procedure proposed in this research. This metric will be defined in Section 4.2.

Periodic disturbance D1

The disturbance D1 is composed of six tones at 500, 930, 1000, 1070, 2000 and 4000 Hz. Their corresponding amplitude values are $\{4, 2, 4, 2, 4, 1\} \times 10^{-02}$ Pa, and their relative-phase function has been deliberately zeroed, in an attempt to reinforce its Roughness score. The time history of D1 has been synthesized by using a sampling rate of $F_s = 10$ kHz. With both time- and frequency-domain data of D1 at hand, the SQ algorithms are calibrated. Thus, the SQ scores for D1 read: $\mathcal{L} = 16.66$ sone; $\mathcal{R} = 0.71$ asper; $\mathcal{S} = 1.41$ acum; $\mathcal{T} = 0.88$ SP, being that Sharpness was determined with the Zwicker's formula, and Tonality with the Aures' one. The disturbance D1 has been assumed as propagating in a free-field condition.

Figure 4.4 illustrates a bar plot of the magnitude function of D1. Markers have been placed on top of the tones, for highlighting the ones that have been identified as the most involved in causing large variations on each of the associated SQ metrics, by carrying out the EE-based sensitivity analyses. Nevertheless, the selection of variables for the decision set has been varied in four different ways.

Figure 4.4: Magnitude function of disturbance D1. Markers highlight the tones that were detected as involved in causing large variations in each single SQ metric.

Optimization results on the full set of tones of D1

Since the disturbance D1 is composed of a small number of tones, it could be interesting to attempt the SQ optimization by using *all its components*. The underlying hypothesis here is that, as long as the size of the performance space is the largest, once that *all* the variables in the sound are brought into play, the Pareto fronts that should cover both of its lower and upper edges will be the largest possible ones.

While this seems to be the case, for the Pareto fronts obtained from the concurrent *maximization*, the lower bound just converged to the origin of coordinates, as it can be observed in Fig. 4.5. This is actually the expected situation, once that no sound (quality) can be expected from reducing *all* the tones to 0 dB_{SPL}. Moreover, it is possible to verify, by comparing Fig. 4.5 and Fig. 4.7, that the solution space obtained from all the tones in D1 is indeed larger than the one obtained with the reduced set of tones retrieved by the EE-based sensitivity analyses.

An aspect that is worth highlighting is that the concurrent minimization of the metrics by using all the tones in D1 comes short in providing interesting solutions for the specialist, as long as the lower bound is settled as 0 dB_{SPL}. While for conventional noise control techniques, this sort of solution would be ideal, for sound quality control this actually becomes an undesired result. For instance, a desired solution might be that Roughness were decreased, while still ensuring optimized values for all the other SQ perceptions. Keeping this in mind, the plots showing the pairs Loudness/Sharpness

Figure 4.5: Pareto fronts obtained for disturbance D1, using the full set of tones that compose D1. NSGA-II results are plotted above the main diagonal. SPEA2 results are plotted below the main diagonal. **Legend:** purple: maximization; yellow: minimization; light-gray: exhaustive search; black unfilled circle: original SQ scores; red markers: extrema from maximization; blue markers: extrema from minimization.

and Roughness/Sharpness in Fig. 4.5 reveal that, since the dot representing the original SQ scores almost belongs to the upper-edge Pareto front, the only option for getting these scores improved, toward *reduced* but still *optimized* values, is that of zeroing all the amplitude values in D1, in other words, to take the "solutions" from minimization, which converged to zero. Therefore, it can be asserted that the effect of taking all the tones into the MOO is positive, as long as the concurrent maximization of the SQ metrics is of concern, while the computational cost is still affordable. Moreover, the concurrent minimization might still offer interesting solutions for the specialist, as long as the lower bound is redefined as being larger than 0 dB_{SPL}.

Sensitivity analyses on D1

Now Fig. 4.6 shows the results of the EE-based sensitivity analyses carried out on D1. Its tones have been numbered in ascending order of their frequencies. In Fig. 4.6, it is possible to pinpoint the tone at 1 kHz as the responsible for Roughness, the one at 2

kHz as responsible for Loudness, the one at 4 kHz as responsible for Sharpness and, for Tonality, the pair of tones at 930 Hz and 1 kHz. The tone at 500 Hz just causes some effect on Loudness, but in general it can be discarded from the optimization procedure, as its effect seems not to be dominant on any of the assessed SQ metrics. In a similar form, since the tone at 1070 Hz has only little effect in both Roughness and Tonality, it can also be safely disregarded from the optimization stage.

Figure 4.6: Results of the sensitivity analyses on disturbance D1.

Optimization results on the set of tones provided by the sensitivity analyses

The second set of MOO results concerns the optimization of D1 by using the tones identified by the sensitivity analyses. Figure 4.7 illustrates the resulting objective space and Pareto fronts. The first observation that can be drafted is that, while the Pareto fronts obtained from the concurrent maximization are wide, the ones from minimization "almost" tend to the origin of coordinates, as the tones amplitudes were allowed to be reduced to 0 dB_{SPL}. Figure 4.7 also shows that the original SQ of D1 can now be noticeably enhanced, since its SQ scores fall at almost the middle of the feasible region. Moreover, it seems that the original Tonality score "almost" belongs to the maximized Pareto front (cf. 4th row/column of Fig. 4.7), so the improvement towards *larger Tonality values* seems to be infeasible, given the bounds for the decision variables. Even so, the improvement of this perception towards *smaller scores* seems quite feasible, by choosing solutions of the Pareto fronts from either the concurrent maximization or the concurrent

minimization.

The visual comparison between the NSGA-II and SPEA2 results verifies that, when using the set of tones provided by the sensitivity analyses, both evolutionary solvers converge to almost the same Pareto fronts. However, there is a subtle difference between both sets of results, which relies on the distribution of the individuals along the Pareto fronts. SPEA2 solver seems to reach at a better distribution of the solution than does NSGA-II, which provides Pareto fronts with a level of overcrowding in some areas. Even so, both solvers are seen to be able to reach both upper and lower edges of the feasible space.

Figure 4.7: Pareto fronts obtained for disturbance D1, using the set of tones provided by the sensitivity analyses. NSGA-II results are plotted above the main diagonal. SPEA2 results are plotted below the main diagonal. **Legend:** purple: maximization; yellow: minimization; light-gray: exhaustive search; black unfilled circle: original SQ scores; red markers: extrema from maximization; blue markers: extrema from minimization.

Optimization results with just two tones

The dimension of the decision space is now further reduced, just for demonstration purposes. Recalling the results of the sensitivity analyses shown in Fig. 4.6, while the tone at 1 kHz was found as the most involved in causing output variations on both

Roughness and Tonality models, the one at 4 kHz was detected as the cause for the largest variations on Sharpness, still having some influence on Loudness. Then, the following analysis concerns just these two tones as the decision space of the MOO.

Figure 4.8 illustrates the results of this optimization scenario, wherein it can be observed that the Pareto fronts are now conformed by well-behaved individual distributions that properly cover the extrema of the feasible space. Now it becomes readily evident that both the blue and red markers in the spreads showed so far are actually placed onto the *extreme values* of the Pareto fronts. These extreme values will be proven to be of the utmost importance when choosing solutions for implementation, since they represent either the lowest or the highest value a given SQ metric can take, while still ensuring *optimum scores* for the remaining metrics.

Figure 4.8: Pareto fronts obtained for disturbance D1, using two decision variables: 1 and 4 kHz. NSGA-II results are plotted above the main diagonal. SPEA2 results are plotted below the main diagonal. **Legend:** purple: maximization; yellow: minimization; light-gray: exhaustive search; black unfilled circle: original SQ scores; red markers: extrema from maximization; blue markers: extrema from minimization.

Unfortunately, the fact that the Pareto fronts obtained by using a low-dimensional decision space are well conformed does not imply that they cover wide SQ bands. For instance, Fig. 4.8 shows that the possibilities for improving Tonality have been

dramatically reduced, just from 0.75 to 0.91 SP, whereas Fig. 4.7 (obtained with the sensitivity analyses), shows a wider band that ranges from 0.55 to 0.91 SP, and Fig. 4.5 (all the tones of D1), ranges from 0.0 to 0.82 SP. This becomes a proof of the compromise between the cost involved in computing (and eventually controlling) a higher number of variables and the maximum achievable performance.

Influence of inappropriate choice of the decision variables

To study the influence of an inappropriate selection of variables for the decision space, this set has been reloaded with just two variables, which have been found as having little effect on the associated SQ metrics. From Fig. 4.6, the tones at 500 Hz and 1070 Hz are seen to meet this criterion.

Figure 4.9: Pareto fronts obtained for disturbance D1, using two decision variables: 0.5 and 1.07 kHz. NSGA-II results are plotted above the main diagonal. SPEA2 results are plotted below the main diagonal. **Legend:** purple: maximization; yellow: minimization; light-gray: exhaustive search; black unfilled circle: original SQ scores; red markers: extrema from maximization; blue markers: extrema from minimization.

Figure 4.9 shows the outcome of this optimization scenario. Notice that, even though the decision set has been again composed by two tones, the resulting Pareto fronts are not so well conformed as the ones obtained in the previous optimization

scenario, which also dealt with a two-dimensional decision space. As the decision set associated to the optimization problem has less influence on the objective function, the multi-objective solvers also seem to face difficulties in converging to the optimal Pareto fronts. A thoroughly visual inspection of the NSGA-II and the SPEA2 results in Fig. 4.9 reveals artifacts such as discontinuities in the attained Pareto fronts, again verifying that the effect of choosing weak tones on the SQ perception hinders the efficiency of the optimization procedure. These facts verify that the proposed EE-based sensitivity analyses lead to the best trade-off between the optimization efficiency and the computational cost. Based on this premise, the optimization of hybrid electric powertrain noise can be safely driven with the help of the EE-based sensitivity analyses, as it will be demonstrated in the following numerical exercise.

Periodic disturbance D2

The disturbance D2 has been synthesized by using both the magnitude and relative-phase data obtained from a real measurement of the acoustic emission of an electric hybrid powertrain. This sound is composed of 142 tones, whose amplitude function is illustrated in Fig. 4.10. Since the relative-phase data is not relevant for the proposed multi-objective SQ optimization framework, this spectral function is not illustrated. The corresponding time history of D2 has been synthesized by using a sampling rate of $Fs = 19537.25$ Hz. This sampling rate has been found by making:

$$\min(Freq(i+1) - Freq(i)) \times L \leq Freq(R), \quad (4.5)$$

where $\min(Freq(i+1) - Freq(i))$ is the minimum difference between contiguous tones that is found in D2; $Freq(R)$ is the highest tone found in D2; and $L = 111$ is the length of the discrete Fourier transform that has been found to hold the expression. For this example, it is possible to observe that, by making $(Fs/L \times \{9, 18, 39\})$, the frequencies of the tones determined by the EE-based sensitivity analyses to drive the MOO are obtained. This Fourier transform is internally calculated in the frequency-domain ASQC, to be used in the implementation of the optimized SQ targets (MOSQUERA-SÁNCHEZ; OLIVEIRA, 2014b), via the *Fastest Fourier Transform in the West* algorithm (JOHNSON; FRIGO, 2007). After synthesizing the time history of D2, its SQ scores are calculated by using the time-domain algorithms, and the frequency-domain models are calibrated. Corrections for accounting for the diffuse measurement field have been applied before each SQ metric calculation. The Sharpness metric has been calculated by using the Zwicker's weights, Tonality metric with the Shin et al. (2009) weighting formula. The nominal SQ scores then read: $\mathcal{L} = 67.96$ sone; $\mathcal{R} = 0.64$ asper; $\mathcal{S} = 1.57$ acum; $\mathcal{T} = 0.30$ SP.

Periodic disturbances like the one illustrated in Fig. 4.10 do demand the reduction of the set of decision variables, in order to work out the MOO in an affordable timeframe.

Figure 4.10: *Magnitude function of the realistic hybrid electric powertrain noise (disturbance D2). Markers highlight the tones that were detected as the most involved in causing large variations on each single SQ metric.*

Therefore, the proposed sensitivity analyses on the associated SQ metrics have been carried out. The results of this step are shown in Fig. 4.11, which make evident that, amongst the large number of tones that compose D2, it is possible to identify a set of tones such that large variations on each single SQ metric can be attributed to that input set. With regard to Loudness, Sharpness and Tonality metrics, it has been possible to identify two tones, whose effect is clearly distinguished. On the other hand, it seems that more than a single tone is involved in generating Roughness variations, but their influence is not so dominant. Then, it has been possible to extract a single tone for Roughness, by allowing 10% of the maximum μ^* value that is caused by the most relevant tone. The set of decision variables for the SQ optimization of D2 has then been dramatically reduced, from 142 to just 3 tones, as follows: the tone at 3168.20 Hz for both Loudness and Tonality, the one at 1584.10 Hz for Roughness, and the one at 6864.44 Hz for Sharpness.

Optimization results

Figure 4.12 shows the results from optimizing the SQ of D2. The visual comparison between the NSGA-II and SPEA2 results unveils that NSGA-II seems again to face difficulties in converging to well-conformed Pareto fronts. Whilst the SPEA2 fronts are well conformed, and cover wide regions of the feasible objective space, the ones

Figure 4.11: Sensitivity analyses carried out on the disturbance D2.

from NSGA-II seems to be rather approximations to the optimal Pareto front. Moreover, given the location of the original SQ scores of D2 in the objective space, there seems to be good room for improving its SQ, being either towards lower or higher optimum scores. Loudness can be varied from 60 to 80 sone, Roughness can be varied from 0.30 to 0.75 asper, Sharpness can be varied from 1.50 to 1.70 acum, but Tonality ranges within a rather short band, between 0.29 and 0.31 SP.

On the choice of optimal solutions for enhancing the SQ of D2

Table 4.1 reports on the *extreme values* extracted from the Pareto fronts, obtained when either concurrently minimizing or concurrently maximizing the SQ metrics. The extrema provided by both multi-objective solvers are contrasted, aiming at illustrating similarities between the results of the evolutionary solvers. Thus, Table 4.1 unveils that the extreme values of the Pareto fronts provided by both multi-objective solvers are practically the same.

At this point, it is convenient recalling that the extrema of the Pareto fronts are the optimal solutions that provide either the maximum or minimum value a given SQ metric can take, while still ensuring that the remaining metrics take optimum values. This comes from the fact that all the SQ metrics are optimized in a concurrent fashion. Since the SQ space associated to periodic disturbances has been composed of four dimensions, four extreme values can be extracted from the Pareto fronts, as follows:

Figure 4.12: Pareto fronts obtained for disturbance D2, using the set of tones provided by the sensitivity analyses. NSGA-II results are plotted above the main diagonal. SPEA2 results are plotted below the main diagonal. **Legend:** purple: maximization; yellow: minimization; light-gray: exhaustive search; black unfilled circle: original SQ scores; red markers: extrema from maximization; blue markers: extrema from minimization.

- The first solution, called Minimum/Maximum 1, which consists on the Maximum/Minimum value that Loudness can take, respectively.
- The second solution, called Minimum/Maximum 2, which consists on the Maximum/Minimum value that Roughness can take, respectively.
- The third solution, called Minimum/Maximum 3, which consists on the Maximum/Minimum value that Sharpness can take, respectively.
- The fourth solution, called Minimum/Maximum 4, which consists on the Maximum/Minimum value that Tonality can take, respectively.

There still exists a fifth solution that is referred to as the *Global Minimum/Maximum* (Min/Max 5). These solutions represent the *optimum balance* of the associated SQ metrics, which would be possible achievable by an active controller acting on the limited set of tones, towards reduced or increased SQ scores. The procedures for obtaining the set of solutions for the implementation have been described at the beginning of this section.

Table 4.1: Comparison between extreme solutions obtained from Pareto fronts of both of NSGA-II and SPEA2 multi-objective solvers.

Solution	Loudness [sone]		Roughness [asper]		Sharpness [acum]		Tonality [SP]	
	NSGA-II	SPEA2	NSGA-II	SPEA2	NSGA-II	SPEA2	NSGA-II	SPEA2
Original	67.96		0.64		1.57		0.30	
Min1	75.91	75.90	0.61	0.61	1.58	1.58	0.30	0.30
Min2	66.59	66.93	0.74	0.74	1.50	1.50	0.30	0.30
Min3	73.19	73.20	0.30	0.30	1.70	1.70	0.30	0.30
Min4	64.88	64.94	0.64	0.64	1.50	1.50	0.31	0.31
Min5	61.85	61.85	0.36	0.36	1.51	1.51	0.31	0.31
Max1	62.70	62.69	0.51	0.51	1.53	1.53	0.31	0.31
Max2	73.21	73.04	0.31	0.31	1.70	1.70	0.30	0.30
Max3	67.80	67.61	0.73	0.74	1.50	1.50	0.30	0.30
Max4	73.19	73.19	0.31	0.31	1.70	1.70	0.30	0.30
Max5	77.84	77.84	0.57	0.57	1.67	1.67	0.30	0.30

Each of the optimal solutions reported on in Table 4.1 is the result of driving the amplitude of the three tones in the decision variable set towards optimized values, as given by the multi-objective SQ optimization. Thus, Table 4.2 reports on the optimized amplitude values, provided by either the NSGA-II or the SPEA2 solvers, which give rise to the results in Table 4.1. These values are again contrasted between each other, for the sake of comparisons. Whilst, for most of the solutions, the optimal amplitude values given by any of the multi-objective solvers are similar between each other, there are some striking solutions that lead to infer that the optimal SQ scores might not be defined by a unique combination of amplitude values. In other words, the mapping of the amplitude function into the associated SQ space seems to be a surjective function. Examples of this are given by solutions **Min2**, **Min4**, **Max2**, **Max3**, and **Max4**, where it can be noticed that, even when the amplitude values differ from one solver to another, the resulting SQ scores are the same, as it can be noticed by examining the same rows in Table 4.1.

Implementation of the selected solutions for enhancing the SQ of D2

This step deals with the implementation of the optimal amplitude values. For the sake of illustration and comparison, this section makes use of two approaches to show how the SQ scores of the disturbance D2 are enhanced, namely: (i) by replacing the original amplitude values of the three targeted tones with the optimized values, in order to "re-synthesize" D2; and (ii) by implementing an ASQC scheme that should attain the

Table 4.2: Comparison between optimized amplitude values that give rise to the SQ scores in Table 4.1.

Solution	H1: 1584 Hz [dBSPL]		H2: 3168 Hz [dBSPL]		H3: 6864 Hz [dBSPL]	
	NSGA-II	SPEA2	NSGA-II	SPEA2	NSGA-II	SPEA2
Original	79.63		80.94		61.57	
Min1	85.65	85.65	86.96	86.96	52.70	52.57
Min2	84.86	85.38	71.39	71.43	51.86	46.84
Min3	0.00	0.00	86.96	86.96	67.58	67.58
Min4	83.32	83.41	0.00	0.33	0.00	11.27
Min5	0.00	0.00	0.00	0.02	0.00	0.03
Max1	74.41	74.63	0.00	0.50	58.24	57.72
Max2	0.00	49.18	86.96	86.82	67.58	67.58
Max3	85.65	85.65	74.88	73.41	0.00	53.48
Max4	0.00	54.83	86.96	86.95	67.59	67.59
Max5	85.65	85.65	86.96	86.96	67.58	67.58

optimal amplitude values, by means of amplitude gains for the three targeted tones. The resulting time histories of both approaches are assessed by using time-domain SQ algorithms, which are supposed to provide the same measures, in the mean sense, as the given ones by the frequency-domain models. Whilst the first approach has been carried out just for demonstration and comparison purposes, the second approach assumes that the signals are propagating through a system with perfect dynamics, i.e. both of the primary and secondary paths have unit dynamics. Results shown in Sections 5.2.5 and 5.2.6 will illustrate control scenarios driven by the SQ MOO with real transfer paths.

Table 4.3 presents the amplitude gains that should be implemented by any ANE or ASQC scheme, in order to attain the optimal amplitude values provided in Table 4.2. All those amplitude gains are comprised between 0.00 and 2.00, which follows from the fact that the *operation modes* of ANE/ASQC systems have been taken into account to provide *feasible bounds* for the amplitudes of the targeted tones in the disturbance D2. At that point, it is worth recalling that the ANE/ASQC operation modes are defined as follows: $g = 0$ is the *cancellation mode*; $0 \leq g \leq 1$ is the *reduction mode*; $g = 1$ is the *preservation mode*, which will become of the utmost importance when the enhancement of the SQ for multiple listeners is of concern; and $1 < g \leq 2$ is the *amplification mode*.

Each of the amplitude gain combinations reported on Table 4.3 is transferred to the single-channel ASQC scheme, in order to implement each of the ten selected solutions. Thus, the ten optimum solutions listed in Tables 4.1, 4.2 and 4.3 are implemented by following both of the approaches mentioned at the beginning of this section. Out of

Table 4.3: Amplitude gains for an active sound quality control scheme to attain the optimized amplitude values provided in Table 4.2.

Solution	H1: 1584 Hz [dBSPL]		H2: 3168 Hz [dBSPL]		H3: 6864 Hz [dBSPL]	
	NSGA-II	SPEA2	NSGA-II	SPEA2	NSGA-II	SPEA2
Original	1.00		1.00		1.00	
Min1	2.00	2.00	2.00	2.00	0.36	0.35
Min2	1.83	1.94	0.33	0.33	0.32	0.18
Min3	0.00	0.00	2.00	2.00	2.00	2.00
Min4	1.53	1.55	0.00	0.00	0.00	0.00
Min5	0.00	0.00	0.00	0.00	0.00	0.00
Max1	0.55	0.56	0.00	0.00	0.68	0.64
Max2	0.00	0.03	2.00	1.97	2.00	2.00
Max3	2.00	2.00	0.50	0.42	0.00	0.39
Max4	0.00	0.06	2.00	2.00	2.00	2.00
Max5	2.00	2.00	2.00	2.00	2.00	2.00

these solutions, only the resulting time histories that correspond to Solutions **Min5** and **Max5** are illustrated in this Chapter. The time histories of the remaining implemented solutions can be found in Appendix A.

Results and remarks on this step are discussed below:

- **First implemented solution:** Figure 4.13 illustrates the assessment of the time-domain SQ metrics on the disturbance D2, after implementing the Global Minimum solution, i.e. solution **Min5**, as provided by both the NSGA-II and SPEA2 solvers. The original time-domain SQ assessment of D2 is plotted in blue dotted lines, i.e. the non-controlled SQ assessment. The time-domain SQ assessments of the controlled disturbance by using the amplitude gains given by either NSGA-II or SPEA2 solvers are plotted by using yellow or green dot-dashed lines, respectively. The time-domain SQ assessments of the resynthesized disturbance via either NSGA-II or SPEA2 solvers are also plotted in the Figure, by using red or purple continuous lines, respectively.

In a first instance, it is possible to observe in Fig. 4.13 that the optimized amplitude gain factors have driven the disturbance D2 to lower SQ scores, which is the expected behavior from the concurrent minimization of the metrics. Although the Tonality metric might appear to be unresponsive to either the replacement of optimum amplitude values, or even the implementation of the amplitude gains via ASQC, this is the expected behavior of this metric for the implemented optimized solution, as predicted by the MOO procedure (cf. row **Min5**, column **Tonality** [SP])

Figure 4.13: Comparison between original, optimized and controlled time histories of disturbance D2, when implemented the Global Minimum from both NSGA-II and SPEA2 solvers.

in Table 4.1). Moreover, since the SQ scores provided by either the NSGA-II or the SPEA2 solvers closely match between each other for this solution, both of the time-domain SQ assessments are also shown to closely match between each other, for all the assessed SQ metrics. This observation holds for the SQ time histories of disturbance D2 that result from either the direct replacement of the optimal amplitude values, or from the ASQC actions taken on the targeted tones.

With regard to the time-domain SQ assessment of the controlled disturbance via the ASQC scheme, it is possible to observe that the SQ metrics are exactly driven to the targeted optimized values. However, it seems that the frequency-domain Tonality model is not so accurate in predicting the time-domain pattern of the assessed noise, as the obtained time histories from the replacement of the optimized amplitude values and the implementation of the SQ targets via ASQC do not match after convergence of the ASQC scheme, in the same extent as the observed one in Loudness, Roughness and Sharpness metrics. Even so, the final Tonality values obtained by any of the two approaches are the same, in the mean sense (mean value of the entire time histories, for each approach).

The close matching between the time-domain SQ assessments serves as a proof of the following two facts: (i) that the frequency-domain SQ models have been properly calibrated against the time-domain ones, and (ii) the time-domain features

of the disturbance D2 have been accurately predicted by the frequency-domain SQ models, except from those related to Tonality, even when the magnitude function of D2 has changed by means of any of the two methods followed for the implementation of the solutions.

- **Second implemented solution:** Figure 4.14 now illustrates the assessment of the time-domain SQ metrics on the disturbance D2, after implementing the Global Maximum solution, i.e. solution **Max5**, as provided by both NSGA-II and SPEA2 solvers. All the time histories in the Figure follow the same plot convention as in Fig. 4.13.

Figure 4.14: Comparison between original, optimized and controlled time histories of disturbance D2, when implemented the Global Maximum from both NSGA-II and SPEA2 solvers.

Figure 4.14 shows that the implementation of the Global Maximum for the disturbance D2 has implied in raising all its SQ scores, except from the Roughness. Then, if enhancement of the Roughness were established as a target for D2, the implementation of Solutions **Min2** or **Max3** should render this result, and this is the case, as observed in Appendix A.

Figure 4.14 again evidences that the calibration of the SQ models has been successful. Also, it is possible to drive the SQ of D2 towards higher optimal scores through the implementation of the prescribed amplitude gains for the ASQC system.

It seems to be the case that the Tonality of D2 is not possible to be noticeably driven towards higher or reduced optimal SQ scores, given the set of tones that was taken into account to carry out its SQ optimization. The addition of more degrees-of-freedom, i.e. tones, to the problem, might help in enlarging the improvement range for this metric, at the cost of raising the complexity of the decision space.

Comparison between optimized and attained SQ scores

In Figs. 4.13 and 4.14, it has remained evident that the SQ scores of the disturbance D2 are effectively enhanced towards the targeted values, once that a comparison between the controlled and the resynthesized disturbance has been established. As resynthesizing the disturbance is not a feasible practice, other means for verifying the effectiveness of the proposed method has been proposed. Hence, provided that the time- and frequency-domain SQ models are properly calibrated, it will be possible to compare the scalar values that are provided by the frequency-domain algorithms, with the *average* of the time-domain SQ histories of the controlled disturbance, just after the ASQC scheme attains complete convergence. For instance, in the figures mentioned earlier, it is possible to observe that the ASQC scheme has attained convergence before $t = 5$ s. Then, it turns out to be reasonable to take the *mean value* of the time-domain SQ history for each metric, after the controlled disturbance to have reached the steady state, i.e. to take the average of the time histories from $t = 5$ to $t = 10$ s, in order to establish a comparison with the SQ score provided by the corresponding frequency-domain SQ model. Finally, the *success percentage*, which is nothing but the relative error between the optimized and the attained SQ score, can be quantified, as follows:

$$\% = \frac{\left(1/N \sum_{j=1}^N F_{TD}(j)\right) - F_{FD}}{F_{FD}} \times 100 \quad (4.6)$$

where F_{TD} and F_{FD} stand for a given SQ metric that is calculated by means of either time- or frequency-domain algorithms; and N is the total amount of samples in the selected timeframe of the time-domain SQ history of metric F_{TD} .

Table 4.4 summarizes the relative errors between the optimized and the attained SQ scores, discriminated by solutions given by each multi-objective solver. The error in attaining solutions provided by either the NSGA-II or the SPEA2 solver is again almost the same. From this Table, it has been determined that the success percentage in attaining any of the provided solutions is of 97%. Whilst the solutions given for Loudness, Sharpness and Tonality are attained with large success percentages (above 99%) the ones given for Roughness were only attained with a mean success percentage of 91.45%.

On the one hand, Table 4.4 shows that solutions **Min3**, **Max2** and **Max4** have the

Table 4.4: Comparison between success percentages obtained when actively attaining SQ solutions given by both NSGA-II and SPEA2 solvers.

Solution	Loudness [sone]				Roughness [asper]				Sharpness [acum]				Tonality [SP]			
	NSGA-II		SPEA2		NSGA-II		SPEA2		NSGA-II		SPEA2		NSGA-II		SPEA2	
	Att.	%	Att.	%	Att.	%	Att.	%	Att.	%	Att.	%	Att.	%	Att.	%
Original	67.96				0.64				1.57				0.30			
Min1	76.05	0.18	75.90	0.19	0.66	7.95	0.66	7.95	1.58	0.00	1.58	0.00	0.30	0.00	0.30	0.00
Min2	66.59	0.02	66.93	0.06	0.74	0.00	0.73	0.74	1.50	0.00	1.50	0.00	0.30	0.00	0.30	0.00
Min3	73.21	0.01	73.21	0.01	0.36	17.02	0.36	17.02	1.70	0.14	1.70	0.14	0.31	4.25	0.31	4.25
Min4	64.86	0.03	64.94	0.04	0.68	6.94	0.68	6.94	1.49	0.13	1.49	0.13	0.31	0.00	0.31	0.00
Min5	61.83	0.03	61.83	0.03	0.40	9.68	0.40	9.68	1.51	0.14	1.51	0.14	0.30	0.65	0.30	0.65
Max1	62.69	0.01	62.68	0.03	0.51	0.38	0.51	0.38	1.53	0.00	1.52	0.26	0.31	0.71	0.31	0.71
Max2	73.21	0.01	73.04	0.22	0.36	17.02	0.36	17.02	1.70	0.14	1.70	0.14	0.31	4.25	0.31	4.25
Max3	67.86	0.09	67.66	0.21	0.72	1.25	0.73	0.29	1.50	0.15	1.50	0.15	0.30	1.33	0.30	1.33
Max4	73.21	0.01	73.21	0.01	0.36	17.02	0.36	17.02	1.70	0.14	1.70	0.14	0.31	4.25	0.31	4.25
Max5	77.94	0.12	77.94	0.12	0.62	8.04	0.62	8.64	1.67	0.17	1.67	0.17	0.31	4.17	0.31	4.17
Mean %	0.05		0.09		8.53		8.57		0.10		0.13		1.96		1.96	
Total %	NSGA-II = 2.66; SPEA2 = 2.69															

largest relative error in Roughness. On the other hand, solutions **Min2**, **Max1** and **Max3** have the smallest relative error in this metric, being that the solution **Min2** provided by the NSGA-II solver was perfectly attained, whereas the solution **Max3** provided by the SPEA2 solver was almost perfectly attained, as well. The cause for the large discrepancy between optimized and attained Roughness scores relies on the inability of the frequency-domain algorithm to predict changes when large variations on the input amplitudes are practiced. This has been observed even when the calibration routine has been successfully carried out. At that point, it is convenient recalling the results of the verification of both the time- and frequency-domain Roughness models, cf. Section 3.6.4, where it was brought into evidence that these models did require calibration before each single frequency-domain model run, in order to improve the quality of the fit. With this in mind, it is possible to conclude from Table 4.1, that the solutions at which Roughness was attained with the lowest success percentages are the ones that required the largest amplitude changes. The tone 1 at 1584 Hz, which was the identified one as the most involved in causing Roughness variations in D2, is requested to change its amplitude in more than 20 dB_{SPL}. What is more surprising is that all these solutions are similar between each other and, even when the solutions given by the SPEA2 solver in the decision space are not as effortful as the ones given by the NSGA-II one, the attained success percentages were found as exactly the same low ones.

On the other hand, Table 4.1 shows that the solutions attained with large success percentages were the ones that did not require such effortful changes in tone 1 at 1584

Hz. It is worth noticing that, while the solution **Max3** provided by the SPEA2 solver was attained with a very small error, the solution that was provided by the NSGA-II one was attained with a larger error. This is mostly due to the fact that the tone 3 at 6864 Hz was requested by the NSGA-II solver to be zeroed, whereas the SPEA2 one provided a not so burdensome solution for the same tone.

Despite the large discrepancy seen in the attainment of the Roughness goals, a global success percentage of 97% verifies that the proposed framework for enhancing the SQ of the disturbance D2 is effective and accurate. One strategy that could be proposed to overcome the Roughness discrepancies is the calibration of the frequency-domain algorithm, before each assessment of the cost function to take place within the multi-objective solvers. However, the extra computation cost that it would bring would put in jeopardy the feasibility of the whole process, hence this strategy will remain as subject for future work.

4.3 Conclusions

This chapter devoted to pose a MOO problem that aims at helping in the task of searching for improved SQ scores, for the sort of auditory stimuli that is emitted by the powertrain in HEVs. Since this sort of noise spreads into a wide frequency range, which covers low-, mid- and high-frequency bandwidths, four SQ dimensions, compatible with such bandwidths, have been associated to the optimization problem, namely Loudness, Roughness, Sharpness and Tonality. The fact that this sort of periodic noise is composed of a large amount of tones also poses a severe drawback for the proposed MOO framework, once that the associated computational cost prohibitively scales as the amount of input variables, or tones in the sound, increases. To this concern, a set of sensitivity analyses on each associated SQ metric that rely on the method of the Elementary Effects has been proposed, in order to reduce the amount of decision variables that should be needed for solving the MOO. In the light of the operation modes provided by single/multi-channel ANE and ASQC systems, each tone in the sound is assigned a set of amplitude bounds, which imposes constraints on the region of experimentation associated to the sensitivity analyses. As soon as the most involved tones in causing large output variations in each SQ metric have been determined, the multi-objective SQ optimization problem can be solved by using either exhaustive searches or multi-objective evolutionary algorithms. Aspects from multi-objective evolutionary algorithms related to the proposed SQ optimization problem, such as the parameter setup for the genetic operators, have also been provided in this chapter.

The effectiveness of the proposed framework in enhancing the SQ of two periodic disturbances has been demonstrated in this chapter through numerical simulations. The optimization of a quite simple periodic disturbance composed of six tones has allowed

for the intuitive verification of some aspects of the methodology. First, although the disturbance D1 is composed of a small amount of tones, which would allow the SQ optimization to use all of them, the proposed sensitivity analyses were seen to allow reducing the complexity of the decision space, in such a way that the resulting Pareto fronts still cover wide bands on each SQ metric. This, in turn, has prevented the multi-objective optimization solvers to use inputs whose influence on the metrics is either negligible or not clear. Moreover, the composition of decision spaces by loading all the tones in the disturbance has been demonstrated to have a positive effect, only when the concurrent maximization of the metrics is pursued, or when the lowest bound of the harmonics amplitudes is set higher than 0 dB_{SPL}. However, this has the cost of raising the complexity of the decision space, as well as of the computational cost required to solve the proposed MOO. Therefore, the step for reducing the complexity of the decision space, based on the proposed sensitivity analyses, is clearly shown to offer the best trade-off between the involved computational complexity, and the quality and ranges of the resulting Pareto fronts.

The second periodic disturbance has been extracted from a real measurement of the acoustic emission of a powertrain in a commercial HEV. The same steps taken with D1 have been repeated here, which eventually resulted in effectively improving its SQ scores. Two approaches for the implementation of ten optimal solutions were contrasted with each other: the replacement of the optimal amplitude values on the targeted tones, which is only possible through numerical simulation, as well as the attainment of the optimal amplitude values via ASQC systems, which is the proposed method in actual applications. Results have demonstrated that, since the SQ scores of the controlled disturbance reached the proposed optimized targets, with a mean *success percentage* in excess of 97%, the method of implementing optimal solutions via ANE/ASQC systems is feasible and promising. This second optimization scenario has also proved that the proper calibration of the time- and frequency-domain SQ models is important in the proposed framework, since the frequency-domain SQ models must properly predict the time-domain pattern of the periodic disturbance under study, which will also allow for meaningful comparisons between the time- and frequency-domain SQ assessments.

Regarding the multi-objective solvers investigated in the task of optimizing the SQ of the synthesized sounds in this chapter, it has been demonstrated that SPEA2 outperforms NSGA-II in a number of aspects, e.g. better distribution of the solutions, better maximization of the hypercube formed by the Pareto fronts, etc. Even so, the large computational cost of the this solver may not be worth, as the NSGA-II results have been consistently similar to those of the SPEA2 one. A number of comparisons have been provided as the proof of this statement. Therefore, the SPEA2 turns out to be the recommended solver for working out the multi-objective SQ optimization, as long as both computation cost and timeframes can be afforded. Otherwise, the NSGA-II

approximations can also be useful for guiding the enhancement of the SQ of periodic disturbances, with the advantage of getting outcomes at reduced computation costs.

As soon as the real dynamics of the (vibro)-acoustic system comes into play, additional comments and remarks on the implementation of the proposed SQ optimization framework should be asserted. Therefore, the next chapter, which presents experimental results, will broaden the discussion on this methodology, and will include the extension of the proposed approach for multichannel control scenarios, where the so-called *inactive*, or *preservation*, operation mode of active noise equalizer/sound quality control systems will take a relevant role.

Chapter 5

Active sound quality control for hybrid electric vehicles: experiments

THIS chapter presents six laboratory experiments, four of which demonstrate the operation and performance of the proposed multichannel control schemes, whereas the remaining two demonstrate the effectiveness of the proposed framework in enhancing the SQ of stationary hybrid electric powertrain noise, in both single-channel and multichannel scenarios.

Experiments 1, 2 and 3 demonstrate the operation of the time- and frequency-domain multichannel Algorithms 1 (Section 2.3.1) and 2 (Section 2.3.2), which carry out amplitude-based multichannel active sound profiling. Experiment 4 is the amplitude- and relative-phase-based active sound profiling one that uses multichannel Algorithm 3 (Section 2.4.1). Comparisons with the multichannel Algorithm 0 (pure-decentralized control scheme - Section 2.2), are provided, in order to highlight the particularities of each control scheme. Finally, Experiments 5 and 6 illustrate all the proposed steps for enhancing the SQ of the powertrain noise in HEVs (Chapter 4), for either single or multiple listeners.

This chapter is organized as follows:

- Section 5.1 illustrates the measurements carried out for the identification of the vibro-acoustic primary paths, as well as of the electro-vibro-acoustic control loops. The parameters for the control schemes are calculated by using both the magnitude and the absolute phase functions of the Frequency Response Functions (FRFs), as it was discussed in Chapter 2.
- Section 5.2 presents the six laboratory experiments that demonstrate the operation of the proposed multichannel control schemes with coupling compensation, as well as the proposed framework for enhancing the SQ of hybrid electric powertrain noise for single and multiple listeners.

- Section 5.3 ends this chapter with conclusions on the experimental results.

5.1 The workbench

A real 1:3-scaled vehicle mock-up has been instrumented such that the passenger cavity is excited via structure-borne disturbances. The vehicle mock-up consists of a couple of 5 mm thick, flexible aluminium plates that emulate the firewall, as well as a rigid-wall cavity, which has been internally conditioned with acoustic-absorbent panels placed onto the floor and rear wall, in an attempt to emulate the absorbent condition of a real car.

Figure 5.1(a) illustrates the exterior of the mock-up, together with the control & measurement equipment. The cavity has been excited with a PZT patch *MIDE QuickPack* mod. QP10N. The PZT patch has been installed in the middle of the upper edge of the bigger firewall partition, as close as possible to the clamping, in order to guarantee a good authority over the main modes. In this way, the sound that reaches the microphones in the passenger compartment is a result of the structure-borne excitation of the vibro-acoustic system. The PZT is capable of exciting the cavity at a bandwidth that is compatible with the noise emitted by the hybrid electric powertrain (cf. Fig. 1.2).

Figure 5.1(b) shows the interior of the cavity, which has been instrumented with four microphones placed at locations close to the actual driver and passengers positions. Four loudspeakers *VISATON* mod. SC 8N have also been placed at locations that emulate the actual positions of the doors of a commercial sedan vehicle. Each microphone has been associated with the closest loudspeaker in the cavity. The microphone brands and sensitivities are listed as follows: (1) *G.R.A.S.* mod. Type 26CA, 46.16 mV.Pa^{-1} , at the Driver's position; (2) *Brüel & Kjær* mod. 4961, 54.20 mV.Pa^{-1} , at the Co-driver's position; (3) *G.R.A.S.* mod. Type 26CA, 53.10 mV.Pa^{-1} , at the Passenger 1's position (behind the driver); and (4) *Brüel & Kjær* mod. 4961, 54.94 mV.Pa^{-1} , at the Passenger 2's position (behind the co-driver).

Figures 5.1(c) and (d) show schematic views with the main dimensions of the mock-up. While the microphone heights have been kept constant along the whole experimental campaign, the distance between microphones and corresponding control loudspeakers was slightly modified from the Experiments 1 - 4 to the Experiments 5 and 6, as is shown in Fig. 5.1(d). This slight displacement of the microphones towards their corresponding control loudspeakers solved instability issues that were found on Experiments 5 to 6, as a result of working in a wider frequency band. This aspect will be described in detail later on.

Antialiasing and reconstruction analog bandpass filters have accordingly been provided for each acquisition channel. The high-pass cutoff frequency has been adjusted at 10 Hz for all the experiments. While the low-pass cutoff frequency has been adjusted at

Figure 5.1: Images and schematics of the experimental workbench (dimensions in mm): (a) exterior; (b) interior; (c) isometric view; (d) top view.

Source: Adapted from Mosquera-Sánchez et al. (2017a), Mosquera-Sánchez et al. (2017b).

1 kHz for the Experiments 1, 2, 3, and 4, this parameter has been configured at 3 kHz for Experiments 5 and 6. The conditioning amplifier, *Brüel & Kjær Nexus* mod. Type 2692-A, only offered those two cutoff frequency options, which turned out to be suitable for the experiments.

The scripts for the control schemes have been written as C S-functions for *Simulink*, and compiled for the DSP platform *dSPACE 1006*. This platform, available at the Dynamics Laboratory from the São Carlos School of Engineering of the University of São Paulo, is equipped with a 16-channel, 16-bit analog-digital converter (ADC), and a 5-channel, 12-bit digital-analog converter (DAC). The control units have been programmed so as to operate in a serial form. In other words, the generation of the control outputs should wait until the communication flow from Channel 1 to

Channel 4 had been completed. Computationally efficient schemes for parallelizing the execution of the control schemes have been described by Lorente et al. (2014), Ferrer et al. (2015) and Lorente et al. (2015), which would allow for the use of larger control arrays, still provided with the proposed schemes for compensating for the acoustic coupling amongst channels.

Table 5.1 summarizes the configuration of some equipment and mounting parameters provided for each experiment.

Table 5.1: *Summary of parameters for each experiment.*

Experiment	Sample rate [Hz]	Low-pass cutoff [Hz]	Filter length	Y-axis dist. [cm]
1 (MIMO)	2920	1000	584	4.75
2 (MIMO)	2920	1000	584	4.75
3 (MIMO)	2920	1000	584	4.75
4 (MIMO)	2920	1000	584	4.75
5 (MIMO)	5899.38	3000	147	3.75
6 (SISO)	5899.38	3000	147	3.75

5.1.1 Dynamics of the acoustic plant

Since the mock-up is airborne-sealed, plant variations due to changes in the acoustic domain are mostly avoided (OLIVEIRA et al., 2012). Hence, a single measurement of the acoustic control plant has been carried out before each Experiment, just to account for long-term environmental changes (air temperature and humidity). While the internal temperature was fairly constant during long timeframes, the external temperature was needed to be monitored more regularly. The fact that the external temperature changed drastically along the days during which the experimental campaign was carried out, forced the experiments to be run at times in which the external temperature was likely to remain constant, as well as the background noise was likely to be low. Therefore, the experiments were carried out mostly at nights, at a mean internal cavity temperature of 21° . Since the Experiments 1 - 4 were run with the same sample rate, at approximately the same environmental conditions, the resulting FRFs turned out to be similar amongst each other. In order to highlight the system variability, this section will only illustrate the FRFs and related functions obtained for Experiments 3 and 5. For the sake of completeness, the more homogeneous set of functions, associated with Experiments 1, 2, 4, and Experiment 6, can be found in Appendix B.

The impulse responses from each actuator to all the microphones within the cavity were identified by following a LMS-based system identification algorithm (KUO; MORGAN, 1996), which uses Gaussian noise as the excitation signal. The length of the

impulse responses, Q , has been determined in a trial-and-error basis, in an attempt to have an accurate representation of the system dynamics, while keeping the computational cost as low as possible. Table 5.1 summarizes the adopted filter lengths for each Experiment. In this Table, it is possible to notice that the filter length had to be reduced, as the sample rate increased, due to the extra computational cost when operating at high sample rates. The control schemes, eventually, operated accurately, even at those high sample rates.

With the identified IRFs at hand, the FRFs are calculated based on their Fourier Transform. The norm-2 condition number is calculated from the matrix $\mathbf{A}(f) = \hat{\mathbf{S}}(f)^H \mathbf{S}(f)$, where $\mathbf{S}(f)$ is the matrix arranged at the frequency f , by putting the direct paths terms of the FRFs onto the main diagonal, and the crossed terms of the FRFs at the corresponding entries in the matrix. The subsequent calculation of the phase delay function, Δ_j , is detailed in Subsection 5.1.2.

The measurements

In Figs. 5.2(a), (b) and Fig. 5.3(b); as well as in Figs. 5.5(a), (b) and Fig. 5.6(b), which illustrate the magnitude, phase and phase delay of the FRFs of the Experiments 3 and 5, respectively, bold continuous lines represent the *direct* secondary paths, i.e. transfer paths between a given loudspeaker and the closest microphone placed within the cavity; while dotted lines represent the *crossed* secondary paths, i.e. transfer paths between a given loudspeaker and other microphones. Moreover, in Fig. 5.3(a) and Fig. 5.6(a), bold continuous lines represent the norm-2 condition number of the control matrices, as a function of the frequency, while dark dots highlight control matrices at which the operation of the proposed multichannel arrays is predicted to require stabilization.

In general terms, since each microphone has been placed as close as possible to its corresponding loudspeaker, magnitude functions with the direct paths larger than the crossed paths have been realized. This feature of the SAP positioning is still more evident in the absolute phase and phase delay functions, where the crossed paths are larger (in absolute value) than the direct paths. However, some magnitude values of the crossed paths that are larger than the ones of the direct paths can still be found. This follows from the observability each microphone may have of the modes being excited by other than its corresponding loudspeaker.

The visual comparison of the condition number functions obtained from Experiments 1, 2, 3 and 4, which are correspondingly shown in Figs. B.2(a) and B.4(a) (cf. Appendix B), and in Figs. 5.3(a) and 5.6(a), reveals that there is a bandwidth comprised between 480 Hz and 900 Hz, at which the density of array-unstable control matrices seems to be low. A zoom has been given to an even smaller bandwidth, comprised between 580 Hz and 620 Hz, cf. Fig. 5.4, in order to gain some insights on the composition of these control matrices. Two datatips have been placed at 607.8 Hz and 615.6

Figure 5.2: *Exp. 3 - Secondary paths: (a) magnitude of the FRFs; (c) phase of the FRFs.*

Source: Mosquera-Sánchez et al. (2017b).

Hz as reference points in the Figure. Thus, in Fig. 5.4 it is possible to observe that, as the magnitude of the crossed path $S_{12}(z)$ becomes larger than the one of the direct path $S_{22}(z)$, unstable control matrices arise. On the contrary, as soon as the magnitude of $S_{22}(z)$ becomes larger than the magnitude of $S_{12}(z)$, stability is regained. Such instability issues can be found at a number of frequencies along the operation bandwidth, indicating that the stability of the multichannel control schemes is influenced by the SAP positioning, as it was already discussed in Chapter 2.

In Fig. 5.4, the marker at 593.1 Hz helps visualizing the configuration of one of

Figure 5.3: *Exp. 3 - Secondary paths: (a) norm-2 condition number of matrix $A(z)$; (b) phase delay of the FRFs.*

Source: Mosquera-Sánchez et al. (2017b).

the control matrices that will be excited in the Experiment 3. It is worth noticing that, although the real part of all the eigenvalues of the matrix $A(593.1)$ is positive, the large difference between the values of the direct paths renders this matrix ill-conditioned for inversion, even when this matrix is array-stable. Even so, the proposed LMS-based control algorithms are able to provide a solution, after a significant amount of iterations (BETLEHEM et al., 2015). This convergence speed issue is present when the control schemes do not correct for the commutation error, such as Algorithms 2 and 3, and

Figure 5.4: *Exp. 3 - Zoom on the magnitude function of the secondary paths in Fig. 5.2(a).*

also explains why Algorithm 1, which does compensate for the commutation error, can overcome matrix ill-conditioning issues and manages to converge quickly.

It is also possible, though, to find quite well conditioned, but array-unstable control matrices, along the studied bandwidth. This might imply that, while the spread of the magnitude values of the direct paths is low, any of the crossed paths has its magnitude value larger than the one of the corresponding direct path. For these cases, the proposed multichannel control schemes are expected to quickly fall into instability. Even so, the stabilization is always assured, by restricting the control output. As discussed in Chapter 2, this will imply in degrading the control performance.

While Figures 5.5(a) and (b) illustrate the magnitude and phase of the FRFs of the Experiment 5, Figs. 5.6(a) and (b) show the norm-2 condition number and phase delay functions of those FRFs. Since the adopted length for the FIR filters was decreased, in relation to the one in the Experiments 1 - 4, cf. Table 5.1, the resolution of the resulting FRFs was also degraded. Even though a negative effect can be seen on the off-line analyses, such as the norm-2 condition number (cf. Fig. 5.6(a)), the controllers did operate properly at these conditions.

5.1.2 Parameters setup for the control schemes

At the frequencies in which the matrix $\mathbf{A}(z) = \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ shows eigenvalues with negative real parts, the regularization parameters for each control unit were calculated by making:

$$\delta = 2 \text{diag} \left(\left| \hat{\mathbf{S}}(z) \right| \right) L, \quad (5.1)$$

where L is the length of the FIR filter that acts as the adaptive controller. It is worth recalling that, for the frequency-domain control schemes, $L = K$, where K is the length

Figure 5.5: *Exp. 5 - Secondary paths: (a) magnitude of the FRFs; (b) phase of the FRFs.*

of the discrete Fourier transform.

The step-sizes for the LMS algorithms were calculated by using the following adapted expression (VICENTE; MASGRAU, 2006):

$$\mu_j = \frac{0.5}{LB_j O (2\Delta_j + 1)}, \quad (5.2)$$

where μ is given for each $j = 1 : M$ control unit as a function of the length of the adaptive filter L ; the number of tones to be controlled O ; the power B of the reference signal, as "seen" by controller j ; and the minimum phase delay Δ amongst a given

Figure 5.6: *Exp. 5 - Secondary paths: (a) norm-2 condition number of matrix $A(z)$; (b) phase delay of the FRFs.*

sensor and all actuators. The last two entities are calculated as follows:

$$B_j = \sqrt{\sum_{j=1}^M |\hat{\mathbf{S}}_{(m,j)}(z)|^2}; \quad \Delta_j = \min \left(-\frac{\phi_{(m,j=1:M)}}{\Omega} \right), \quad (5.3)$$

where $\phi_{(m,j=1:M)}$ is the unwrapped absolute phase of the secondary paths, and Ω is the normalized frequency vector, $2\pi\mathbf{f}/Fs$, at which the secondary paths have been identified.

As it can be observed in Eqs. 5.1, 5.2 and 5.3, the success of these calculations strongly

relies on an accurate plant identification.

5.2 Experiments

The first four experiments deal with low-frequency periodic sounds that are not fully representative of the hybrid electric powertrain noise. The remaining two experiments are intended to demonstrate the proposed method for enhancing the SQ of the hybrid electric powertrain noise that propagates within a cavity, which address either single or multiple listeners. Specific control targets have been defined for each experiment. The methodology followed by the data acquisition is particular for each experiment, as well. Below is a list of the different control targets and data acquisition methodologies, which have been defined for each of them, as follows:

- Experiments 1 and 2 deal with a single-tone primary sound. The control target for these experiments is to reduce the sound at Channels 1, 2 and 3, as much as possible, while preserving the primary sound at Channel 4 at its original condition. Three multichannel control schemes are compared, namely the Algorithm 0 (pure-decentralized control scheme), and the proposed amplitude-based Algorithms 1 and 2. A single measurement, for each of the multichannel control schemes under test, is taken in the following manner:
  - The primary sound is left unchanged, or in preservation mode ($g = 1.0$), during the first 2 s. This ensures the primary sound reaches the steady state within the cavity.
  - The control scheme under test is activated in the cancellation mode ($g = 0.0$) at Channels 1, 2 and 3, at $t = 2$ s, whereas the preservation mode ($g = 1.0$) is left active at Channel 4.
  - In order to demonstrate that the operations modes can be switched between states during uptime, without causing instability, Channels 1, 2 and 3 are brought back to preservation mode at $t = 25$ s.

The resulting time series are 30 s long per independent run. This process is repeated 20 times, for each of the tested configurations, to allow for statistical analysis.

- Experiment 3 deals with a multi-frequency primary sound composed by 10 harmonics. The compared multichannel control schemes, control targets and data acquisition procedures are similar to the ones designed for the Experiments 1 and 2.

- Experiment 4 deals with a multi-frequency primary sound composed by just 4 harmonics. The amount of tones was reduced from that of the previous Experiment, aiming at easing the visualization of the time history of the controlled primary sound. This Experiment is concerned with the amplitude and relative-phase functions of the primary sound. Two multichannel control schemes are compared, namely the Algorithm 0, which is the current pure-decentralized control scheme, and the Algorithm 3, which is the proposed multichannel control scheme.

Two control targets are proposed to be accomplished at Channels 1, 2 and 3, while *preserving* the primary sound at its original condition at Channel 4, as follows:

- Amplitude modes: implementation of both cancellation and amplification modes, i.e. $g = 0.0$ and $g = 2.0$.
- Relative-phase modes: implementation of eight operation modes, ranging from $-\pi$ to π rad, with steps of $\pi/4$ rad.

Each of the operation modes is tested by following the same data acquisition procedure as in Experiments 1, 2 and 3. Ten independent observations of each operation mode have been acquired for each multichannel control scheme tested. Further SQ analyses based on Loudness and Roughness are carried out off-line. A detailed description of these results can be found in Mosquera-Sánchez et al. (2017a).

- Experiment 5 deals with realistic hybrid electric powertrain noise, as perceived at the four instrumented positions inside the cavity. The proposed framework for approaching the SQ of the primary sound, cf. Chapter 4, is summarized below:
  - The first procedure consists on the measurement of the noise at the relevant locations in the cavity. Twenty seconds long measurements have been acquired.
  - Time-domain SQ algorithms are used for determining the SQ scores of the noise, for each sensor location. At this point, the frequency-domain SQ algorithms are also calibrated.
  - Next, the EE-based sensitivity analyses, as well as the multi-objective SQ optimization routines, are executed for each measurement from the sensor locations.
  - The controller is eventually implemented, by using the optimal amplitude gain factors for each targeted tone, which are expected to drive the sound towards the enhanced SQ goals. Therefore, the control target pursued in the Experiment 5 is to implement the optimal solutions at each of the four targeted

locations, with the aid of the multichannel cost-effective amplitude-based Algorithm 2, which features compensation for cross-channel interferences. The procedure for the data acquisition follows a similar procedure as detailed before: 2 s of latency are used for attaining the steady-state conditions, after which Algorithm 2 is turned on for 8 s. The control parameters used for the control operation, i.e. the amplitude gain factors, are those provided by the MOO. Off-line analyses on the norm-2 condition number of the physical array suggested that the controllers would be able to accomplish convergence and steady state in a short timeframe, since the tones of the primary sound requiring control excite well-conditioned control system matrices. On the other hand, it is worth noticing that all the system frequencies requiring control for this Experiment needed to be constrained, in order to guarantee stable operation. As discussed before, it can be expected that the implementation of constraints has a negative impact on the control performance.

- The last Experiment, namely Experiment 6, has been designed to verify the effectiveness of the proposed framework for enhancing the SQ of the hybrid electric powertrain noise for single listeners, while also investigating possible causes for the multichannel controller not giving good Roughness results. The primary sound used for this Experiment is similar to that of the Experiment 5. This allows for the direct comparison of the results in Experiments 5 and 6, as well as the numerical simulation given in Section 4.2. Both control targets and data acquisition procedures for Experiment 6, are similar to the ones in Experiment 5.

5.2.1 Experiment 1

This experiment illustrates details on the operation of the proposed time-domain multichannel control schemes with coupling compensation. For the sake of clarity, the primary sound has been simplified to a single tone at $f = 390$ Hz, which excites an array-stable control matrix.

After performing the system identification (cf. Fig. B.1), the matrix that is identified at the excitation frequency of the primary sound is as follows:

$$\hat{\mathbf{S}}(390_{Hz}) = \begin{bmatrix} 1.06 + 0.39i & 0.22 + 0.19i & -0.41 - 0.48i & -0.27 + 0.64i \\ 0.70 + 0.12i & 0.24 + 0.33i & -0.40 + 0.77i & -0.39 - 0.39i \\ -1.12 + 0.33i & -0.40 - 4.0e^{-04}i & 0.53 + 0.61i & 0.39 - 0.20i \\ -0.68 + 0.42i & -0.36 - 4.0e^{-03}i & 0.46 - 0.24i & 0.31 + 0.67i \end{bmatrix}$$

The eigenvalues and condition number of $\mathbf{A}(z) = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$ are: $\lambda_{(f=390Hz)} = \{1.31 - 0.61i, 1.01 + 0.18i, \mathbf{0.04+0.04i}, 0.28 + 0.39i\}$, and $\text{CN} = 48.91$. Therefore, since

the eigenvalue of $\mathbf{A}(390)$ with the smallest real part (highlighted in boldface) is positive, it is said that the array disposed as in Fig. 5.1 is stable at 390 Hz, which in turn will demand no control output constraints for the operation of any of the proposed multi-channel control schemes. However, since the norm-2 condition number is somewhat large, the LMS-based algorithms are expected to take long to converge.

Table 5.2 summarizes the parameters calculated for Algorithm 1. Algorithms 0 and 2 use half these step sizes, as the quickest that still ensure fast and stable operation.

Table 5.2: *Exp. 1 - The smallest real part of any of the eigenvalues and norm-2 condition number of matrix $\mathbf{A} = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$, and parameters for the LMS adaptive algorithm at $f = 390$ Hz, for each sensor location: Algorithm 1 uses the step-sizes (μ) reported on in this Table; and Algorithms 0 and 2 use half the μ values for Algorithm 1.*

Freq. [Hz]	$Re(\lambda_{(\mathbf{A}(z))})$	CN.	Position 1		Position 2		Position 3		Position 4	
			δ	μ	δ	μ	δ	μ	δ	μ
390	0.04	48.91	0	$1.49e^{-03}$	0	$1.33e^{-03}$	0	$6.11e^{-04}$	0	$1.08e^{-03}$

Figure 5.7(a) illustrates the running RMS of the mean error signal, which was calculated after acquiring 20 independent observations of the same process, at each microphone location. Figure 5.7(a) evidences that, while the Algorithm 0 has caused an undesired reduction of the signal at Ch. 4, the Algorithms 1 and 2 have managed to *preserve* the signal amplitude, while attaining the requested *cancellation* at Channels 1, 2 and 3. It is worth noticing that the Algorithm 2 takes longer to accomplish the cancellation mode in Ch. 2, whereas that the Algorithm 1 converges at almost the same speed as Algorithm 0, which is a computationally decoupled multichannel control scheme. It can then be asserted that the matrix conditioning does impose a convergence drawback for Algorithm 2, which is solved by Algorithm 1, at the expense of an extra computational effort.

Figure 5.7(b) illustrates the entire spectrum for the 4 channels. From there, it is clear that the tone is completely canceled at Channels 1 - 3 without introducing undesired artifacts at other frequencies. Moreover, Fig. 5.8 shows a group of bar plots that illustrates the 390 Hz peak value attained by each Algorithm at the 4 channels. The Figure reveals very good control performances for Algorithms 1 and 2, while showing an undesired reduction of 4 dB_{SPL} promoted by Algorithm 0 at Ch. 4. On the other hand, Algorithms 1 and 2 seem effective in preserving the primary sound at the original 81 dB_{SPL} in Ch. 4, even in the presence of the control signals coming from the actuators in SAPs 1, 2 and 3.

Therefore, provided that the control matrix being excited shows all its eigenvalues with their real parts positive, the proposed control schemes will attain the targeted control actions in an *independent-zone* manner, as the crossed interference between

channels is efficiently solved.

5.2.2 Experiment 2

This experiment shows the results of the proposed time-domain multichannel control schemes, when dealing with an array-unstable control matrix. The incoming sound is redefined as a single tone at $f = 300$ Hz. In this case, the matrix $\mathbf{A}(z)$ shows one of its eigenvalues with a negative real part.

The matrix extracted from the FRFs at $f = 300$ Hz is as follows:

$$\hat{\mathbf{S}}(300_{\text{Hz}}) = \begin{bmatrix} 0.35 - 0.43i & -0.22 + 0.14i & 0.03 - 0.17i & 0.03 - 0.11i \\ -0.32 + 0.25i & 0.17 - 0.18i & 0.04 - 0.16i & 0.03 - 0.11i \\ 0.04 - 0.26i & -0.06 + 0.03i & -0.09 + 0.14i & -0.02 - 0.08i \\ -0.09 + 2.4e^{-03}i & 5.0e^{-03} - 0.14i & -0.02 - 0.16i & -0.16 + 0.15i \end{bmatrix}$$

The eigenvalues and condition number of $\mathbf{A}(z) = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$ are: $\lambda_{(f=300\text{Hz})} = \{0.35 + 0.03i, \mathbf{-0.01-0.04i}, 0.05 + 0.03i, 0.05 - 0.02i\}$, and $\text{CN} = 14.33$. Notice that this is the case of a well-conditioned but array-unstable control matrix, where the multichannel control schemes are expected to quickly diverge. Therefore, some sort of stabilization mechanism is needed. The step sizes, μ , and constraints, δ , are then calculated by following Eqs. 5.1, 5.2 and 5.3, which reads: $\delta_{(f=300\text{Hz})} = \{11.08, 4.95, 3.33, 4.39\}$. These results have been rounded.

Table 5.3: *Exp. 2 - The smallest real part of any of the eigenvalues and norm-2 condition number of matrix $\mathbf{A} = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$, and parameters for the LMS adaptive algorithm, at each controlled discrete frequency, for each sensor location: Algorithms 0, 1 and 2 use the same constraint value (δ); Algorithm 1 uses the step-sizes (μ) reported on in this Table; and Algorithms 0 and 2 use half the μ values values for Algorithm 1.*

Freq. [Hz]	$\text{Re}(\lambda_{(\mathbf{A}(z))})$	CN.	Position 1		Position 2		Position 3		Position 4	
			δ	μ	δ	μ	δ	μ	δ	μ
300	-0.01	14.33	11.10	$1.03e^{-02}$	5.04	$8.72e^{-03}$	3.25	$1.13e^{-02}$	4.43	$1.39e^{-02}$

In a similar form as in Experiment 1, Fig. 5.9(a) illustrates the running RMS of the mean error signal, which was calculated after acquiring 20 independent observations of the same process, at each microphone location. Figure 5.9(a) reveals that all the multichannel control schemes showed the same convergence speed, and that they almost attained the same reduction levels. Algorithm 0 slightly outperforms the multichannel control schemes with coupling compensation at Channel 1. However, the interference caused by this multichannel control scheme at Channel 4 is way larger than the one caused by Algorithms 1 and 2.

Figure 5.7: *Exp. 1 - Comparison amongst the results of Algorithms 0, 1 and 2, at each sensor location: (a) running RMS of the mean error signals; (b) spectra.*

Figure 5.8: *Exp. 1 - Grouped bar plot of the final amplitude values, at each sensor position.*

Figure 5.9 shows the resulting spectra for the 4 channels. It can be seen that, again, some level of noise reduction is attained, without causing other disturbances to the sound (distortions, spillover, etc.) and that the performance obtained here is not as good as in Experiment 1. In fact, Algorithm 0 outperforms Algorithms 1 and 2 in Ch. 1, as it can be seen in the bar plot of Fig. 5.10. This lack of performance was expected, as a consequence of the use of constraints, which is even evidenced when trying to preserve the sound level at Ch. 4. As it can be seen, Algorithms 1 and 2 amplify the noise at that channel by 3 dB, while Algorithm 0 delivered a reduction of 9 dB, behaving similarly as seen before.

5.2.3 Experiment 3

This experiment is concerned with a multi-frequency primary sound composed of 10 harmonics. These harmonics excite a combination of array-stable and array-unstable control matrices. This sort of sounds is better tackled by using the proposed frequency-domain multichannel control schemes, due to their computational efficiency.

To face this primary sound, the multichannel control schemes have been equipped with fast Fourier transforms of length $K = L = 64$ bins. Thus, the frequency of each of the $K/2 - 1$ operational Fourier bins matches the ones of the primary sound, i.e. $\{Fs/K\} \times (12, 13, \dots, 21) = (547.50, \dots, 958.13)$. This matching condition is also referred to as the *synchronously sampled sinusoid*. Provided this operating condition is met,

Figure 5.9: *Exp. 2 - Comparison amongst the results of Algorithms 0, 1 and 2, at each sensor location: (a) running RMS of the mean error signals; (b) spectra.*

Figure 5.10: *Exp. 2 - Grouped bar plot of the final amplitude values, at each sensor position.*

the control schemes will behave in a pure linear, time-invariant (LTI) form at those frequencies (VICENTE; MASGRAU, 2006). Therefore, the same formulae provided for calculating the parameters of the time-domain multichannel control schemes can be used for the frequency-domain ones.

Table 5.4 reports on the parameters used in this experiment. According to the off-line analyses, only two harmonics were detected as being array-unstable (730 and 912 Hz). However, during the control practice, two more harmonics, located at 593.13 Hz and 638.75 Hz, also resulted in instability, for reasons yet unknown. The issue with those two tones has been solved, again, by means of adding effort constraints.

Figure 5.11 illustrates the time histories of the control schemes operation, recorded at each channel. These results show, again, a good level of reduction for Channels 1 - 3, regardless of the control scheme used, while Ch. 4 shows a slight increase promoted by Algorithms 1, 2 and 3 and, this time, a considerable amplification caused by Algorithm 0. The output provided by the Algorithm 1 is free of oscillatory patterns when at steady-state, and suggests that it owns better convergence properties than Algorithm 2, the latter one being more prone to matrix ill-conditioning influences.

Figure 5.11(b) illustrates the spectra discriminated by channels. These figures reveal some high-frequency spurious tones that do not belong to the primary sound, which are likely due to a limitation of the DSP instrumentation (low bit-rate of the DAC, non-linear distortions of the loudspeakers, etc.). Effortful reductions are evidenced in

Figure 5.11: *Exp. 3 - Comparison amongst the results of Algorithms 0, 1 and 2, at each sensor location: (a) running RMS of the mean error signals; (b) spectra.*

Source: Mosquera-Sánchez et al. (2017b).

Table 5.4: Exp. 3 - The smallest real part of the eigenvalues and norm-2 condition number of matrix $\mathbf{A} = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$, and parameters for the LMS adaptive algorithm, at each controlled discrete frequency, for each sensor location: Algorithms 0, 1 and 2 use the same constraint value (δ); Algorithm 1 uses the step-sizes (μ) reported on in this Table; and Algorithms 0 and 2 use half the μ values in this Table.

Freq. [Hz]	$\text{Re}(\lambda_{(\mathbf{A}(z))})$	CN.	Position 1		Position 2		Position 3		Position 4	
			δ	μ	δ	μ	δ	μ	δ	μ
547.50	0.90	7.90	0.00	$5.73e^{-05}$	0.00	$2.11e^{-05}$	0.00	$2.61e^{-05}$	0.00	$2.09e^{-05}$
593.13	0.04	86.17	150.00	$4.46e^{-05}$	150.00	$3.02e^{-05}$	150.00	$1.51e^{-05}$	150.00	$1.64e^{-05}$
638.75	0.38	9.67	850.00	$1.54e^{-05}$	850.00	$1.04e^{-05}$	850.00	$7.54e^{-06}$	850.00	$9.56e^{-06}$
684.38	0.14	22.72	0.00	$2.73e^{-05}$	0.00	$1.95e^{-05}$	0.00	$1.36e^{-05}$	0.00	$1.64e^{-05}$
730.00	-0.07	10.01	183.22	$7.50e^{-05}$	161.09	$8.67e^{-05}$	119.73	$7.99e^{-05}$	120.81	$7.83e^{-05}$
775.63	0.47	17.04	0.00	$5.16e^{-05}$	0.00	$2.41e^{-05}$	0.00	$7.36e^{-05}$	0.00	$5.39e^{-05}$
821.25	0.71	3.74	0.00	$1.76e^{-04}$	0.00	$8.63e^{-05}$	0.00	$7.56e^{-05}$	0.00	$8.10e^{-05}$
866.88	0.59	4.58	0.00	$1.13e^{-04}$	0.00	$6.42e^{-05}$	0.00	$1.43e^{-04}$	0.00	$1.37e^{-04}$
912.50	-0.21	3.75	610.88	$1.94e^{-04}$	662.72	$1.41e^{-04}$	383.28	$1.09e^{-04}$	301.70	$1.71e^{-04}$
958.13	0.04	5.18	0.00	$1.29e^{-04}$	0.00	$1.29e^{-04}$	0.00	$1.13e^{-04}$	0.00	$1.91e^{-04}$

Source: Mosquera-Sánchez et al. (2017b).

this Figure, but some harmonics that were supposed to be canceled have remained almost unaltered, due to the use of the control output restrictions.

The grouped bar plot shown in Fig. 5.12 helps visualizing a comparison of the final amplitude values of the controlled sound, attained by each multichannel control scheme. On the one hand, it has been found that the three multichannel control schemes have performed well in reducing the primary sound at the three targeted locations, showing large reductions, some cases even on the order of 70 dB_{SPL}. This is the case in which Algorithm 0 has caused the largest variations on the primary sound at Channel 4, as well. This result is dramatically contrasted with that of Algorithms 1 and 2, which have managed to *preserve* the sound at this Channel. In other words, no perceivable difference has resulted in the sound recorded at Channel 4, from controlling the noise at Channels 1, 2 and 3, when using the multichannel control schemes with coupling compensation.

The following remarks can eventually be stated after Experiment 3:

- Algorithm with no compensation mechanism (Algorithm 0): it exhibits the fastest convergence, as it is computationally decoupled, but in turn causes the largest cross-channel interferences, due to the same reason.
- Algorithm 1 with compensation mechanism: its convergence rate is comparable with the one of the Algorithm 0 and is the best one in rejecting cross-channel inter-

Figure 5.12: *Exp. 3 - Grouped bar plot of the final amplitude values, at each sensor position.*

Source: Mosquera-Sánchez et al. (2017b).

Table 5.5: *Exp. 3 - Absolute value of relative error with respect to the non-controlled primary sound at Position 4.*

Freq. (Hz)	Ctrl.OFF (dB)	Control ON					
		Alg. 0		Alg. 1		Alg. 2	
		dB	%	dB	%	dB	%
547.50	59	63	7	60	2	60	2
593.13	48	58	21	48	0	48	0
638.75	52	60	15	51	4	50	2
684.34	57	63	11	57	0	57	0
730.00	65	75	15	67	3	67	3
775.63	59	57	3	59	0	59	0
821.25	61	61	0	61	0	61	0
866.88	49	57	16	49	0	49	0
912.50	59	64	8	61	3	61	3
958.13	47	58	23	46	0	47	2
Mean	-	-	11.9	-	1.2	-	1.2

Source: Mosquera-Sánchez et al. (2017b).

ferences. However, its computational complexity would render its implementation in low-power DSP boards unfeasible.

- Algorithm 2 with compensation mechanism: derived from Algorithm 1 by eliminating the internally estimated quantity $\check{d}[n]$, this Algorithm can be regarded as a cost-effective solution that is still able to solve cross-channel interferences. However, its convergence process is slower and more prone to matrix ill-conditioning.

5.2.4 Experiment 4

A periodic disturbance composed of four harmonics at 425.83, 486.67, 547.50 and 608.34 Hz is used as the primary sound for this Experiment. The combination of a few harmonics enables to readily detect changes in their relative-phase function, still in the time histories. Internal discrete Fourier transforms of length $K = L = 48$ bins have been used in the control loops. The parameters used in this experiment are reported in Table 5.6.

Table 5.6: *Exp. 4 - The smallest real part of any of the eigenvalues and norm-2 condition number of matrix $\mathbf{A} = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$, and parameters for the LMS adaptive algorithm, at each controlled discrete frequency, for each sensor location.*

Freq. [Hz]	$\text{Re}(\lambda_{(\mathbf{A}(z))})$	CN.	Position 1		Position 2		Position 3		Position 4	
			δ	μ	δ	μ	δ	μ	δ	μ
425.83	0.21	21.66	0.00	$5.77e^{-05}$	0.00	$1.05e^{-04}$	0.00	$1.19e^{-04}$	0.00	$8.70e^{-05}$
486.67	0.41	5.12	0.00	$1.29e^{-04}$	0.00	$2.07e^{-04}$	0.00	$3.56e^{-05}$	0.00	$1.28e^{-04}$
547.50	1.06	6.96	0.00	$8.42e^{-05}$	0.00	$3.26e^{-05}$	0.00	$2.74e^{-05}$	0.00	$6.06e^{-05}$
608.33	-0.02	738.43	$5.75e^{01}$	$3.98e^{-05}$	$1.59e^{02}$	$1.83e^{-05}$	$3.21e^{03}$	$6.69e^{-06}$	$2.51e^{03}$	$2.11e^{-05}$

Source: Mosquera-Sánchez et al. (2017a).

The off-line analyses reported on in Table 5.6 reveal that the tone at 608.33 Hz is the most problematic one, as it exhibits a rather large condition number, and, still worse, one of its eigenvalues has a negative real part. On the contrary, the tone at 547.50 Hz excites a quite well-conditioned matrix, which has all its eigenvalues with a positive real part. For this Experiment, the off-line prediction of array stability agreed well with the control practice.

Amplitude control

Table 5.7 contrasts small portions of the time-domain data of the controlled primary sound at steady state, after implementing two amplitude operation modes, i.e. $g = 2.0$ and $g = 0.0$, by using the multichannel Algorithms 0 and 3. The time series are plotted

by channels. In this Table, dotted lines represent the non-controlled, primary sound, whereas bold continuous lines represent the controlled primary sound.

Table 5.7: *Exp. 4 - Comparison between uncontrolled (dotted lines) and controlled (continuous lines) sounds for the multichannel Algorithms 0 and 3, in different modes of amplitude control.*

Source: Mosquera-Sánchez et al. (2017a).

The implementation of amplitude modes did drive the harmonics of the primary sound to the desired values, i.e. to reduction (mode 0.0), and to amplification up to twice its original amplitude values (mode 2.0), except from the tone at 608.33 Hz, which required stabilization via regularization. Therefore, some level of residual noise is still apparent when mode 0.0 is applied, at Channels 1, 2 and 3. This goal was attained by both of the multichannel control schemes in a similar form.

The implementation of the amplitude modes by the multichannel control scheme with no compensation mechanism undesirably altered the relative phase of the primary sound at all the error sensor locations. In contrast, the proposed control scheme with compensation just reshaped the amplitude function, while avoiding interferences on the relative-phase function of the primary sound. This is the targeted control goal, which also has an important effect on auditory Roughness, as it can be seen at Figs. 5.13(c) and

(e), to be introduced further on.

The proposed multichannel control scheme again kept the cross-channel influences as low as possible. However, since the tone at 608.33 Hz required regularization, the total cancellation of the cross-channel influences was not possible. Even so, the result attained by Algorithm 3 noticeably overcome that of Algorithm 0.

Relative-phase control

Table 5.8 compares small portions of the time data for the relative-phase control, after implementing eight relative-phase operation modes between $\pm\pi$ rad, in intervals of $\pi/4$ rad, i.e. $g^{(p)} = \{-1, -0.75, -0.5, -0.25, 0.25, 0.5, 0.75, 1\}$, by using the multichannel control schemes being compared. As in Table 5.7, dotted lines represent the non-controlled primary sound whereas bold continuous lines represent the controlled sound.

Table 5.8: *Exp. 4 - Comparison between uncontrolled (dotted lines) and controlled (continuous lines) sounds for the multichannel Algorithms 0 and 3, in different modes of relative-phase control.*

Mode	Algorithm 0		Algorithm 3	
$-\pi$	Ch. 01 	Ch. 02 	Ch. 01 	Ch. 02
	Ch. 03 	Ch. 04 	Ch. 03 	Ch. 04
	Ch. 01 	Ch. 02 	Ch. 01 	Ch. 02
	Ch. 03 	Ch. 04 	Ch. 03 	Ch. 04
$-3\pi/4$	Ch. 01 	Ch. 02 	Ch. 01 	Ch. 02

Source: Mosquera-Sánchez et al. (2017a).

The implementation of some relative-phase modes, i.e. modes $-\pi$, $-3\pi/4$, $-\pi/2$, $3\pi/4$ and π , was shown to be infeasible via Algorithm 0. The controller ran into instability when trying to cope with these requirements. This result is dramatically contrasted with the ones attained by Algorithm 3, which was able to implement all the relative-phase operation modes, thus driving the primary sound to the targeted relative-phase shifts. Algorithm 0 caused undesired amplitude changes as well, even when trying to cope with the stable phase modes. This result was overcome by Algorithm 3.

Regarding cross-channel interferences, it is possible to see that, as the relative-phase operation mode becomes more demanding (i.e. modes tending to $\pm\pi$ rad), Algorithm 0 causes stronger interferences. Algorithm 3 did attempt to cancel out the cross-channel influences, but since the tone at 608.33 Hz required regularization, the total cancellation was not attained.

Influence of the amplitude operation modes on the Loudness and Roughness metrics

The results from Experiment 4 are analyzed in terms of two SQ metrics, Loudness and Roughness. Based on the discussion presented in Chapter 3 and the results presented here, Loudness is expected to be controlled in terms of the amplitude operation modes,

whereas Roughness is expected to be controlled in terms of both the amplitude and relative-phase operation modes.

Figure 5.13 illustrates time-histories of both the non-controlled and controlled sound, after applying the amplitude operation modes. In this Figure, the mode $g^{(a)} = 2.0$ is plotted by using light-gray lines; the mode $g^{(a)} = 1.0$ uses gray lines; and the mode $g^{(a)} = 0.0$ uses dark lines.

Below is a list of statements that can be formulated from visually inspecting Fig. 5.13:

- Generally speaking, the implementation of any of the amplitude modes is stable, regardless of the multichannel algorithm used. However, the implementation of the mode $g^{(a)} = 2.0$ by Algorithm 0 resulted in a strong amplitude modulation, cf. Fig. 5.13(a). This is mainly due to the fact that the control units continuously attempt to converge to the targeted value, but each of them is at its own not aware that the incoming sound they are "observing" is indeed a linear superposition of the primary sound itself, the corresponding control signals *and* the cross-channel interferences. This oscillatory pattern has a rather negative effect on both Loudness and Roughness perceptions, as it can be observed in Figs. 5.13(c) and (e). Moreover, since the implementation of the mode $g^{(a)} = 0.0$ does not show that oscillatory behavior, it can be asserted that it is neither due to the magnitude of the imaginary part of the matrix $\hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ (ELLIOTT; BOUCHER, 1994), nor to a poor plant identification (REES; ELLIOTT, 2006).
- The time-histories apparently reveal that both control schemes have similar convergence rates, cf. Figs. 5.13(a) and (b). However, the time-domain Loudness metric shows that this is not the case, once that Algorithm 3 clearly takes more time to converge, cf. Figs. 5.13(c) and (d). Since the Algorithm 3 takes both direct and coupling terms to converge to the targeted values, it is expected that the convergence times are longer for the coupled control scheme than for the decoupled one.
- Regarding Loudness, cf. Figs. 5.13(c) and (d), Algorithm 3 has been shown to effectively drive the primary sound to either amplification or reduction, as prescribed by the selected modes. Furthermore, Loudness at Channel 4 was effectively *preserved* at its original condition, which indicates that the cross-channel interferences were properly solved, except from the ones induced by the tone at 608.33 Hz, which required stabilization. Even so, this was already expected.
- On the one hand, Roughness decreased when mode $g^{(a)} = 0.0$ was implemented at Channels 1, 2 and 3, which is the expected behavior. On the other hand, Roughness was almost unresponsive to the amplitude mode $g^{(a)} = 2.0$ at Channels 1 and 3, cf. Figs. 5.13(e) and (f), and surprisingly when mode $g^{(a)} = 2.0$ was used at Channel 2.

Figure 5.13: *Exp. 4 - Time histories and corresponding SQ assessment of amplitude control: (a) Algorithm 0; (b) Algorithm 3; (c) Loudness of time histories in literal (a); (d) Loudness of time histories in literal (b); (e) Roughness of time histories in literal (a); (f) Roughness of time histories in literal (b).*

Source: Mosquera-Sánchez et al. (2017a).

Furthermore, Roughness at Channel 4 was kept as close as possible to the original value, which means that the cross-channel interferences were effectively rejected, except, once again, from the induced ones by the tone at 608.33[Hz].

Influence of the relative-phase operation modes on the Loudness and Roughness metrics

Figure 5.14 illustrates time-histories of both the non-controlled and controlled sounds, after applying the relative-phase modes. In literals (a), (c), and (e), the mode $g^{(p)} = 0.5$, i.e. $\theta \rightarrow \pi/2$ rad, is plotted by using dark-gray lines; the mode $g^{(p)} = 0.0$ (inactive relative-phase mode), is plotted by using light-gray lines; and the remaining modes, i.e. $g^{(p)} = -0.25, 0.25$, are plotted by using different gray lines. At literals (b), (d), and (f), grayscale tones are used to distinguish lines, in which dark gray tones represent the modes that tend to $\theta \rightarrow \pm\pi$ rad whereas lighter gray tones represent the operation modes that tend to the inactive, or the *preservation* mode.

Below is a list of statements that can be formulated from visually inspecting Fig. 5.14:

- The proposed multichannel control scheme allowed the stable implementation of all the relative-phase modes. With regard to its non-compensated counterpart, the *feasible* relative-phase modes were seen to be $g^{(p)} = \{-\pi/4, \pi/4, \pi/2\}$. The implementation of mode $g^{(p)} = 0.5$ with Algorithm 0 induced a strong amplitude modulation (cf. Fig. 5.14a), similar to that observed in the amplitude modes. It again showed an undesired effect on both of Loudness and Roughness perceptions, as it can be observed in Figs. 5.14(c) and (e). Since at the remaining relative-phase modes this behavior is not observed, one could again conclude that it is not due to magnitude or imaginary part issues of matrix $\hat{\mathbf{S}}(z)^H \mathbf{S}(z)$, nor to a poor plant identification.
- The control effort requirements for controlling the relative-phase function are more demanding than the ones for controlling the amplitude, which poses an even bigger challenge to Algorithm 0 to avoid cross-channel interferences. This is clear when analyzing the results for Loudness perception at all the sensor positions in Fig. 5.14(c). On the other hand, Fig. 5.14(d) shows that the relative-phase modes only caused small amplifications on the Loudness perception implemented by Algorithm 3, which is due to the loss of control performance when controlling the harmonic at 608.33 Hz.
- With regard to the Roughness perception handled by Algorithm 0 (Figs. 5.14e and f), it is possible to observe that, whilst the oscillatory behavior induced by the implementation of the mode $g^{(p)} = 0.5$ had a strong effect on all the Channels, the implementation of the remaining modes delivered a stable Roughness value when

Figure 5.14: *Exp. 4 - Time histories and corresponding SQ assessment of relative-phase control: (a) Algorithm 0; (b) Algorithm 3; (c) Loudness of time histories at literal (a); (d) Loudness of time histories in literal (b); (e) Roughness of time histories in literal (a); (f) Roughness of time histories at literal (b).*

Source: Mosquera-Sánchez et al. (2017a).

at steady state. However, it has to be recalled that the control of the relative phase should not alter the Loudness perception, as it did, and hence it can be said that Algorithm 0 failed in attaining the pursued goal on just reshaping the Roughness perception.

- On the other hand, Fig. 5.14(f) reveals that the results by Algorithm 3 outperform those of Algorithm 0. It is also clear that all the implemented relative-phase operation modes did drive the primary sound to Roughness reshaping, with just a small level of interference on Loudness (cf. comparison of Figs. 5.14d, and f, with respect to Figs. 5.14c, and e). The relative-phase shifts tested always delivered stable Roughness values when at steady-state, in the following ways:
  - The operation modes close to the inactive one resulted in a slight Roughness alteration, at positions 1 and 3.
  - The operation modes close to $\pm\pi$ rad resulted in reduction of Roughness.
  - None of the operation modes resulted in Roughness alteration at position 2.
  - The position 4, which was supposed to be *preserved* against cross-channel influences, exhibited unexpected Roughness reductions, on the order of 0.1 asper. This is only due to the loss of performance in controlling the tone that excited the control signal with its smallest eigenvalue with negative real part.

Discussion

All the unexpected SQ perturbations perceived at Channel 4 are caused by the lack of control performance, which resulted from the constraint imposed at 608.33 Hz. Figure 5.15 illustrates the sound spectra after applying the amplitude control modes, for each channel. Auxiliary dot-dashed lines highlight the targeted harmonics. Regarding Channels 1, 2 and 3, it is evident that, while harmonics at 425.83, 486.67 and 547.50 Hz reacted properly to the control actions, the harmonic at 608.33 Hz was almost completely unresponsive. At Channel 4, the amplitude of the first three harmonics were properly preserved while the fourth exhibited undesired amplifications. Then, an important conclusion that arises at this point is that both Loudness and Roughness perceptions can be significantly affected by a multichannel controller based on Algorithm 3. However, the use of effort constraints as a stabilization mechanism may prevent any multichannel control scheme from accurately reaching a predefined target for those psycho-acoustic perceptions.

Figure 5.16 illustrates the relative-phase function for different control modes. Auxiliary dot-dashed lines, as well as the relative-phase function when at inactive mode (dotted lines), have been included, for the sake of illustration. Since the wrapped relative-phase function is discontinuous, the lines that follow the controlled harmonics

Figure 5.15: *Exp. 4 - Magnitude function of spectra of amplitude-controlled primary disturbance at each position by using Algorithm 3, before finishing 10 s: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch. 4.*

Source: Mosquera-Sánchez et al. (2017a).

show jumps at $\pm\pi$ rad. Regarding Channels 1, 2 and 3, it is clear that, while the harmonics at 425.83, 486.67 and 547.50 Hz properly reacted to the control actions, the tone at 608.33 Hz showed an erratic behavior, which is again due to the constraint imposed to the control output at this frequency. With regard to the Channel 4, it is possible to notice that, while the harmonics at 425.83, 486.67 and 547.50 Hz were properly *preserved* from cross-channel interferences, the tone at 608.33 Hz is constantly varying. This behavior is responsible for the unexpected Loudness and Roughness variations at Channel 4. These results also prove that the proposed multichannel Algorithm 3 is able to reject cross-channel interferences, due to the relative-phase operation modes.

Figure 5.16: *Exp. 4 - Relative-phase function of spectra of phase-controlled primary disturbance at each position by using Algorithm 3, before finishing 10 s: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch. 4.*

Source: Mosquera-Sánchez et al. (2017a).

5.2.5 Experiment 5

This experiment demonstrates the effectiveness of the multichannel Algorithm 2 in delivering prescribed SQ targets for each of the four locations, as designed at the proposed MOO step. The multichannel Algorithm 2 has been chosen due to its low computational cost, which, in turn, has enabled its on-line implementation at a high sampling rate, compatible with that of the realistic hybrid electric powertrain noise.

In actual single- and multichannel control scenarios, the sound emitted by a given source is propagated through the vibro-acoustic system under study. As it can be expected, the dynamics of the system modifies the original time/frequency pattern of the auditory stimulus, such that both the magnitude and relative-phase spectral functions of the noise perceived at each of the targeted locations are reshaped. Whereas

in both free field radiation and enclosures the system delay has an important role in defining the relative-phase function, the amplitude function is strongly affected by the mode shapes and damping. Moreover, the location of the error sensor(s), or listener(s), play(s) an important role in the perception of the noise, since at some locations, the modal features may either reinforce or mitigate some harmonics originally present in the source. Hence, it is expected that the perception of the primary sound differs from one location to another.

These effects, which are particularly relevant in cavities with low damping, require the proposed methodology for approaching the SQ of periodic disturbances to be carried out for each targeted location. As a result, it is possible that the sensitivity analyses highlight different sets of harmonics to be controlled at each location. At this point, it is worth noticing that, if a certain harmonic needs to be changed at one single location, it does not mean it should not be controlled at the other targeted locations; it does mean that it should be preserved at those places, requiring the cross-channel interference feature to work properly. Therefore, the controller will eventually have to cope with all the harmonics highlighted by each of the sensitivity analysis, in some places by adjusting the gain factors according to the SQ optimization and, at others, by preserving its original amplitude.

As soon as the multichannel control scheme to be used delivers *free-of-interference* multichannel active sound profiling, the proposed multi-objective SQ optimization framework can be independently executed for each of the targeted locations in the system. Thanks to the multichannel Algorithm 2, the results of the present multichannel Experiment show small differences between the optimized and attained SQ scores.

Noise measurement, diagnostics and calibration of frequency-domain SQ algorithms

The first step of the proposed framework is concerned with the measurement and the SQ diagnostics of the primary sound, which must be repeated for each targeted location. The primary sound has been synthesized at a sampling rate of $F_s = 5899.38$ Hz, which is compatible with the number of Fourier bins, $L = 38$, of the discrete Fourier transform algorithms into the frequency-domain version of the multichannel Algorithm 2, as well as with the frequencies of the targeted tones in the sound.

As described in Chapter 4, some data post-processing steps should be carried out, in order to extract the frequencies of the tones, as well as their amplitudes and relative phases. From this procedure, it has been possible to identify 43 tones whose amplitude is larger than zero dB_{SPL} . Notice that not all of the tones should fall into each single Fourier bin, but only the ones that will be addressed, as prescribed by the EE-based sensitivity analyses. Figure. 5.17 illustrates the magnitude function extracted from the measurements of the primary sound, at each of the four targeted locations in the cavity.

As usual, a correction for accounting for the diffuse field (measurements within the

Figure 5.17: *Exp. 5 - Magnitude functions of the measured primary sound at: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch. 4.*

cavity) is applied before each SQ metric is calculated. The Sharpness metric has been calculated with the Zwicker's weights, and the Tonality metric with the Shin et al. (2009) weighting formula. The obtained SQ scores for the original primary sound are reported in Table 5.9. This Table also unveils that both the co-driver and the passenger located behind the driver are exposed to the highest Loudness values whereas the passenger behind the co-driver is exposed to the highest Roughness value and the passenger behind the driver is exposed to the highest Sharpness. All the passengers inside the cavity perceive the same Tonality.

As soon as the time-domain SQ metrics are assessed, the frequency-domain algorithms are calibrated. These calibrated algorithms are to be used in the following MOO procedures.

Table 5.9: *Exp. 5 - SQ scores of the primary sound, as determined at each location.*

Position	Loudness [sone]	Roughness [asper]	Sharpness [acum]	Tonality [SP]
1	38.88	0.66	1.29	0.96
2	50.00	0.68	1.42	0.90
3	49.60	0.64	1.59	0.97
4	42.73	0.79	1.21	0.96

Multi-objective SQ optimization - composition and examination of the decision and objective spaces

The composition of the decision space has been carried out by means of the EE-based sensitivity analyses proposed in Section 4.1. Figure 5.18 illustrates the results of the sensitivity analyses, discriminated by locations. It is possible to observe that, while the identification of the most involved tones in causing large variations on the SQ metrics at Positions 1 and 4 has been relatively straightforward, some tones at Positions 2 and 3 are rather close to the prescribed threshold for Roughness, which is imposed by the largest elementary effect, plotted in dashed lines. Even so, since the elementary effect of these tones did not exceed the threshold, it has been possible to extract a single tone related to that metric. Hence, it has also been possible to compose a set of decision variables for each position, such that the amount of tones to be controlled is way smaller than the total amount of tones in the primary sound itself.

Table 5.10 reports on the 6 tones, discriminated by locations, which require either preservation, or other than the inactive ASQC operation mode, i.e. cancellation, reduction or amplification. The frequencies marked with "X" in the Table are the ones that require the application of other than the *preservation* operation mode, i.e. cancellation, reduction, or amplification, at the corresponding locations. Table 5.10 also shows that all the decision sets are composed by three tones, except for the set related to Position 4, which is composed of just two tones.

Table 5.10: *Exp. 5 - List of harmonics to be controlled at each targeted location.*

Harmonic [Hz]	Position 1	Position 2	Position 3	Position 4
155.25	X		X	
620.99		X		X
776.23	X		X	
931.48	X	X	X	
1862.96		X		
2794.45				X

Figure 5.18: *Exp. 5 - Sensitivity analyses of the SQ metrics, based on the method of the Elementary Effects, for each position: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch. 4.*

Now that the decision spaces have been composed, the MOO procedure takes place for each sensor location. Both of the multi-objective SQ evolutionary solvers tested in Chapter 4, namely the NSGA-II and the SPEA2, have been used for solving the vector SQ optimization. The results considered for further implementation were the ones that reached the best global minimum/maximum solutions. While the results of the NSGA-II solver were considered for Positions 1, 2 and 3, the ones from the SPEA2 solver were the considered for Position 4.

Figure 5.19 illustrates the scatter-plot matrices obtained after concurrently minimizing and maximizing the associated SQ vector, at each location. The big red dot refers to the original SQ scores of the measured primary sound. The feasible objective space, which has been brought up by extensive search procedures on the multi-objective formulation, is represented by using little light-gray dots. The results of the MOO have been discriminated by using black dots for illustrating the concurrent minimization, and light-blue dots for plotting the concurrent maximization.

From the Pareto fronts in Fig. 5.19, ten optimal SQ scores have been extracted for implementation, five of which belong to the front obtained from the concurrent minimization, and the remaining five from the one of the concurrent maximization. This procedure has been carried out for the four locations considered. These ten optimal solutions have been highlighted in the scatter-matrix plots by using markers: squares for the minimization, and stars for the maximization. Each solution has been plotted by using the corresponding color, cf. legend for Fig. 5.19.

In general terms, the Pareto fronts obtained for the four locations of interest are not as regularly distributed as expected. Even when the decision spaces were composed of a few tones, the resulting Pareto fronts in Fig. 5.19 are rather irregular. While for the NSGA-II this result could have been anticipated, based on the analysis of Section 4.2, the SPEA2 results for Position 4 are better conformed, cf. Fig. 5.19(d), which also agrees with earlier results. Even so, it is possible to see that the solutions selected for implementation are located at the extrema of the optimum Pareto fronts, which match the ones of the feasible objective space, as well. The choice of the extreme values ensures that the maximum and the minimum feasible values of each SQ metric will be tested. This fact agrees with the discussions provided in Chapter 4, where it was stated that the most interesting solutions in the Pareto fronts are those of the extrema, as well as the given by the Global minimum/maximum ones.

Multichannel active sound quality control

With the optimal amplitude gain factors for each tone in the decision sets, as prescribed by the MOO for each targeted location, the next procedure deals with the implementation of the optimal SQ scores. The control stage was practiced when the external and internal temperatures were as close as possible to those during the initial measurements,

Figure 5.19: *Exp. 5 - Multi-objective SQ optimization outcomes: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch. 4. **Legend:** (1) light-gray dots: exhaustive search; (2) black dots: minimization; (3) light-blue dots: maximization; (4) red dot: original SQ scores; (5 – 9) optimum/attained pairs (color squares): min1: blue; min2: red; min3: orange; min4: purple; min5: green; (10 – 15) optimum/attained pairs (color stars): max1: blue; max2: red; max3: orange; max4: purple; max5: green.*

(c)

(d)

in order to avoid influences due to system variability. Based on that initial measurement, stability predictions, as well as the calculations for the control parameters, were carried out.

Table 5.11 reports on the parameter values for the frequency-domain multichannel Algorithm 2, together with the norm-2 condition number of the system matrices being excited, as well as the smallest real part of the eigenvalues of the matrix $\mathbf{A}(z) = \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$. The off-line analyses on the stability of the control scheme predicted that just one tone would require control output limitation. However, the actual control practice verified that all the tones were to require stabilization. This is probably the main reason for the performance of the coupling compensation mechanism to have been degraded. The constraint values, other than the predicted one by the stability analyses, were determined in a trial-and-error basis. Since the norm-2 condition numbers determined for the matrices are small, as compared to the ones obtained in previous Experiments, it was expected that Algorithm 2 would be able to converge quickly, so the allowed timeframe for each observation was limited to 10 s.

Table 5.11: *Exp. 5 - The smallest real part of any of the eigenvalues and norm-2 condition number of matrix $\mathbf{A} = \text{diag}(\hat{\mathbf{S}}(z))^H \mathbf{S}(z)$, together with parameters for the LMS adaptive algorithm, at each controlled discrete frequency, for each sensor location.*

Freq. [Hz]	$Re(\lambda_{\mathbf{A}(z)})$	CN.	Position 1		Position 2		Position 3		Position 4	
			δ	μ	δ	μ	δ	μ	δ	μ
154.98	-0.01	42.23	17.77	$1.19e^{-04}$	9.01	$1.13e^{-04}$	7.03	$6.02e^{-04}$	7.84	$5.95e^{-04}$
619.94	0.68	12.93	10	$3.35e^{-06}$	10	$3.54e^{-06}$	10	$1.37e^{-06}$	10	$1.33e^{-06}$
774.92	0.66	16.40	20	$4.87e^{-06}$	20	$2.79e^{-06}$	20	$1.71e^{-05}$	20	$1.32e^{-05}$
929.90	0.23	25.94	10	$8.36e^{-06}$	10	$7.60e^{-06}$	10	$3.76e^{-05}$	10	$4.51e^{-05}$
1862.31	0.04	36.86	10	$3.47e^{-05}$	10	$5.05e^{-05}$	10	$1.67e^{-04}$	10	$1.18e^{-04}$
2792.21	0.90	7.71	10	$1.76e^{-05}$	10	$2.33e^{-05}$	10	$4.66e^{-05}$	10	$4.15e^{-05}$

Table 5.12 that reports the amplitude values obtained during the control practice reveals that they have noticeably changed from the initial measurement to the control stage. By just taking the relative error between the initially measured amplitude values and the ones that were measured immediately before the control stage, it is possible to observe that the differences amount to 17.52% at Position 1, 13.28% at Position 2, 14.24% at Position 3 and 12.94% at Position 4.

Table 5.12 also reports the optimized amplitude gain factors discriminated by positions, which should drive the primary sound to the targeted SQ scores. In the Table, the gain factors of the tones that are required to be *preserved* have been merged into a single cell. It was expected that all the amplitude values within the merged cells match those of the corresponding cells titled as **Ctrl.**, which are the amplitude values measured

Table 5.12: Exp. 5 - List of optimized amplitude gain factors and actively attained amplitude values for each harmonic in the sets of decision variables, discriminated by positions. The mean of the relative error between the original amplitude value and the resulting one after applying control, $\bar{E}$, is only given for the harmonics that were required to be preserved against cross-channel interferences.

Ch.	Sol.	H1: 155.25 [Hz]		H2: 620.99 [Hz]		H3: 776.23 [Hz]		H4: 931.48 [Hz]		H5: 1862.96 [Hz]		H6: 2794.45 [Hz]	
		Gain	Amp. [dB]	Gain	Amp. [dB]	Gain	Amp. [dB]	Gain	Amp. [dB]	Gain	Amp. [dB]	Gain	Amp. [dB]
1	Meas.	–	64.16	–	65.36	–	63.87	–	67.35	–	60.22	–	64.36
	Ctrl.	1.00	59.05	1.00	74.21	1.00	44.69	1.00	76.52	1.00	48.69	1.00	50.93
	Min1	2.00	59.82		76.24	2.00	55.71	2.00	82.96		57.05		49.37
	Min2	0.00	60.55		68.25	1.99	54.05	0.63	65.87		46.18		51.81
	Min3	0.00	54.28		70.82	0.11	34.33	0.02	38.58		50.95		53.41
	Min4	0.00	54.56		70.12	0.16	38.65	0.00	26.65		52.15		57.82
	Min5	0.00	54.89	1.00	69.39	0.04	28.88	0.01	34.57	1.00	53.09	1.00	58.28
	Max1	0.00	55.11		68.78	0.00	18.81	0.00	20.63		53.71		58.72
	Max2	0.31	58.36		69.59	0.33	48.00	2.00	76.89		54.59		57.43
	Max3	2.00	65.22		69.89	2.00	60.96	2.00	79.31		50.74		57.69
	Max4	0.00	56.97		69.29	2.00	62.18	1.74	77.30		50.98		57.71
	Max5	2.00	65.65		68.65	2.00	62.85	2.00	78.34		50.41		59.17
	$\bar{E}$				6.08%						7.80%		10.84%
2	Meas.	–	67.66	–	75.16	–	56.14	–	66.54	–	75.03	–	68.92
	Ctrl.	1.00	55.92	1.00	69.46	1.00	47.87	1.00	77.08	1.00	66.04	1.00	60.49
	Min1		56.45	2.00	70.60		45.87	2.00	81.99	2.00	72.08		60.03
	Min2		59.88	0.00	24.25		42.63	0.04	48.22	0.61	63.51		62.83
	Min3		57.81	0.00	41.36		45.87	0.05	47.64	0.00	25.96		63.84
	Min4		58.97	0.06	48.83		44.22	0.00	34.12	0.00	25.76		66.61
	Min5	1.00	59.92	0.00	37.91	1.00	42.51	0.05	46.93	0.00	25.76	1.00	67.31
	Max1		60.66	0.00	39.65		42.95	0.00	33.16	0.07	46.85		67.82
	Max2		61.29	0.13	45.26		39.34	0.25	62.25	0.00	26.47		65.17
	Max3		64.83	2.00	63.62		44.15	2.00	77.85	2.00	75.42		67.57
	Max4		62.54	2.00	63.61		45.07	1.56	75.87	1.47	73.50		66.98
	Max5		65.39	2.00	63.67		46.99	2.00	76.93	2.00	75.94		66.53
	$\bar{E}$		8.68%				8.17%						8.38%
3	Meas.	–	69.15	–	64.61	–	60.35	–	67.04	–	62.05	–	71.98
	Ctrl.	1.00	54.56	1.00	68.25	1.00	54.10	1.00	71.14	1.00	56.35	1.00	48.19
	Min1	2.00	55.97		72.95	1.99	61.20	2.00	73.96		51.83		52.64
	Min2	0.00	59.05		65.54	2.00	62.46	0.67	68.66		57.47		54.35
	Min3	0.00	62.11		65.97	0.06	35.13	0.05	44.28		59.24		57.50
	Min4	0.00	63.06		65.06	0.00	25.75	0.00	22.21		59.55		52.74
	Min5	0.00	63.87	1.00	63.95	0.06	35.96	0.05	43.12	1.00	59.88	1.00	54.81
	Max1	0.00	64.53		62.75	0.00	24.93	0.00	21.67		59.95		56.30
	Max2	0.20	64.42		61.26	0.11	39.99	2.00	70.48		60.36		63.94
	Max3	2.00	63.77		59.92	2.00	62.59	2.00	70.77		55.11		61.34
	Max4	1.19	66.52		58.61	1.99	62.75	1.86	70.13		56.94		63.83
	Max5	2.00	64.74		56.81	2.00	63.17	2.00	70.09		55.65		65.61
	$\bar{E}$				8.65%						4.51%		21.00%
4	Meas.	–	68.51	–	76.87	–	60.78	–	53.22	–	59.38	–	74.85
	Ctrl.	1.00	50.44	1.00	77.24	1.00	37.66	1.00	53.63	1.00	55.94	1.00	70.24
	Min1		52.80	2.00	84.10		44.78		59.86		54.96	1.56	73.87
	Min2		51.91	0.00	21.10		46.73		58.30		57.15	1.05	71.81
	Min3		57.04	0.00	46.38		48.69		63.08		57.26	1.17	73.32
	Min4		58.40	0.07	50.27		51.14		62.58		57.63	0.02	48.32
	Min5	1.00	59.53	0.00	42.67	1.00	52.75	1.00	61.42	1.00	57.85	0.00	46.49
	Max1		60.40	0.00	44.71		53.74		60.96		57.99	0.00	46.50
	Max2		61.02	2.00	74.88		53.96		56.04		58.04	2.00	78.76
	Max3		61.65	1.74	74.12		55.78		58.83		58.86	0.72	70.92
	Max4		61.99	2.00	73.92		56.34		57.09		58.79	1.40	76.45
	Max5		62.62	2.00	72.77		57.09		58.83		59.23	2.00	79.45
	$\bar{E}$		16.44%				38.34%		11.32%		3.63%		

immediately before the control practice, still at the inactive operation mode. However, since all the control units were applied control effort limitation, the final obtained values were seen to differ from those of the original ones.

The effectiveness of the coupling compensation mechanism at each control location, which is based on the average error indicated in Tab. 5.12 ($\bar{E}$), yields the following efficiency values: 91.76% at Position 1, 91.59% at Position 2, 88.61% at Position 3 and 82.57% at Position 4. This, in turn, reads an overall efficiency rate of 88.64%, which means that the average difference between a given amplitude value to be preserved and the final value from applying any of the solutions, at any of the targeted locations, is of 11.36%. Therefore, the efficiency of the coupling compensation mechanism is shown to be negatively affected, as a result of using constraints on the outputs of the control units.

Figure 5.20 shows a bar plot of the amplitude values discriminated by locations, which correspond to the tones that required any control mode. While Fig. 5.20(a) illustrates the final amplitude values after applying the solutions from the concurrent minimization, Fig. 5.20(b) illustrates the final amplitude values after applying the solutions from the concurrent maximization. The tones that required cancellation, reduction or amplification, are highlighted by using numbers. While the tones that required other than the preservation mode are clearly profiled, the ones expected to keep their original amplitude values are close to the non-controlled level.

SQ assessment of the controlled sound

The assessment of the time-domain SQ metrics on the controlled sound will show whether the optimized amplitude gain factors effectively drove the SQ scores to enhanced values, at all the targeted locations within the cavity.

Figures 5.21, 5.22, 5.23 and 5.24 illustrate the time-domain SQ histories that result from applying each of the optimum solutions on the primary sound, as measured at each of the four controlled locations. While Figs. 5.21 and 5.22 show the time-domain SQ histories obtained from applying solutions from the concurrent minimization, Figs. 5.23 and 5.24 show the time-domain SQ histories obtained from the concurrent maximization. It is worth recalling that, for instance, solution **Min1** was simultaneously applied at the four locations, being that this solution is determined by different operation modes, for different tones, for each single location. This follows from the fact that the MOO and related procedures were worked out independently for each single location. The application of solution **Min1** has the effect that is illustrated with blue continuous lines, on all the four SQ metrics, at all the four targeted locations. The remaining solutions are plotted by using different colors, cf. legends in corresponding Figures, and the interpretation of the results follows what it has already been discussed in this paragraph.

With regard to the solutions obtained from the concurrent minimization, illustrated

Figure 5.20: *Exp. 5 - Grouped bar plot of the final amplitude values, after implementing the optimized SQ targets: (a) solutions from minimization; (b) solutions from maximization.*

Figure 5.21: *Exp. 5 - Time-domain SQ assessment of the primary sound, after applying active control guided by concurrent **minimization**: (a) Ch. 1; (b) Ch. 2.*

in Figs. 5.21 and 5.22, it is possible to observe that the solution **Min1** is noticeably different from the remaining ones. Even though, solutions **Min2** - **Min5** are also shown

Figure 5.22: *Exp. 5 - [cont'] Time-domain SQ assessment of the primary sound, after applying active control guided by concurrent minimization: (a) Ch. 3; (b) Ch. 4.*

to drive the SQ of the primary sound to desired scores, as prescribed by the MOO stage. In this set of results, the unexpected behaviors are those regarding the Roughness

metric, which seemed to be rather unresponsive to the control actions. Whilst large Roughness changes were predicted at the optimization step, the control practice verifies that this was not the case, unfortunately.

With regard to the solutions obtained from the concurrent maximization, illustrated in Figs. 5.23 and 5.24, it is possible to observe that the solution **Max1** has noticeably driven each of the associated perceptions to a new balance of SQ scores. The remaining solutions are also shown to drive the SQ of the original sound to new balances, but their effect seems less noticeable. Roughness is again almost unresponsive to any of the implemented solutions.

The solutions **Min5** and **Max5**, which refer to the Global minimum and maximum respectively, seemed rather difficult to be attained. This is mostly due to the fact that the multichannel system had all its control outputs limited, which hindered the attainment of the most effortful amplitude modes, i.e. cancellation and amplification by twice the original amplitude value. This can be verified in Table 5.12, rows **Min5** and **Max5**, where the expected value for mode $g = 0.00$ was 0 dB_{SPL} , and for mode $g = 2.00$ was the amplitude value reported on at rows **Ctrl.**, plus 6 dB_{SPL} . Amongst the obtained time histories from either concurrent minimization or maximization, only the results from applying the solution **Max5** at Channel 4, i.e. the Global Maximum solution, cf. Fig. 5.24(b), illustrate a good example of what it was intended to be delivered, in raising all the SQ scores in a controlled way.

Discussion: success percentages and attained solutions in perspective

Figures 5.21, 5.22, 5.23 and 5.24 have demonstrated that the SQ scores of the primary sound have been noticeably enhanced at each of the targeted locations, as a function of the optimized amplitude values that were tackled by the multichannel Algorithm 2. The results shown so far have also unveiled, though, that the effectiveness of the proposed framework for enhancing the SQ of periodic disturbance was compromised, mainly due to two aspects:

- The strength of the acoustic coupling amongst channels, which in turn enforced the use of control effort constraints that degraded the performance of the multichannel control schemes.
- External influences that caused the sound reaching each SAP to change its time-frequency pattern, from the initial measurement to the active control stages.

At this point, it turns out to be convenient to examine the so-called *success percentage*, which quantify the extent at which the attained SQ scores matched those of the designed ones when at the optimization stage.

Table 5.13 reports the optimized and attained SQ scores discriminated by positions, which correspond to the results shown in Figs. 5.21, 5.22, 5.24 and 5.24. After calculating

Figure 5.23: *Exp. 5 - Time-domain SQ assessment of the primary sound, after applying active control guided by concurrent maximization: (a) Ch. 1; (b) Ch. 2.*

the relative errors between the optimized and attained SQ scores, it is possible to determine that the overall success percentage in attaining any of the designed solutions

Figure 5.24: *Exp. 5 - [cont'] Time-domain SQ assessment of the primary sound, after applying active control guided by concurrent maximization: (a) Ch. 3; (b) Ch. 4.*

for Position 1 is of 89.02%, for Position 2 is 90.35%, for Position 3 is 92.04% and for

Position 4 is 90.50%. This, in turn, yields an overall success percentage of 90.48%, for any of the targeted locations within the cavity. In special, Table 5.13 shows that the obtained success percentage in attaining Roughness targets is the lowest one, just amounting to 81.83%, whereas the success percentage of Loudness, Sharpness and Tonality targets are all above 92%.

The impact on the SQ scores of the original sound can also be seen by means of Radar Plots shown in Figs. 5.25 and 5.26. These radar plots contrast the original SQ scores, i.e. the ones that were determined at the initial measurement, with the attained ones. The axes of the radar plots have been normalized, and corresponding scales have been provided to each axis. In the radar plots, it is possible to observe that a variety of *sound quality balances* can be attained, as dictated by each implemented solution. In this sense, the most interesting results are those given by the so-called Global minima and maxima, cf. green plots in the cited Figures, which, despite the difficulties faced by the multichannel control scheme 2, still represent *the best balance of the SQ metrics*. Moreover, as previously observed, the solutions regarding the Loudness sensation are the ones that have produced the most noticeable changes in the perception of the sound. This observation holds for both set of results from the concurrent minimization in Fig 5.25 and the concurrent maximization in Fig 5.26.

The overall success rate obtained in this experiment can be contrasted with that of the single-channel numerical result given in Section 4.2. Numerical simulations carried out with the so-called realistic *Disturbance D2* showed a success percentage of 97.33%, being that Roughness exhibited the lowest value, i.e. 91.45%, with respect to the other SQ metrics that were attained with success percentages in excess of 99%. Changes in the time-frequency pattern of the primary sound, as well as the cross-channel interferences, are thus verified as the main cause for the loss of the efficiency of the proposed framework when addressing multiple listeners. Based on the agreement between the numerical exercises, it can be stated that the proposed framework for enhancing the SQ of the hybrid electric powertrain noise is able to drive the primary sound to the designed targets, with a quite acceptable level of accuracy.

The results presented in this multichannel ASQC experiment eventually demonstrate that, even when variations in the vibro-acoustic system, as well as acoustic coupling amongst channels, had to be faced to, the proposed framework for enhancing the SQ of stationary hybrid electric powertrain noise is able to deliver the desired soundscape, for a number of listeners within a cavity. The experimentally obtained success percentage of 90.48% in attaining any of the proposed solutions, for all the targeted locations within the experimental cavity, strongly verifies the effectiveness of the proposed method and remarks discussed in this section.

Table 5.13: *Exp. 5 - Comparison between optimized and actively attained SQ scores, and corresponding relative errors. The mean of the relative errors, %, is also provided, for each metric and for each position.*

Ch.	Sol.	Loudness [sone]			Roughness [asper]			Sharpness [acum]			Tonality [SP]		
		Opt.	Att.	E. %	Opt.	Att.	E. %	Opt.	Att.	E. %	Opt.	Att.	E. %
1	Min1	42.64	51.39	20.52	0.62	0.66	5.65	1.23	1.24	0.74	0.93	0.94	1.11
	Min2	37.45	39.39	4.92	0.86	0.66	24.05	1.34	1.38	3.30	0.94	1.04	10.09
	Min3	34.91	39.22	12.34	0.53	0.68	29.59	1.38	1.41	1.66	1.02	1.00	2.05
	Min4	34.92	39.45	12.98	0.52	0.68	30.45	1.38	1.41	2.28	1.04	0.98	5.84
	Min5	34.90	39.55	13.33	0.53	0.69	29.43	1.38	1.42	3.00	0.98	0.98	0.00
	Max1	34.90	39.63	13.58	0.53	0.69	28.78	1.38	1.43	3.47	1.04	0.98	6.03
	Max2	39.40	46.18	17.20	0.43	0.66	52.24	1.30	1.36	4.11	0.94	0.97	3.26
	Max3	42.64	49.43	15.93	0.62	0.65	4.27	1.23	1.32	7.09	0.93	0.97	4.35
	Max4	39.20	46.96	19.81	0.69	0.65	6.03	1.32	1.36	3.48	0.92	0.96	4.99
	Max5	42.64	49.09	15.12	0.62	0.65	4.02	1.23	1.33	8.25	0.93	0.96	3.86
	%	14.57			21.45			3.74			4.16		
2	Min1	56.69	56.88	0.32	0.51	0.66	30.17	1.34	1.43	7.02	0.88	0.90	2.85
	Min2	44.63	44.00	1.42	0.85	0.66	21.73	1.50	1.62	7.76	0.95	0.96	0.47
	Min3	44.24	43.84	0.90	0.59	0.67	14.28	1.50	1.64	8.90	0.97	0.96	1.41
	Min4	44.25	44.00	0.56	0.56	0.68	20.78	1.50	1.65	9.43	1.01	0.96	4.75
	Min5	44.24	43.94	0.68	0.59	0.68	15.47	1.50	1.66	10.13	0.97	0.95	1.94
	Max1	44.24	43.94	0.66	0.62	0.68	9.56	1.50	1.66	10.38	1.00	0.95	4.56
	Max2	44.53	44.42	0.25	0.50	0.71	41.18	1.50	1.66	10.38	0.99	0.94	4.34
	Max3	56.69	55.01	2.97	0.51	0.70	36.79	1.34	1.52	13.09	0.88	0.87	0.32
	Max4	54.87	52.76	3.85	0.60	0.69	15.30	1.35	1.55	14.43	0.87	0.89	3.01
	Max5	56.69	54.76	3.41	0.51	0.70	36.79	1.34	1.53	13.89	0.88	0.88	0.00
	%	1.50			24.21			10.54			2.37		
3	Min1	53.27	44.32	16.80	0.62	0.69	11.07	1.51	1.46	3.28	0.95	0.96	0.86
	Min2	47.07	41.69	11.42	0.84	0.71	15.82	1.67	1.55	6.92	1.00	1.00	0.00
	Min3	45.77	41.23	9.92	0.66	0.68	2.28	1.69	1.58	6.54	0.99	1.00	0.83
	Min4	45.77	41.65	9.00	0.68	0.68	0.00	1.69	1.60	5.82	1.06	1.00	5.27
	Min5	45.77	42.14	7.92	0.66	0.68	3.34	1.69	1.61	5.15	0.99	1.01	1.51
	Max1	45.77	42.41	7.34	0.68	0.69	2.23	1.69	1.62	4.59	1.06	1.01	4.49
	Max2	49.45	45.14	8.72	0.41	0.67	61.42	1.61	1.59	1.56	0.94	0.99	5.87
	Max3	53.27	45.55	14.48	0.62	0.69	11.17	1.51	1.59	5.08	0.95	0.99	3.65
	Max4	51.73	46.06	10.96	0.64	0.69	8.61	1.55	1.59	2.41	0.93	0.99	7.20
	Max5	53.27	46.03	13.58	0.62	0.69	11.52	1.51	1.60	6.01	0.95	0.99	3.77
	%	11.01			12.75			4.74			3.35		
4	Min1	49.89	50.06	0.33	0.63	0.67	5.66	1.21	1.27	5.42	0.93	0.94	1.00
	Min2	36.84	34.35	6.75	0.85	0.67	21.14	1.31	1.52	15.83	1.02	0.94	7.45
	Min3	37.28	36.62	1.78	0.85	0.67	21.28	1.33	1.49	12.16	1.02	0.96	5.84
	Min4	34.89	35.78	2.55	0.56	0.65	17.27	1.25	1.44	15.25	1.08	0.93	13.75
	Min5	34.63	35.97	3.88	0.60	0.68	12.47	1.25	1.43	14.41	1.07	0.92	13.36
	Max1	34.63	36.36	5.00	0.60	0.68	12.47	1.25	1.42	13.60	1.06	0.92	13.32
	Max2	51.67	47.23	8.59	0.55	0.68	24.44	1.25	1.39	11.37	0.94	0.94	0.00
	Max3	45.72	43.88	4.03	0.65	0.67	3.86	1.15	1.32	15.15	0.95	0.92	3.97
	Max4	49.30	45.79	7.12	0.67	0.68	1.53	1.19	1.36	14.08	0.93	0.92	0.98
	Max5	51.67	47.43	8.21	0.55	0.67	22.27	1.25	1.40	12.67	0.94	0.94	0.00
	%	4.82			14.27			12.99			5.97		

Figure 5.25: *Exp. 5: Radar plots of the SQ of the controlled primary sound, after applying solutions from the concurrent minimization: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch. 4.*

5.2.6 Experiment 6

As it has been discussed in the previous Experiment, multichannel ASQC performance may suffer from either (or both), the system variations due to external influences, and/or the strength of the acoustic coupling amongst channels. Therefore, Experiment 6 has been designed to verify the effect of these issues on the proposed methodology. In order to isolate the acoustic coupling issue, which is only present in the multichannel approach, a single-channel experiment is conducted, with the same primary sound used before, targeting only the Driver's position (Channel 1 of the MIMO exercises).

Figure 5.26: *Exp. 5: Radar plots of the SQ of the controlled primary sound, after applying solutions from the concurrent **maximization**: (a) Ch. 1; (b) Ch. 2; (c) Ch. 3; (d) Ch 4.*

Noise measurement, diagnostics and calibration of frequency-domain SQ algorithms

The SQ of the primary sound, generated by the PZT excitation of the firewall, uses the same sampling rate as the one in Experiment 5. The usual procedures for extracting the spectral functions, e.g. identification of the magnitude and relative-phase data, are performed only for the Driver's position for this Experiment. Since the proposed framework is only concerned with the magnitude function of sounds, Fig. 5.27 only illustrates the amplitudes of the primary sound. This Figure almost matches Fig. 5.17(a), although slight differences can be appreciated, which are due to the system variability.

The time-domain SQ metrics are assessed, and corrections for accounting for the diffuse measurement field carried out. The Sharpness metric was calculated using the

Figure 5.27: *Exp. 6 - Magnitude functions of the measured primary sound at Driver's position (MIMO Ch. 1).*

Zwicker's weighting formula, and Tonality was calculated with the Shin et al. (2009) weighting formula. The obtained SQ scores for the primary sound are as follows: Loudness: 38.89 sone, Roughness: 0.66 asper, Sharpness: 1.29 acum and Tonality: 0.96 SP. These scores can be directly compared to those reported onto the row 1 of Table 5.9, and indeed are an almost perfect match. The frequency-domain SQ algorithms are calibrated at this point, for the subsequent stages of the methodology.

Multi-objective SQ optimization - composition and examination of the decision and objective spaces

Since the primary sound for the Experiments 5 and 6 is similar, both the sensitivity analyses and MOO steps were taken from the results obtained for the Driver's position in Experiment 5. Therefore, the set of decision variables for the Driver's position is composed by three tones, located at 155.25 Hz, 776.23 Hz and 931.48 Hz and the MOO results can be found in Fig. 5.19(a).

Single-channel ASQC

Ten optimal solutions, five from the concurrent minimization and five from the concurrent maximization, have been selected in order to demonstrate the performance of the SISO ASQC system. The amplitude gain factors that should drive the SQ of the primary sound to enhanced scores are reported on in Table 5.14, together with the attained amplitude values at each targeted tone. Table 5.14 also verifies that the amplitude differences between the initial measurement and the active control stages just amount to 4.27%. It is expected, then, that the present analysis will benefit from less variability and no cross-channel interference issues.

Table 5.14 indicates that effortful reductions of more than 55 dB_{SPL}, as well as accurate amplifications of 6 dB_{SPL}, were possible to attain. Since the SISO active control, which is based on the multichannel Algorithm 2, does not need control effort constraints, it should always outperform its MIMO counterpart.

Table 5.14: *Exp. 6 - List of optimized amplitude gain factors and actively attained amplitude values for each harmonic in the set of decision variables.*

Solution	H1: 155.25 [Hz]		H3: 776.23 [Hz]		H4: 931.48 [Hz]	
	Gain	Amp. [dB]	Gain	Amp. [dB]	Gain	Amp. [dB]
Measurement	–	63.25	–	64.95	–	69.45
Control	1.00	58.65	1.00	66.21	1.00	66.96
Min1	2.00	64.49	2.00	72.11	2.00	72.82
Min2	$8.60e^{-03}$	5.49	1.99	72.01	0.63	62.85
Min3	$6.20e^{-04}$	25.39	0.11	46.58	0.02	17.43
Min4	$6.20e^{-04}$	3.88	0.16	49.95	$4.29e^{-04}$	29.79
Min5	$4.52e^{-03}$	17.69	0.04	35.87	0.01	16.14
Max1	$6.30e^{-04}$	20.24	$7.96e^{-04}$	28.35	$4.62e^{-04}$	29.57
Max2	0.31	47.86	0.33	56.69	2.00	72.71
Max3	2.00	64.64	2.00	72.11	2.00	72.73
Max4	$4.28e^{-03}$	23.95	2.00	72.11	1.74	71.54
Max5	2.00	64.58	2.00	72.12	2.00	72.68

SQ assessment of the controlled primary sound

Figure 5.28 illustrates the time-domain SQ assessment of the controlled sound at the Driver's position, by using each of the optimal solutions listed in Table 5.14. The Figure makes evident that the SISO controller has delivered each of the targeted solutions in a stable and fast manner, attaining convergence in less than a second. It can also be asserted that each of the optimal sets of amplitude gains effectively drove the SQ of the primary sound to the targeted scores, except for the ones related to Roughness. Roughness is again rather unresponsive to the different amplitude gain factors applied on the primary sound, showing a narrow variation in between 0.65 and 0.70 asper, even when the multi-objective SQ optimization procedure had predicted an operation range of 0.43 - 0.86 asper, cf. Tab. 5.15. Only solution **Max1**, cf. Fig. 5.28, seemed to cause a noticeable change in this perception, even so, the experimental Roughness score is far away from that, cf. Table 5.15.

Figure 5.28: *Exp. 6 - Time-domain SQ assessment of the primary sound, after applying active control guided by solutions chosen from: (a) concurrent minimization; (b) concurrent maximization.*

Discussion: success percentages and attained solutions in perspective

Table 5.15 reports on both the optimized and actively attained SQ scores for the sound tackled at the Driver's position. This Table shows that the mean relative error values obtained for Loudness, Sharpness and Tonality have noticeably improved from the multichannel experiment (14.57%, 3.74% and 4.16%, respectively) to the single-channel one (3.39%, 2.02% and 3.15%, respectively). Roughness perception remained unresponsive to the control actions, so the relative error again read 21.45%. Even so, while the mean success percentage for Position 1 when MIMO control was 89.02%, the mean success percentage for the SISO experiment is of 92.51%.

Table 5.15: *Exp. 6 - Comparison between optimized and actively attained SQ scores, and corresponding relative errors.*

Solution	Loudness [sone]			Roughness [asper]			Sharpness [acum]			Tonality [SP]		
	Opt.	Att.	%	Opt.	Att.	%	Opt.	Att.	%	Opt.	Att.	%
Min1	42.64	41.95	1.61	0.62	0.66	5.65	1.23	1.27	2.86	0.93	0.94	1.11
Min2	37.45	38.81	3.63	0.86	0.68	20.67	1.34	1.33	0.93	0.94	0.97	3.12
Min3	34.91	36.91	5.75	0.53	0.69	30.17	1.38	1.35	2.18	1.02	0.98	4.09
Min4	34.92	37.02	6.03	0.52	0.68	30.45	1.38	1.35	2.31	1.04	0.98	5.84
Min5	34.90	36.91	5.78	0.53	0.68	28.41	1.38	1.36	1.45	0.98	0.98	0.00
Max1	34.90	36.97	5.95	0.53	0.69	28.78	1.38	1.36	1.99	1.04	0.98	6.03
Max2	39.40	39.63	0.59	0.43	0.66	52.24	1.30	1.32	1.57	0.94	0.98	4.46
Max3	42.64	42.20	1.04	0.62	0.66	5.83	1.23	1.27	3.23	0.93	0.94	1.66
Max4	39.20	40.20	2.55	0.69	0.64	6.03	1.32	1.32	0.00	0.92	0.95	3.56
Max5	42.64	42.24	0.93	0.62	0.66	6.13	1.23	1.27	3.30	0.93	0.94	1.62
$\bar{\%}$	3.39			21.44			1.98			3.15		

Figure 5.29 eventually illustrates the Radar Plots of both the original and enhanced SQ scores for the Driver's location. These radar plots show that a number of sound quality balances can be achieved on the sound, by means of the variety of solutions provided by the proposed methodology, applied for a single location within a cavity.

5.3 Conclusions

In this Chapter, experimental evidence has been provided on the operation of the proposed multichannel control schemes with coupling compensation, as well as on the effectiveness of the proposed framework for enhancing the SQ of periodic disturbance for either single or multiple listeners within a cavity. In special, the SQ of the noise emitted by the powertrain in a HEVs, measured in the interior of a laboratory 1:3-scaled cavity with a simplified cabin geometry, has been dealt with in a deep level of detail.

Figure 5.29: *Exp. 6 - Radar plots of the SQ of the controlled primary sound at the Driver's position, after applying solutions chosen from: (a) concurrent minimization; (b) concurrent maximization.*

The experimental evidence presented in this Chapter leads to the following statements:

- The effectiveness of the proposed mechanism for dealing with cross-channel interferences has been extensively demonstrated through Experiments 1, 2, 3 and 4. It has been shown that, when the real part of all the eigenvalues of the matrix $\mathbf{A}(z) = \hat{\mathbf{S}}(z)^H \mathbf{S}(z)$ is positive, any of the proposed multichannel control schemes with coupling compensation can operate with no control output limitations. This, in turn, enables the proposed multichannel control schemes to operate at full range, thus attaining even the most burdensome operation modes, such as the cancellation, amplification by twice, as well as relative-phase shifts from $-\pi$ rad to π rad. If the stability condition is not met at a certain system frequency, stabilization can always be ensured by imposing constraints to the control output. However, this strategy has the effect of reducing the control performance. The impact of such constraints on the control performance has been shown experimentally and the impact on the attained SQ perception discussed, as well.
- The active control of the relative-phase function of periodic disturbances has been demonstrated in Experiment 4, which addressed four error sensor locations within the cavity. The proposed multichannel Algorithm 3 (MOSQUERA-SÁNCHEZ et al., 2017a), which deals with both the amplitude and relative-phase functions of periodic sounds, shares the same stability conditions derived for the amplitude-based multichannel Algorithms 1 and 2 (MOSQUERA-SÁNCHEZ et al., 2017b). This follows from the fact that all the proposed multichannel control schemes minimize independent cost functions associated to every sensor location, while also taking into account the cross dynamics between a given actuator and each of the remaining

sensors.

- Provided that the multichannel control scheme ensures the independent implementation of the operation modes for each targeted location, the multi-objective SQ optimization procedure can be independently worked out for each single listener within the cavity. In other words, the fact that the multichannel control scheme effectively solves interferences amongst channels implies in that the problem of searching for enhanced SQ conditions for a given primary sound, for multiple listeners within a cavity, can be *decoupled*.
- Loudness, Sharpness and Tonality-based targets have been concurrently attained with a good level of accuracy, for the hybrid electric powertrain noise. Results are presented and discussed in Experiment 5 for the MIMO and Experiment 6 for the SISO controller. Whilst the mean *success percentages* in attaining targets based on those metrics with the MIMO controller were: Loudness = 92.03%, Sharpness = 92.00% and Tonality = 96.04%; the success percentages in the SISO scenario improved to: Loudness = 96.61%, Sharpness = 98.02% and Tonality = 96.85%. If these success percentages are compared with those of the single-channel numerical example given in Section 4.2, i.e. Loudness = 99.93%, Sharpness = 99.85%, Tonality = 98.04%, it can be concluded that the issues related to the experimental implementation of these techniques do not affect significantly their performance. However, the system variability and the strength of the acoustic coupling did show some impact on the MIMO performance.
- Roughness-based targets were not attainable with the same level of accuracy as the other ones. While both the multichannel Experiment 5 and the single-channel Experiment 6 verified the same mean success percentage of 78.55%, the numerical single-channel simulation in Section 4.2 predicted a success percentage of 91.45%. Recalling the results from the validation of the time- and frequency-domain Roughness models, given in Section 3.6.4, two workarounds are proposed for overcoming the relatively low level of accuracy of the frequency-domain Roughness algorithm:
  - To re-calibrate the frequency-domain Roughness algorithm along iterations executed in both the sensitivity analyses and the MOO stages. To do that, it will be necessary to resynthesize time histories of the noise being tackled along iterations. This workaround will arguably be computationally costly.
  - Depending on the added computational cost of the last proposition, it might be interesting to run all the proposed procedures by just using the time-domain SQ metrics. While it may be expected that no differences will arise, the computational cost would (currently) jeopardize the methodology.

The overall success percentage attained by the proposed methodology, when Loudness, Roughness, Sharpness *and* Tonality are considered, is of 90.48% for the multichannel scenario, and of 92.51% for the single-channel scenario. Since these indicators are above 90%, it can be stated that the proposed methodology owns an acceptable level of effectiveness and accuracy in enhancing the SQ of stationary hybrid electric powertrain noise.

The experimental results discussed in this Chapter allows concluding that the implementation of the proposed methodology in real HEVs is promising, once that the strength of acoustic coupling amongst channels is expected to be lower than the one observed in the investigated workbench. Even so, further studies on both the influence of system variations on the SQ metrics, with some preliminary results presented in Oliveira et al. (2012), as well as on the time- and frequency-domain Roughness models, are needed in order to improve the success percentage of the whole method.

Chapter 6

Conclusion and future directions

As the level of powertrain electrification rises, as well as the use of lightweight materials in HEVs, novel NVH control methods are needed to cope with the sound stimuli provided by the internal combustion engine (ICE) and the electric motor (EM). The sound quality (SQ) of the powertrain noise can be even worsen by the poor transmission loss feature low-mass panels usually own. Since current vehicle users are more used to experience low-frequency sound fields, such as the ICE-induced ones, the exposure to such broadband noise may elicit negative perceptions on a variety of vehicle attributes, presumably to the extent that a wider acceptance of the HEVs could be hindered.

On the basis that active control techniques are the most versatile ones in profiling periodic sounds, the present research has relied on the extensive use of the class of active noise controllers referred to as active noise equalizers (ANEs), for proposing a framework to enhance the sound qualities of the powertrain within the passenger cabin in HEVs. The key feature of ANE systems in reshaping the magnitude and relative-phase spectral functions of periodic disturbances is extensively used, by means of providing other than pure-reduction solutions, such as equalization, amplification, phase shifts, and even preservation of (parts of the) original time-frequency pattern of the noise. The effect of such control actions has been associated to modifications on SQ metrics, such as Loudness, Roughness, Sharpness and Tonality. To this regard, a mathematical expression based on multi-objective optimization (MOO) theories is posed, which associates all the relevant SQ metrics to the noises emitted by the powertrain in HEVs. The concurrent optimization of the SQ metrics has been shown as a powerful means of guiding the active noise equalizer actions, which are expected to drive the SQ of the original soundscape to a variety of enhanced scores.

As the proposed search procedure for the best powertrain noise SQ has been posed in a multi-objective form, a variety of optimal SQ scores are provided, which present compromise solutions between the selected SQ metrics. These SQ scores are calculated by varying amplitudes (and/or phases) of a reduced set tones in the original sound.

Within the procedure, the tuning of such tones is directly linked to the actual control parameters, which result from the MOO exercise and can be feed to the proposed single/multichannel ANE schemes.

The implementation of optimized active sound profiling decisions for more than a single listener within a cavity often confronts challenges posed by the acoustic coupling between control units, which causes the control signals to reach each others sensors locations. The linear superposition of the primary sound to other than the corresponding control signal is referred to as the cross-channel interference, which has been the cause for current decentralized multichannel systems to be unable to deliver improved soundscapes for multiple listeners. In that sense, a part of the present research has focused on the development of a set of multichannel control schemes that feature a novel concept on counterbalancing cross-channel interferences, which enables the specialist to profile either the amplitude or relative-phase function of multi-frequency signals, at a number of locations within cavities. While the so-called *Algorithm 1* is the fastest converging system proposed, which in turn demands high-power DSP boards for its implementation, the *Algorithm 2* is a cost-effective alternative that still allows the implementation of free-of-interference multichannel active sound profiling tasks, with convergence speeds inferior to that of Algorithm 1. Moreover, the *Algorithm 3* owns the feature of profiling both the amplitude and relative-phase functions at a number of sensor locations, which in turn allows controlling amplitude-based SQ metrics, such as Loudness, Sharpness and Tonality, as well as SQ metrics that are sensitive to relative-phase shifts, such as Roughness. The performance and implementation aspects that involve stability, convergence, robustness to plant variability, and computational complexity, have thoroughly been assessed by carrying out computer simulations and experiments. In this way, the present research has introduced a number of control schemes that extend single-channel ANE systems to the most general multichannel case.

This research has also shown that, provided the sounds excite frequencies at which the system is unconditionally stable and the available internal plant representation is sufficiently accurate, the proposed multichannel control systems are able to properly attain any of the ANE's operation modes (cancellation, reduction, amplification and preservation) at the requested locations. However, when the stability condition at any of the excited system frequencies is not met, the use of constraint outputs helps stabilizing the controllers, at the cost of reducing their performance.

All the proposed techniques for optimizing and controlling the time-frequency pattern of periodic disturbances have been motivated towards the enhancement of the SQ of the powertrain noise, for either single and multiple listeners. Whilst computer simulations have shown success rates as high as 97%, the experiments have unveiled that, while Loudness, Sharpness and Tonality targets can be attained with precision, even for single (97%) and multiple listeners (93%), Roughness goals deviated from the

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expected values (79%, for both single and multichannel scenarios). These deviations are presumably due to disparities between the time- and frequency-domain algorithms, which were unable to be solved by means of the proposed calibration procedure. Even so, since the overall achievement levels observed during the experimental stage are of 90% for the multichannel scenario, and of 93% for the single-channel one, the present research concludes that the SQ of the hybrid electric powertrain noise, perceived at single or multiple locations inside the passenger cavity, can be substantially enhanced by following the proposed framework.

Future works

This thesis presented a method to analyze, optimize and control stationary harmonic noise, in terms of SQ perception. The following aspects could not be covered during the development of this work and remain as suggestions for future work:

- Search for proper bounds for the δ parameter, such that an estimate of the constrained control action on the disturbance can be foreseen before implementation. This estimate will allow the multi-objective optimization problem to include constraints on the allowed amplitude bounds for each targeted tone.
- Search for alternative solutions for the constraint outputs, that would not affect performance as much, e.g. physical modifications to the SAP; modifications to the control schemes in order to include (part) of the coupling terms.
- Improvement of the convergence process of the multichannel control schemes.
- Development of scripts for parallelizing the implementation of the multichannel control schemes.
- Improvement on the computer efficiency of Roughness models.
- Extension of the present methodology to cope with non-stationary disturbances, slowly (and fast changing) RPMS, run-ups and run-downs, etc.
- Although recent papers put forward on similarities between gradient descent and recursive state-space estimators, e.g. the Kalman filter and the LMS/RLS algorithms via the *optimal learning gain matrix* (MANDIC et al., 2015), respectively, advantages of the Kalman filter, such as immunity against matrix ill-conditioning and tracking capabilities in non-stationary situations, despite the widely known numerical issues of the gain matrix and high computation cost for its real-time implementation (OPHEM; BERKHOF, 2013), deserve attention for future research in the multichannel control strategies derived in this manuscript.

Bibliography

ALIVE. **Advanced high volume affordable lightweighting for future electric vehicles**. 2012. Website. Disponível em: <<http://www.project-alive.eu/>>. Acesso em: 18 feb. 2017.

ALMEIDA-AGURTO, D. de; GERGES, S. N. Y.; ARENAS, J. P. MIRE-IL methodology applied to measuring the noise attenuation of earmuff hearing protectors. **Applied Acoustics**, v. 72, p. 451 – 457, 2011.

ANTONI, J.; DUCLEAUX, N.; GHIEM, G. N.; WANG, S. Separation of combustion noise in IC engines under cyclo-non-stationary regime. **Mechanical Systems and Signal Processing**, v. 38, p. 223 – 236, 2013.

ARDEKANI, I. T.; ABDULLA, W. H. Adaptive signal processing algorithms for creating spatial zones of quiet. **Digital Signal Processing**, v. 27, p. 129 – 139, 2014.

ASA. **Specification for octave-band and fractional-octave-band analog and digital filters**. 1986.

ASIMAKOPOULOS, A. P.; BOUMIS, B. T.; PATSIAS, C. E.; SAFACAS, D. A.; MITRONIKAS, E. E. Experience derived from the conversion of a conventional car to a hybrid electric vehicle - analysis of the powertrain. In: **International Symposium on Power Electronics, Electrical Drives, Automation and Motion - SPEEDAM2010**. [S.l.: s.n.], 2010.

AUWERAER, H. van der; SABBATINI, D.; SANA, E.; JANSSENS, K. Analysis of electric vehicle noise in view of vulnerable road user safety. In: **18th International Congress on Sound & Vibration, ICSV18**. [S.l.: s.n.], 2011.

BAEK, K. H.; ELLIOTT, S. J. Natural algorithms for choosing source locations in active control systems. **Journal of Sound and Vibration**, v. 186, p. 245 – 267, 1995.

BAENE, W. de; VANDIERENDONCK, A.; LEMAN, M.; WIDMANN, A.; TERVANIEMI, M. Roughness perception in sounds: behavioral and ERP evidence. **Biological Psychology**, v. 67, p. 319 – 330, 2004.

BALAMURUGAN, S.; ARUMUGAM, R. Estimation of vibrations in switched reluctance motor drives. **American Journal of Applied Sciences**, v. 2, p. 791 – 795, 2005.

BEIN, T.; MAYER, D.; HAGEBEUKER, L.; BACHINGER, A.; BASSAN, D.; PLUYMERS, B.; DELOGU, M. Enhanced lightweight design – first results of the FP7 project ENLIGHT. **Transportation Research Procedia**, v. 14, p. 1031 – 1040, 2016.

- BERKHOF, A. P. Optimum sensor-actuator distance for decentralized acoustic control. **Journal of the Acoustical Society of America**, v. 110, p. 260 – 266, 2001.
- BETLEHEM, T.; ZHANG, W.; POLETTI, M. A.; ABHAYAPALA, T. D. Personal sound zones: delivering interface-free audio to multiple listeners. **IEEE Signal Processing Magazine**, v. 32, p. 81 – 91, 2015.
- BISMARK, G. V. Sharpness as an attribute of the timbre of steady state sounds. **Acustica**, v. 30, p. 159 – 172, 1974.
- BISNETTE, J. B.; SMITH, A. K.; VIPPERMAN, J. S.; BUDNY, D. D. Active noise control using phase-compensated, damped resonant filters. **Journal of Vibration and Acoustics**, v. 128, p. 148 – 155, 2006.
- BOHN, C.; CORTABARRIA, A.; HÄRTEL, V.; KOWALCZYK, K. Active control of engine-induced vibrations in automotive vehicles using disturbance observer gain scheduling. **Control Engineering Practice**, v. 12, p. 1029 – 1039, 2004.
- BOUCHER, C. C.; ELLIOTT, S. J.; NELSON, P. A. Effect of errors in the plant model on the performance of algorithms for adaptive feedforward control. **IEE Proceedings F - Radar and Signal Processing**, v. 138, p. 313 – 319, 1991.
- BRIZON, C. J. S.; MEDEIROS, E. B. Combining subjective and objective assessments to improve acoustic comfort evaluation of motor cars. **Applied Acoustics**, v. 73, p. 913 – 920, 2012.
- CAI, W.; PILLAY, P.; OMEKANDA, A. Low vibration design of SRMs for automotive applications using modal analysis. In: **Electric Machines and Drives Conference, 2001. IEMDC 2001**. [S.l.: s.n.], 2001.
- CAMINO, J. F.; ARRUDA, J. R. F. $\mathcal{H}_2$ and $\mathcal{H}_\infty$ feedforward and feedback compensators for acoustic isolation. **Mechanical Systems and Signal Processing**, v. 23, p. 2538 – 2556, 2009.
- CAMPELLO-VICENTE, H.; PERAL-ORTS, R.; CAMPILLO-DAVO, N.; VELASCO-SANCHEZ, E. The effect of electric vehicles on urban noise maps. **Applied Acoustics**, v. 116, p. 59 – 64, 2017.
- CAMPOLONGO, F.; CARIBONI, J.; SALTELLI, A. An effective screening design analysis for sensitivity analysis of large models. **Environmental Modelling & Software**, v. 22, p. 1509 – 1518, 2007.
- CHAI, J. Y.; LIN, Y. W.; LIAW, C. M. Comparative study of switching controls in vibration and acoustic noise reductions for switched reluctance motor. **IEE Proceedings**, v. 153, p. 348 – 360, 2006.
- CHAN, C. C. The state of the art of electric, hybrid, and fuel cell vehicles. **Proceedings of the IEEE**, v. 95, p. 704 – 718, 2007.
- CHANG, C. Y.; SISWANTO, A.; HO, C.-Y.; YEH, T.-K.; CHEN, Y.-R.; KUO, S. M. Listening in a noisy environment: integration of active noise control in audio products. **IEEE Consumer Electronics Magazine**, v. 5, p. 34 – 43, 2016.
-

- CHEAH, L.; HEYWOOD, J. Meeting U.S. passenger vehicle fuel economy standards in 2016 and beyond. **Energy Policy**, v. 39, p. 454 – 466, 2011.
- CHEER, J.; ELLIOTT, S. J. Multichannel control systems for the attenuation of interior road noise in vehicles. **Mechanical Systems and Signal Processing**, v. 60 - 61, p. 753 – 769, 2015.
- _____. Active noise control of a diesel generator in a luxury yacht. **Applied Acoustics**, v. 105, p. 209 – 214, 2016.
- CHO, W.-H.; IH, J.-G.; SHIN, S.-H.; KIM, J.-W. Quality evaluation of car window motors using sound quality metrics. **Int. J. Automotive Technology**, v. 12, p. 443 – 450, 2011.
- CHO, W.-H.; IH, J.-G.; TOI, T. Positioning actuators in efficient locations for rendering the desired sound field using inverse approach. **Journal of Sound and Vibration**, v. 358, p. 1 – 19, 2015.
- CLAEYS, C. C.; DECKERS, E.; PLUYMERS, B.; DESMET, W. A lightweight vibro-acoustic metamaterial demonstrator: numerical and experimental investigation. **Mechanical Systems and Signal Processing**, v. 70 - 71, p. 853 – 880, 2016.
- CLAEYS, C. C.; VERGOTE, K.; SAS, P.; DESMET, W. On the potential of tuned resonators to obtain low-frequency vibrational stop bands in periodic panels. **Journal of Sound and Vibration**, v. 332, p. 1418 – 1436, 2013.
- COLBY, R. S.; MOTTIER, F. M.; MILLER, T. J. E. Vibration modes and acoustic noise in a four-phase switched reluctance motor. **IEEE Transactions on Industry Applications**, v. 32, p. 1357 – 1364, 1996.
- COUVREUR, C. **Environmental Sound Recognition: A Statistical Approach**. Tese (Doutorado) — Faculté Polytechnique de Mons, June 1997.
- DANIEL, P.; WEBER, R. Psychoacoustical roughness: implementation of an optimized model. **Acustica - Acta Acustica**, v. 83, p. 113 – 123, 1997.
- DEB, K. **Multi-Objective Optimization using Evolutionary Algorithms**. [S.l.]: John Wiley & Sons, 2001.
- DEB, K.; PRATAP, A.; AGARWAL, S.; MEYARIVAN, T. A fast and elitist multiobjective genetic algorithm: NSGA-II. **IEEE Transactions on Evolutionary Computation**, v. 6, n. 2, p. 182 – 197, 2002.
- DIEGO, M. de; GONZÁLEZ, A.; FERRER, M.; PIÑERO, G. Multichannel active noise control system for local spectral reshaping of multifrequency noise. **Journal of Sound and Vibration**, v. 274, p. 249 – 271, 2004.
- DIEZ-IBARBIA, A.; BATTARRA, M.; PALENZUELA, J.; CERVANTES, G.; WALSH, S.; CRUZ, M. de la; THEODOSSIADIS, S.; GAGLIARDINI, L. Comparison between transfer path analysis methods on an electric vehicle. **Applied Acoustics**, v. 118, p. 83 – 101, 2017.
- DRAGONETTI, R.; PONTICORVO, M.; DOLCE, P.; FILIPPO, S. di; MERCOGLIANO, F. Pairwise comparison psychoacoustic test on the noise emitted by dc electrical motors. **Applied Acoustics**, v. 119, p. 108 – 118, 2017.
-

- ELGRICHI, Y.; ZEHEB, E. Stability of multichannel sound control systems. **IEE Proceedings Vision, Image & Signal Processing**, v. 144, p. 1 – 7, 1997.
- ELLIOTT, S. J. **Signal Processing for Active Control**. [S.l.]: Academic Press, 2001. 531 p.
- ELLIOTT, S. J.; BAEK, K. H. Effort constraints in adaptive feedforward control. **IEEE Signal Processing Letters**, v. 3, p. 7 – 9, 1996.
- ELLIOTT, S. J.; BOUCHER, C. C. Interaction between multiple feedforward active control systems. **IEEE Transactions on Speech and Audio Processing**, v. 2, p. 521 – 530, 1994.
- ELLIOTT, S. J.; STOTHERS, I.; NELSON, P. A multiple error LMS algorithm and its application to the active control of sound and vibration. **IEEE Transactions on Acoustics, Speech and Signal Processing**, v. 35, p. 1423 – 1434, 1987.
- EMVEM. **Energy efficiency management for vehicles and machines**. 2013. Website. Disponível em: <<http://www.emvem.org/>>. Acesso em: 18 feb. 2017.
- FASTL, H. Psycho-acoustics and sound quality. In: _____. **Communication Acoustics**. Berlin: Springer Berlin Heidelberg, 2005. cap. 6, p. 139 – 162.
- FASTL, H.; VÖLK, F.; STRAUBINGER, M. Standards for calculating loudness of stationary or time-varying sounds. In: BOLTON, J. S. (Ed.). **38th International Congress and Exposition on Noise Control Engineering 2009 (INTER-NOISE 2009)**. [S.l.: s.n.], 2009. p. 1508 – 1513.
- FASTL, H.; ZWICKER, E. **Psychoacoustics: Facts and Models**. [S.l.]: Springer-Verlag, 2007.
- FERRER, M.; DIEGO, M. de; PIÑERO, G.; GONZÁLEZ, A. Active noise control over adaptive distributed networks. **Signal Processing**, v. 107, p. 82 – 95, 2015.
- FUJIMOTO, S.; ADACHI, K.; ASHIZAWA, H.; MOTOSUGI, J. HEV application of shaking vibration control system based on advanced motor control. **SAE Technical Paper**, Paper no. 2012-01-0622, p. 1 – 8, 2012.
- GAO, D. W.; C., M.; EMADI, A. Modeling and simulation of electric and hybrid vehicles. **Proceedings of the IEEE**, v. 95, p. 729 – 745, 2007.
- GARCIA-BONITO, J.; ELLIOTT, S. J.; BOUCHER, C. C. Generation of zones of quiet using a virtual microphone arrangement. **Journal of the Acoustical Society of America**, v. 101, p. 3498 – 3516, 1997.
- GARVIN, D. A. What does product quality really mean? **Sloan Management Review**, v. 26, p. 25 – 44, 1984.
- GAUTHIER, P.-A.; CAMIER, C.; LEBEL, F.-A.; PASCO, Y.; BERRY, A.; LANGLOIS, J.; VERRON, C.; GUASTAVINO, C. Experiments of multichannel least-square methods for sound field reproduction inside aircraft mock-up: objective evaluations. **Journal of Sound and Vibration**, v. 376, p. 194 – 216, 2016.
- GENUIT, K. The future of NVH research - a challenge by new powertrains. **SAE Technical Paper**, No. 2010-36-0515, p. 1 – 11, 2010.
-

- GERGES, S. N. Y. Earmuff comfort. **Applied Acoustics**, v. 73, p. 1003 – 1012, 2012.
- GILMORE, H. L. Product conformance cost. **Quality Progress**, v. 7, p. 16 – 19, 1974.
- GONZÁLEZ-PALENCIA, J. C.; FURUBAYASHI, T.; NAKATA, T. Energy use and CO₂ emissions reduction potential in passenger car fleet using zero emission vehicles and lightweight materials. **Energy**, v. 48, p. 548 – 565, 2012.
- GONZÁLEZ, A.; DIEGO, M. de; FERRER, M.; PIÑERO, G. Multichannel active noise equalization of interior noise. **IEEE Transactions on Audio, Speech and Language Processing**, v. 14, n. 1, p. 110 – 122, 2006.
- GONZÁLEZ, A.; FERRER, M.; DIEGO, M. de; PIÑERO, G.; GARCIA-BONITO, J. J. Sound quality of low-frequency and car engine noises after active noise control. **Journal of Sound and Vibration**, v. 265, p. 663 – 679, 2003.
- GOVINDSWAMY, K.; WELLMANN, T.; EISELE, G. Aspects of NVH integration in hybrid vehicles. **SAE International Journal of Passenger Cars – Mechanical Systems**, No. 2009-01-2085, p. 1 – 10, 2009.
- GUIRAO, M.; GARAVILLA, J. M. Perceived roughness of amplitude-modulated tones and noise. **Journal of the Acoustical Society of America**, v. 60, p. 1335 – 1338, 1976.
- GUO, R.; CAO, C.; MI, Y.; HUANG, Y. Experimental investigation of the noise, vibration and harshness performances of a range-extended electric vehicle. **Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering**, doi: 10.1177/0954407015591329, p. 1 – 14, 2015.
- HANSEN, C.; SNYDER, S.; QIU, X.; BROOKS, L.; MOREAU, D. **Active control of noise and vibration**. [S.l.]: CRC Press, 2012. v. 2. 1529 p.
- HASTINGS, A. L. **Sound Quality of Diesel Engines**. Tese (Doutorado) — Purdue University, August 2004.
- HOELDRICH, R.; PFLUEGER, M. A parametrized model of psychoacoustical roughness for objective vehicle noise quality evaluation. **Journal of the Acoustical Society of America**, v. 105, n. 2, p. 1371 – 1379, 1999.
- HU, S. D.; LI, H.; TZOU, H. S. Distributed flexoelectric structural sensing: theory and experiment. **Journal of Sound and Vibration**, v. 348, p. 126 – 136, 2015.
- HUANG, H. B.; LI, R. X.; YANG, M. L.; LIM, T. C.; DING, W. P. Evaluation of vehicle interior sound quality using a continuous restricted Boltzmann machine-based DBN. **Mechanical Systems and Signal Processing**, v. 84, p. 245 – 267, 2017.
- JAMES, B.; HOFFMAN, A.; DONCKER, R. W. de. Reducing noise in an electric vehicle powertrain by means of numerical simulation. In: _____. **Automotive NVH Technology**. [S.l.]: Springer International Publishing, 2016. cap. 3, p. 29 – 46.
- JANSSENS, K.; AHRENS, S.; BERTRAND, A.; LANSLOTS, J.; PONSELEE, P. van de; VECCHIO, A.; AUWERAER, H. van der. An on-line, order-based roughness algorithm. **SAE Technical Paper**, Paper no. 2007-01-2397, n. 07NVC-173, p. 1 – 11, 2007.
-

JAY, G. C. Sound/vibration quality engineering. **Sound and vibration**, v. 41, p. 2 – 9, 2007.

JEON, J. Y.; YOU, J.; CHANG, H. Y. Sound radiation and sound quality characteristics of refrigerator noise in real living environments. **Applied Acoustics**, v. 68, p. 1118 – 1134, 2007.

JEONG, U.-C.; KIM, J.-S.; JEONG, J.-E.; YANG, I.-H.; OH, J.-E. Development of a sound quality index for the wash cycle process of front-loading washing machines considering the impacts of individual noise sources. **Applied Acoustics**, v. 87, p. 183 – 189, 2015.

JOHNSON, S. G.; FRIGO, M. A modified split-radix FFT with fewer arithmetic operations. **IEEE Transactions on Signal Processing**, v. 55, p. 111 – 119, 2007.

KAMALAKANNAN, C.; KAMARAJ, V.; PARAMASIVAM, S.; PARANJOTHI, S. R. Switched reluctance machine in automotive applications - a technology status review. In: **International Conference on Electrical Energy Systems**. [S.l.: s.n.], 2011.

KINNEY, C. E.; CALLAFON, R. A. de; DUNENS, E.; BARGERHUFF, R.; BASH, C. E. Optimal periodic disturbance reduction for active noise cancellation. **Journal of Sound and Vibration**, v. 305, p. 22 – 33, 2007.

KOHLRAUSCH, A.; HERMES, D.; DUISTERS, R. Modeling roughness perception for sounds with ramped and damped temporal envelopes. In: **Forum Acusticum**. [S.l.: s.n.], 2005. p. 1719 – 1724.

KUO, S. M.; GUPTA, A.; MALLU, S. Development of adaptive algorithm for active sound quality control. **Journal of Sound and Vibration**, v. 299, p. 12 – 21, 2007.

KUO, S. M.; MORGAN, D. R. **Active Noise Control Systems: algorithms and DSP implementations**. [S.l.]: Wiley, 1996. 389p p.

KUO, S. M.; TAHERNEZHADI, M.; JI, L. Frequency-domain periodic active noise control and equalization. **IEEE Transactions on Speech and Audio Processing**, v. 5, n. 4, p. 348 – 358, 1997.

KUO, S. M.; YENDURI, R. K.; GUPTA, A. Frequency-domain delayless active sound quality control algorithms. **Journal of Sound and Vibration**, v. 318, p. 715 – 724, 2008.

LA, C.; POGGI, M.; MURPHY, P.; ZITKO, O. NVH considerations for zero emissions vehicle driveline design. **SAE Technical Paper**, Paper no. 2011-01-1545, p. 1 – 9, 2011.

LABEYE, E.; HUGOT, M.; BRUSQUE, C.; REGAN, M. A. The electric vehicle: a new driving experience involving specific skills and rules. **Transportation Research Part F: Traffic Psychology and Behaviour**, v. 37, p. 27 – 40, 2016.

LEBOUCHER, E.; MICHEAU, P.; BERRY, A.; ESPÉRANCE, A. L. L. A stability analysis of a decentralized adaptive feedback active control system of sinusoidal sound in free space. **Journal of the Acoustical Society of America**, v. 111, p. 189 – 199, 2002.

LEE, C. H. T.; LIU, C.; CHAU, K. T. A magnetless axial-flux machine for range-extended electric vehicles. **Energies**, v. 7, p. doi:10.3390/en7031483, 2014.

- LEE, S.-K. Objective evaluation of interior sound quality in passenger cars during acceleration. **Journal of Sound and Vibration**, v. 310, p. 149 – 168, 2008.
- LEE, S.-K.; KIM, H.-W.; NA, E.-W. Improvement of impact noise in a passenger car utilizing sound metric based on wavelet transform. **Journal of Sound and Vibration**, v. 329, p. 3606 – 3619, 2010.
- LEITE, R. P.; PAUL, S.; GERGES, S. N. Y. A sound quality-based investigation of the HVAC system noise of an automobile model. **Applied Acoustics**, v. 70, p. 636 – 645, 2009.
- LIAO, C.; LIN, J. New FIR filter-based adaptive algorithms incorporating with commutation error to improve active noise control performance. **Automatica**, v. 43, p. 325 – 331, 2007.
- LIU, F.; MILLS, J. K.; DONG, M.; GU, L. Active broadband sound quality control algorithm with accurate predefined sound pressure level. **Applied Acoustics**, v. 119, p. 78 – 87, 2017.
- LIU, H.; ZHANG, J.; GUO, P.; BI, F.; YU, H.; NI, G. Sound quality prediction for engine-radiated noise. **Mechanical Systems and Signal Processing**, v. 56 - 57, p. 277 – 287, 2015.
- LIU, Z.; ZHANG, X.; MAO, Y.; ZHU, Y. Y.; YANG, Z.; CHAN, C. T.; SHENG, P. Locally resonant sonic materials. **Science**, v. 289, p. 1734 – 1736, 2000.
- LIU, Z. S.; LEE, H. P.; LU, C. Passive and active interior noise control of box structures using the structural intensity method. **Applied Acoustics**, v. 67, p. 112 – 134, 2006.
- LORENTE, J.; FERRER, M.; DIEGO, M. de; GONZÁLEZ, A. GPU implementation of multichannel adaptive algorithms for local active noise control. **IEEE/ACM Transactions on Audio, Speech, and Language Processing**, v. 22, p. 1624 – 1635, 2014.
- _____. The frequency partitioned block modified filtered-X NLMS with ortogonal correction factors for multichannel active noise control. **Digital Signal Processing**, v. 43, p. 47 – 58, 2015.
- LUEG, P. **Process of silencing sound oscillations**. [S.l.], 1934.
- MANDIC, D. P.; KANNA, S.; CONSTANTINIDES, A. G. On the intrinsic relationship between the least mean square and Kalman filters. **IEEE Signal Processing Magazine**, v. 32, p. 117 – 122, 2015.
- MARLER, R. T.; ARORA, J. S. Survey of multi-objective optimization methods for engineering. **Structural and Multidisciplinary Optimization**, v. 26, p. 369 – 395, 2004.
- MATHWORKS. **Global Optimization Toolbox: User's Guide (R2016a)**. 2016. Website. Disponível em: <<https://www.mathworks.com/help/optim/index.html>>.
- _____. **Simulink: User's Guide (R2016a)**. 2016. Website. Disponível em: <<https://www.mathworks.com/help/optim/index.html>>.
-

MEI, J.; MA, G.; YANG, M.; YANG, Z.; WEN, W.; SHENG, P. Dark acoustic metamaterials as super absorbers for low-frequency sound. **Nature Communications**, v. 3, p. 1 – 7, 2012.

MELLER, M.; NIEDŹWIECKI, M. Multichannel self-optimizing narrowband interference canceller. **Signal Processing**, v. 98, p. 396 – 409, 2014.

MEMOLI, G.; CALEAP, M.; ASAKAWA, M.; SAHOO, D. R.; DRINKWATER, B. W.; SUBRAMANIAN, S. Metamaterial bricks and quantization of meta-surfaces. **Nature Communications**, <http://dx.doi.org/10.1038/ncomms14608>, 2017.

MITCHELL, L. **Toyota service blog: Toyota Prius 2010 Manual**. 2016. Website. Disponível em: <<http://www.toyotaguru.us/prius-2010-manual/hybrid-system-1.html>>. Acesso em: 10 out. 2016.

MOLLET, Y.; SARRAZIN, M.; AUWERAER, H. Van der; GYSELINCK, J. Experimental noise and vibration analysis of switched reluctance machines - comparison of soft and hard chopping in transient conditions. In: **4th International Conference on Renewable Energy Research and Applications**. [S.l.: s.n.], 2015.

_____. Noise and vibrations of switched reluctance machine drives - influence of the current hysteresis control. **Electrotehnica, Electronica, Automatica**, v. 64, p. 33 – 41, 2016.

MOSQUERA-SÁNCHEZ, J. A. **Controle Ativo Acústico Estrutural: Projeto, Simulação e Análise de Qualidade Sonora (in Portuguese)**. Dissertação (Mestrado) — São Carlos School of Engineering - University of São Paulo, 2012.

MOSQUERA-SÁNCHEZ, J. A.; DESMET, W.; JANSSENS, K.; OLIVEIRA, L. P. R. de. Towards sound quality metrics balance on hybrid powertrains. In: **Proceedings of ICEDyn**. [S.l.: s.n.], 2015.

MOSQUERA-SÁNCHEZ, J. A.; DESMET, W.; OLIVEIRA, L. P. R. de. A multichannel amplitude and relative-phase controller for active sound quality control. **Mechanical Systems and Signal Processing**, v. 88, p. 145 – 165, 2017.

_____. Multichannel feedforward control schemes with coupling compensation for active sound profiling. **Journal of Sound and Vibration**, <http://dx.doi.org/10.1016/j.jsv.2017.02.016>, 2017.

MOSQUERA-SÁNCHEZ, J. A.; JANSSENS, K.; DESMET, W.; OLIVEIRA, L. P. R. de. Multichannel active sound quality control for independent-channel sound profiling. In: **Euronoise2015**. [S.l.: s.n.], 2015.

_____. Active noise control in hybrid powertrains guided multi-objective optimization of sound quality metrics. In: KU LEUVEN. **Proceedings of ISMA2016**. [S.l.], 2016.

MOSQUERA-SÁNCHEZ, J. A.; OLIVEIRA, L. P. R. de. Frequency correction algorithm for narrowband active noise control systems. In: ABCM. **Anais do CONEM 2014**. [S.l.], 2014. p. 1 – 10.

_____. A multi-harmonic amplitude and relative-phase controller for active sound quality control. **Mechanical Systems and Signal Processing**, v. 45, n. 2, p. 542 – 562, 2014.

MOSQUERA-SÁNCHEZ, J. A.; VILLALBA, J. D.; JANSSENS, K.; OLIVEIRA, L. P. R. de. A multi-objective sound quality optimization of electric motor noise in hybrid vehicles. In: KU LEUVEN. **Proceedings of ISMA2014**. [S.l.], 2014.

MOSQUERA-SÁNCHEZ, J. A.; VILLALBA, J. D.; OLIVEIRA, L. P. R. de. A multi-objective optimization procedure for guiding the active sound quality control of multi-harmonic disturbances in cavities. In: **Proceedings of Internoise**. [S.l.: s.n.], 2013.

MULLER, J.-M. **Elementary Functions - Algorithms and Implementation**. [S.l.]: Birkhäuser, 2006.

NYKÄNEN, A.; SIRKKA, A. Specification of component sound quality applied to automobile power windows. **Applied Acoustics**, v. 70, p. 813 – 820, 2009.

OLIVEIRA, L. P. R. de; JANSSENS, K.; GAJDATSY, P.; AUWERAER, H. van der; VAROTO, P. S.; SAS, P.; DESMET, W. Active sound quality control of engine induced cavity noise. **Mechanical Systems and Signal Processing**, v. 23, p. 476 – 488, 2009.

OLIVEIRA, L. P. R. de; SILVA, M. M. da; MOSQUERA-SÁNCHEZ, J. A.; GONÇALVES, L. A. M. Loudness scattering due to vibro-acoustic model variability. **Journal of the Brazilian Society of Mechanical Sciences & Engineering**, v. 34, n. spe2, p. 604 – 611, 2012.

OLIVEIRA, L. P. R. de; SILVA, M. M. da; SAS, P.; BRUSSEL, H. van; DESMET, W. Concurrent mechatronic design approach for active control of cavity noise. **Journal of Sound and Vibration**, v. 314, p. 507 – 525, 2008.

OLIVEIRA, L. P. R. de; STALLAERT, B.; JANSSENS, K.; AUWERAER, H. van der; SAS, P.; DESMET, W. NEX-LMS: A novel adaptive control scheme for harmonic sound quality control. **Mechanical Systems and Signal Processing**, v. 24, p. 1727 – 1738, 2010.

OLIVEIRA, L. P. R. de; VAROTO, P. S.; SAS, P.; DESMET, W. A state-space modeling approach for active structural acoustic control. **Shock and Vibration**, v. 16, p. 607 – 621, 2009.

OLSSON, C. Active automotive engine vibration isolation using feedback control. **Journal of Sound and Vibration**, v. 294, p. 162 – 176, 2006.

OPHEM, S. van; BERKHOFF, A. P. Multi-channel Kalman filters for active noise control. **Journal of the Acoustical Society of America**, v. 133, p. 2105 – 2115, 2013.

_____. A numerically stable, finite memory, fast array recursive least squares filter for broadband active noise control. **International Journal of Adaptive Control and Signal Processing**, v. 30, p. 31 – 45, 2015.

PIETILA, G.; LIM, T. C. Intelligent system approaches to product sound quality evaluations - a review. **Applied Acoustics**, v. 73, p. 987 – 1002, 2012.

POLLOCK, C.; WU, C.-Y. Acoustic noise cancellation techniques for switched reluctance drives. **IEEE Transactions on Industry Applications**, v. 33, p. 477 – 484, 1997.

PRESSNITZER, D.; MCADAMS, S. Two phase effects in roughness perception. **Journal of the Acoustical Society of America**, v. 105, p. 2773 – 2782, 1999.

QIU, X.; HANSEN, C. H. A study of time-domain FxLMS algorithms with control output constraints. **Journal of the Acoustical Society of America**, v. 109, p. 2815 – 2823, 2001.

REES, L. E.; ELLIOTT, S. J. Adaptive algorithms for active sound-profiling. **IEEE Transactions on Audio, Speech and Language Processing**, v. 14, n. 2, p. 711 – 719, March 2006.

ROUT, N. K.; DAS, D. P.; PANDA, G. Computationally efficient algorithm for high sampling-frequency operation of active noise control. **Mechanical Systems and Signal Processing**, v. 56 - 57, p. 302 – 319, 2015.

RUIZ, H.; CLAEYS, C. C.; DECKERS, E.; DESMET, W. Numerical and experimental study of the effect of microslits on the normal absorption of structural metamaterials. **Mechanical Systems and Signal Processing**, v. 70 - 71, p. 904 – 918, 2016.

RUST, A.; GRAF, B. J. NVH of electric vehicles with range extender. **SAE International Journal of Passenger Cars – Mechanical Systems**, No. 2010-01-1404, p. 1 – 8, 2010.

SARRAZIN, M.; JANSSENS, K.; AUWERAER, H. van der. Virtual car sound synthesis technique for brand sound design of hybrid and electric vehicles. **SAE Technical Paper**, Paper no. 2012-36-0614, p. 1 – 11, 2012.

SCHNEIDER, D. Plug-ins proliferate. **IEEE Spectrum**, 2012. Disponível em: <<http://spectrum.ieee.org/transportation/advanced-cars/plugin-vehicles-proliferate>>.

SCHROEDER, M. R.; ATAL, B. S.; HALL, J. L. Optimizing digital speech coders by exploiting masking properties of the human ear. **Journal of the Acoustical Society of America**, v. 66, n. 6, p. 1647–1652, 1979.

SEBA, B.; NEDELJKOVIC, N.; PASCHEDAG, J.; LOHMANN, B. H_{∞} feedback control and FxLMS feedforward control for car engine vibration attenuation. **Applied Acoustics**, v. 66, p. 277 – 296, 2005.

SHIN, S.-H.; CHEONG, C. Experimental characterization of instrument panel buzz, squeak, and rattle (bsr) in a vehicle. **Applied Acoustics**, v. 71, p. 1162 – 1168, 2010.

SHIN, S.-H.; IH, J.-G.; HASHIMOTO, T.; HATANO, S. Sound quality evaluation of the booming sensation for passenger cars. **Applied Acoustics**, v. 70, p. 309 – 320, 2009.

SHIN, T.; LEE, Y.-J.; LEE, S.-K. A modified tonality and its application to objective evaluation of laser printers noise. **Applied Acoustics**, v. 79, p. 9 – 15, 2014.

SHOURESHI, R.; KNUREK, T. Automotive applications of a hybrid active noise and vibration control. **IEEE Control Systems**, v. 16, p. 72 – 78, 1996.

SINGH, O. P.; SREENIVASULU, T.; KANNAN, M. The effect of rubber dampers on engine's NVH and thermal performances. **Applied Acoustics**, v. 75, p. 17 – 26, 2014.

SKIPPON, S. M. How consumer drivers construe vehicle performance: implications for electric vehicles. **Transportation Research Part F: Traffic Psychology and Behaviour**, v. 23, p. 15 – 31, 2014.

- SONTACCHI, A.; FRANK, M.; ZOTTER, F.; KRANZLER, C.; BRANDL, S. Sound optimization for downsized engines. In: _____. **Automotive NVH Technology**. [S.l.]: Springer International Publishing, 2016. cap. 2, p. 13 – 27.
- SOVACOOOL, B. K.; HIRSH, R. F. Beyond batteries: an examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. **Energy Policy**, v. 37, p. 1095 – 1103, 2009.
- STALLAERT, B.; PINTE, G.; SAS, P.; DESMET, W.; SWEVERS, J. A novel design strategy for iterative learning and repetitive controllers of systems with a high modal density: Application to active noise control. **Mechanical Systems and Signal Processing**, v. 24, p. 444 – 454, 2010.
- SUN, J.; ZHAN, Q.; WANG, S.; MA, Z. A novel radiating rib structure in switched reluctance motors for low acoustic noise. **IEEE Transactions on Magnetics**, v. 43, p. 3630 – 3637, 2007.
- SWEVERS, J.; LAUWERYS, C.; VANDERSMISSEN, B.; MAES, M.; REYBROUCK, K.; SAS, P. A model-free control structure for the on-line tuning of the semi-active suspension of a passenger car. **Mechanical Systems and Signal Processing**, v. 21, p. 1422 – 1436, 2007.
- TAN, G.; WANG, D.; CHEN, S.; SONG, J. Active noise control method considering auditory characteristics. **SAE Technical Paper**, Paper no. 2012-01-0993, p. 1 – 6, 2012.
- TRINDADE, M. A.; PAGANI, C. C.; OLIVEIRA, L. P. R. de. Semi-modal active vibration control of plates using discrete piezoelectric modal filters. **Journal of Sound and Vibration**, v. 351, p. 17 – 28, 2015.
- VARNHAGEN, S.; SAME, A.; REMILLARD, J.; PARK, J. W. A numerical investigation on the efficiency of range extending systems using advanced vehicle simulator. **Journal of Power Sources**, v. 196, p. 3360 – 3370, 2011.
- VICENTE, L.; MASGRAU, E. Novel FxLMS convergence condition with deterministic reference. **IEEE Transactions on Signal Processing**, v. 54, p. 3768 – 3774, 2006.
- VOLD, H.; MAINS, M.; BLOUGH, J. Theoretical foundations for high performance order tracking with the Vold-Kalman tracking filter. **SAE Technical Paper**, Paper no. 972007, p. 1 – 6, 1997.
- WANG, D.-F.; JIANG, J.-G.; LIU, Z.-W.; CAO, X.-L. Research on ANE algorithm for sound quality control of vehicle interior noise. In: **2010 Third International Conference on Information and Computing**. [S.l.: s.n.], 2010.
- WANG, Y. S.; GUO, H.; FENG, T. P.; JU, J.; WANG, X. L. Acoustic behavior prediction for low-frequency sound quality based on finite element method and artificial neural network. **Applied Acoustics**, v. 122, p. 62 – 71, 2017.
- WANG, Y. S.; LEE, C.-M.; KIM, D.-G.; XU, Y. Sound-quality prediction for nonstationary vehicle interior noise based on wavelet pre-processing neural network model. **Journal of Sound and Vibration**, v. 299, p. 933 – 947, 2007.
-

WANG, Y. S.; SHEN, G. Q.; GUO, H.; TANG, X. L.; HAMADE, T. Roughness modelling based on human auditory perception for sound quality evaluation of vehicle interior noise. **Journal of Sound and Vibration**, v. 332, p. 3893 – 3904, 2013.

WEBDEVSTUDIOS. **Electric and Hybrid Vehicles**. visited in 2016. Website. Disponível em: <<http://quierounphotoblog.tk/hizix/electric-and-hybrid-vehicles-jita.php>>.

WILLS, A. G.; BATES, D.; FLEMING, A. J.; NINNESS, B.; MOHEIMANI, S. O. R. Model predictive control applied to constraint handling in active noise and vibration control. **IEEE Transactions on Control Systems Technology**, v. 16, p. 3 – 12, 2008.

WU, L.; QIU, X.; BURNETT, I. S.; GUO, Y. A recursive least square algorithm for active control of mixed noise. **Journal of Sound and Vibration**, v. 339, p. 1 – 10, 2015.

WU, L.; QIU, X.; GUO, Y. A simplified adaptive feedback active noise control system. **Applied Acoustics**, v. 81, p. 40 – 46, 2014.

XING, Y. F.; WANG, Y. S.; SHI, L.; GUO, H.; CHEN, H. Sound quality recognition using optimal wavelet-packet transform and artificial neural network methods. **Mechanical Systems and Signal Processing**, v. 66 - 67, p. 875 – 892, 2016.

ZHANG, L.; TAO, J.; QIU, X. Performance analysis of decentralized multi-channel feedback systems for active noise control in free space. **Applied Acoustics**, v. 74, p. 181 – 188, 2013.

ZHANG, Z.; SHRESTHA, M. **Sound Quality User-defined Cursor Reading Control - Tonality Metric**. Dissertação (Mestrado) — Technical University of Denmark - Brüel & Kjaer, 2003.

ZITZLER, E.; LAUMANN, M.; THIELE, L. **SPEA2: Improving the strength Pareto evolutionary algorithm**. [S.l.], 2001.

ZITZLER, E.; THIELE, L. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach. **IEEE Transactions on Evolutionary Computation**, v. 3, n. 4, p. 257 – 271, 1999.

Appendices

Appendix A

Time-domain SQ assessment of optimized solutions for disturbance D2

Figure A.1: Comparison between original, optimized and controlled time histories of disturbance D2, when implemented the solution "Minimum 1" (Highest Loudness), from both NSGA-II and SPEA2 solvers.

Figure A.2: Comparison between original, optimized and controlled time histories of disturbance D_2 , when implemented the solution "Minimum 2" (Highest Roughness), from both NSGA-II and SPEA2 solvers.

Figure A.3: Comparison between original, optimized and controlled time histories of disturbance D_2 , when implemented the solution "Minimum 3" (Highest Sharpness), from both NSGA-II and SPEA2 solvers.

Figure A.4: Comparison between original, optimized and controlled time histories of disturbance D2, when implemented the solution "Minimum 4" (Highest Tonality), from both NSGA-II and SPEA2 solvers.

Figure A.5: Comparison between original, optimized and controlled time histories of disturbance D2, when implemented the solution "Maximum 1" (Lowest Loudness), from both NSGA-II and SPEA2 solvers.

Figure A.6: Comparison between original, optimized and controlled time histories of disturbance D_2 , when implemented the solution "Maximum 2" (Lowest Roughness), from both NSGA-II and SPEA2 solvers.

Figure A.7: Comparison between original, optimized and controlled time histories of disturbance D_2 , when implemented the solution "Maximum 3" (Lowest Sharpness), from both NSGA-II and SPEA2 solvers.

Figure A.8: Comparison between original, optimized and controlled time histories of disturbance D2, when implemented the solution "Maximum 4" (Lowest Tonality), from both NSGA-II and SPEA2 solvers.

Appendix B

Frequency response functions of Experiments 1, 2 and 4

As discussed in Chapter 5, the FRFs obtained in the Experiments 1 - 4 turned out to be similar amongst each other, as a result of carrying out the experiments at approximately the same temperature and background noise conditions. The FRFs shown in this Appendix demonstrate that effort was made in carrying out the experiments at the same external conditions, in order to gain repeatability of the procedure and results.

The FRFs are calculated based on the Fourier Transform of the identified FIR filters. The norm-2 condition number is calculated from the matrix $\mathbf{A}(f) = \hat{\mathbf{S}}(f)^H \mathbf{S}(f)$, where $\mathbf{S}(f)$ is the matrix arranged at the frequency f , by putting the direct paths terms of the FRFs onto the main diagonal, and the crossed terms of the FRFs at the corresponding entries in the matrix. More details on how to arrange these matrices can be found in Sections 5.2.1 and 5.2.2.

In Figs. B.1(a), (b) and Fig. B.2(b); as well as in Figs. B.3(a), (b) and Fig. B.4(b), bold continuous lines represent the *direct* secondary paths, i.e. transfer paths between a given loudspeaker and the closest microphone placed within the cavity, while dotted lines represent *crossed* secondary paths, i.e. transfer paths between a given loudspeaker and other than its corresponding microphone. Moreover, in Figs. B.2(a) and B.4(a), bold continuous lines represent the norm-2 condition number of the control matrices as a function of the frequency, while little dark dots highlight control matrices at which the operation of the proposed multichannel arrays has been found to require stabilization.

The visual inspection of the spectral functions plotted in this Appendix reveals that there are small differences that are only evident in the norm-2 condition number function, at very low and high frequency bandwidths. At these bandwidths, uncertainties arise as a result of the poor dynamic behavior of the loudspeakers. Aside from such occurrences, the spectral functions reveal little or even no differences among measurements. It can be then stated that the acoustic plant remained -almost- insensitive to external influences along the whole experimental campaign. Since the sampling rate

of the Experiments 1, 2 and 4 is the same as the one of Experiment 3, cf. Section 5.1.1, these FRFs can be directly compared to each other.

Figure B.1: *Exp. 1 and 2 - Secondary paths: (a) magnitude of the FRFs; (b) phase of the FRFs.*

Figure B.5 illustrates the magnitude and absolute phase functions of the SISO control scheme that is discussed in Section 5.2.6. Similar as in the MIMO experiments, these spectral functions are required for calculating the step sizes of the control schemes.

Figure B.2: *Exp. 1 and 2 - Secondary paths: (a) norm-2 condition number of matrix $A(z)$; (b) phase delay of the FRFs.*

Figure B.3: *Exp. 4 - Secondary paths: (a) magnitude of the FRFs; (b) phase of the FRFs; (c) norm-2 condition number of matrix $A(z)$; (d) phase delay function.*

Figure B.4: *Exp. 4 - Secondary paths: (a) norm-2 condition number of matrix $A(z)$; (b) phase delay function.*

Figure B.5: *Exp. 6 - Secondary paths: (a) magnitude of the FRF; (b) phase of the FRF.*

Biography

JAIME ALBERTO MOSQUERA-SÁNCHEZ was born in Popayán, Colombia, on June 30, 1984. Son of Jaime Hernán Mosquera Sandoval, lawyer, and Guimar Sánchez Gómez[†], clerk, ended the high-school in 2001. After being enrolled into the undergraduate program in physics engineering at the University of Cauca during one and a half years, he decided to move to Bogotá, Colombia, to pursue a BSc degree in sound engineering, at the University of San Buenaventura. In 2006, he took part in the electronics program at the same university, to pursue a secondary degree as a technologist. Later in 2009, he spent a semester conducting research on ultrasonic instrumentation at the Department of Electrical Engineering of the São Carlos School of University of the University of São Paulo (USP), Brazil, in order to complete his final undergraduate report on ultrasound, instrumentation and signal processing. In the same year, he met Prof. Dr. Leopoldo de Oliveira. Motivated by his research topics, he decided to start the master studies at the Department of Mechanical Engineering of the São Carlos School of University of the University of São Paulo. In 2012, he defended a dissertation on active sound quality control, thus accomplishing the MSc. degree in mechanical engineering. His doctoral studies started the same year. After the birth of his first daughter, Valéria, in 2014, he started studies at the Department of Mechanical Engineering of the Catholic University of Leuven, KU Leuven, as part of an academic agreement aiming at a double-degree PhD programme. He conducted research during one year, under the supervision of Prof. dr. ir. Wim Desmet. This PhD manuscript is finally defended on April 5th, 2017, date at which is handed to the Department of Mechanical Engineering of USP, Brazil, and to the Arenberg Doctoral School of the Faculty of Engineering Science of the KU Leuven, Belgium.

The research of Mr. Mosquera-Sánchez has mainly been concerned with active sound quality control. His research interests also include acoustics, vibro-acoustics, numerical/hybrid simulations, signal processing, optimization theory and algorithms, instrumentation and ultrasonics.

Education

- **2012 - 2017:** enrolled in an academic agreement for a double-degree PhD diploma between the University of São Paulo, Brazil and the KU Leuven, Belgium.
- **2010 - 2012:** master degree in Mechanical Engineering from University of São Paulo, São Carlos, Brazil. Dissertation: *Active structural acoustic control: design, simulation and sound quality analysis* (available in Portuguese).
- **2006 - 2009:** minor degree (technologist) in Electronics from University of San Buenaventura, Bogotá, Colombia.
- **2003 - 2009:** bachelor degree in Sound Engineering from University of San Buenaventura, Bogotá, Colombia. Final report: *Ultrasound device for liquid-media identification* (available in Spanish).
- **1990 - 2001:** elementary/high school from Seminario Menor Arquidiocesano, Popayán, Colombia.

Publications

Journal articles

- [1] Mosquera-Sánchez, J. A., Sarrazin, M., Janssens, K., de Oliveira, L. P. R., Desmet, W. "Multiple target sound quality balance for hybrid electric powertrain noise". Manuscript submitted to *Mechanical Systems and Signal Processing* on April 19th, 2017.
- [2] Mosquera-Sánchez, J. A., Desmet, W., de Oliveira, L. P. R. "A multichannel amplitude and relative-phase controller for active sound quality control". *Mechanical Systems and Signal Processing*, v. 88, p. 145 - 165, 2017.
- [3] Mosquera-Sánchez, J. A., Desmet, W., de Oliveira, L. P. R. "Multichannel feedforward control schemes with coupling compensation for active sound profiling". *Journal of Sound and Vibration*, 2017. Accepted for Publication.
- [4] Mosquera-Sánchez, J. A., de Oliveira, L. P. R. "A multi-harmonic amplitude and relative-phase controller for active sound quality control". *Mechanical Systems and Signal Processing*, v. 45, n. 2, p. 542 - 562, 2014.
- [5] de Oliveira, L. P. R., da Silva, M. M., Mosquera-Sánchez, J. A., Gonçalves, L. A. M. "Loudness scattering due to vibro-acoustic model variability". *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, v. 34, n. 2, p. 604 - 611, 2012.

Full papers in congress/symposia proceedings

- [1] Mosquera-Sánchez, J. A., Janssens, K., Desmet, W., de Oliveira, L. P. R. "Active noise control in hybrid powertrains guided multi-objective optimization of sound quality metrics". In: International Conference on Noise and Vibration Engineering - ISMA 2016, 2016, Leuven. Proceedings of ISMA 2016. Leuven: KU Leuven, 2016. p. 1 - 15.
- [2] Mosquera-Sánchez, J. A., Desmet, W., Janssens, K., de Oliveira, L. P. R. "Multichannel Active Sound Quality Control for Independent-Channel Sound Profiling". In: Euronoise 2015, 2015, Maastricht. Proceedings of Euronoise, 2015. p. 2177 - 2182.
- [3] Mosquera-Sánchez, J. A., Desmet, W., Janssens, K., de Oliveira, L. P. R. "Towards SQ Metrics Balance on Hybrid Powertrains". In: ICEDyn 2015, 2015, Lagos. Proceedings of ICEDyn 2015, 2015. p. 1-10.
- [4] Mosquera-Sánchez, J. A., de Oliveira, L. P. R. "Frequency Correction Algorithm for Narrowband Active Noise Control Systems". In: Congresso Nacional de Engenharia Mecânica - CONEM2104, 2014, Uberlândia. Anais do CONEM2014. Rio de Janeiro: ABCM, 2014. p. 1-10.
- [5] Mosquera-Sánchez, J. A., Villalba, J. D., Janssens, K., de Oliveira, L. P. R. "A Multi-Objective Sound Quality Optimization of Electric Motor Noise in Hybrid Vehicles". In: International Conference on Noise and Vibration Engineering - ISMA2014, 2014, Leuven. Proceedings of ISMA2014. Leuven: KU Leuven, 2014. p. 1379-1394.
- [6] Melo, F. X., Mosquera-Sánchez, J. A., de Oliveira, L. P. R. "A Hybrid Simulation Technique for the Active Control of Engine Noise". In: International Conference on Structural Engineering Dynamics - ICEDyn 2013, 2013, Sesimbra. Proceedings of ICEDyn 2013. Lisbon: Technical University of Lisbon, 2013. p. 1-10.
- [7] Mosquera-Sánchez, J. A., Villalba, J. D., de Oliveira, L. P. R. "A Multi-Objective Optimization Procedure for Guiding the Active Sound Quality Control of Multi-Harmonic Disturbances in Cavities". In: 42nd International Congress and Exposition on Noise Control Engineering, 2013, Innsbruck. Proceedings of Internoise 2013, 2013. p. 1-10.
- [8] Mosquera-Sánchez, J. A., de Oliveira, L. P. R. "A MIMO Control Strategy for the Sound Quality of Multi-harmonic Disturbances Transmitted into Cavities". In: 22nd International Congress of Mechanical Engineering, 2013, Ribeirão Preto. Proceedings of COBEM2013. Rio de Janeiro: Associação Brasileira de Engenharia e Ciências Mecânicas, 2013. p. 9027-9038.

- [9] de Oliveira, L. P. R., da Silva, M. M., Mosquera-Sánchez, J. A., Gonçalves, L. A. M. "Sound Quality Scattering due to Vibro-acoustic Model Variability". In: *Uncertainties2012*, 2012, Maresias. Proceedings of the 1st International Symposium on Uncertainty Quantification and Stochastic Modeling. Rio de Janeiro: Associação Brasileira de Engenharia e Ciências Mecânicas, ABCM, 2012. p. 628-636.
- [10] Mosquera-Sánchez, J. A., de Oliveira, L. P. R. "An Adaptive Controller for Amplitude and Relative Phase Control of Periodic Disturbance". In: *International Conference on Noise and Vibration Engineering*, 2012, Leuven. Proceedings of International Conference on Noise and Vibration Engineering (ISMA2012). Leuven: Katholieke Universiteit Leuven, 2012. p. 357-368.
- [11] de Oliveira, L. P. R., Mosquera-Sánchez, J. A. "An Adaptive Control for Engine Loudness and Roughness". In: *International Congress and Exposition on Noise Control Engineering*, 2012, Nova Iorque. Proceedings of INTERNOISE2012. Indianapolis: Institute of Noise Control Engineering of the USA, 2012. v. 12. p. 9181-9192.
- [12] Mosquera-Sánchez, J. A., Janssens, K., Van der Auweraer, H., de Oliveira, L. P. R. "Multi-Harmonic Adaptive Control for Roughness". In: *14th International Symposium on Dynamic Problems of Mechanics (DINAME 2011)*, 2011, São Sebastião, SP. Proceedings of the 14th International Symposium on Dynamic Problems of Mechanics. Rio de Janeiro, RJ: Associação Brasileira de Engenharia e Ciências Mecânicas, ABCM, 2011. p. 204-214.
- [13] Mosquera-Sánchez, J. A., de Oliveira, L. P. R. "Frequency-Domain Delayless Adaptive Control for Roughness". In: *18th International Congress on Sound & Vibration, ICSV18*, 2011, Rio de Janeiro. Proceedings of the ICSV'18, 2011. p. 1-8.
- [14] Muñoz, J. A. V., Mosquera-Sánchez, J. A. "Characterization of a Time-Varying Medium by Ultrasonic Parameter Variations". In: *IWSSIP 2010: 17th International Conference on Systems, Signals and Image Processing*, 2010, Rio de Janeiro. Proceedings of the IWSSIP 2010. Rio de Janeiro: EdUFF Editora da Universidade Federal Fluminense, 2010. p. 207-210.
- [15] Muñoz, J. A. V., Mosquera-Sánchez, J. A. "Estimativa da Atenuação Ultrassônica em Estruturas Biológicas Mediante a Aplicação do Filtro de Wiener". In: *9th Brazilian Conference on Dynamics, Control and Their Applications (DINCON'2010)*, 2010, Serra Negra. Proceedings of the 9th Brazilian Conference on Dynamics, Control and Their Applications. São Carlos: Sociedade Brasileira de Matemática Aplicada e Computacional, 2010. p. 232-237.

- [16] Mosquera-Sánchez, J. A., Muñoz, J. A. V. "El Intercambio Estudiantil como Herramienta de Aprendizaje Cultural, Académico y Tecnológico en el Desarrollo de un Sistema de Ultrasonido como Trabajo de Grado en Ingeniería". In: INTERTECH'2010, 2010, Ilhéus, Brasil. XI International Conference on Engineering and Technology Education. Ilhéus: Council of Researches in Education and Sciences, 2010. v. 1. p. 1039-1043.