MIGUEL ANGELO DE CARVALHO MICHALSKI

**ROTATING MACHINERY FAULT IDENTIFICATION USING MODEL-BASED AND
DATA-BASED TECHNIQUES INTEGRATION**

São Paulo
2021

MIGUEL ANGELO DE CARVALHO MICHALSKI

**ROTATING MACHINERY FAULT IDENTIFICATION USING MODEL-BASED AND
DATA-BASED TECHNIQUES INTEGRATION**

Revised Version

Thesis presented to the Escola Politécnica of the University of
São Paulo to obtain the title of Doctor of Sciences

Concentration area: Mechanical Engineering of Design and
Manufacturing

Advisor: Prof. Dr. Gilberto Francisco Martha de Souza

São Paulo
2021

Autorizo a reprodução e divulgação total ou parcial deste trabalho, por qualquer meio convencional ou eletrônico, para fins de estudo e pesquisa, desde que citada a fonte.

Este exemplar foi revisado e corrigido em relação à versão original, sob responsabilidade única do autor e com a anuência de seu orientador.

São Paulo, 1 de abril de 2021

Assinatura do autor:

Assinatura do orientador:

Catálogo-na-publicação

Michalski, Miguel Angelo de Carvalho

Rotating machinery fault identification using model-based and data based techniques integration / M. A. C. Michalski -- versão corr. -- São Paulo, 2021. 256 p.

Tese (Doutorado) - Escola Politécnica da Universidade de São Paulo. Departamento de Engenharia Mecânica.

1.Engenharia (sistemas; diagnóstico) 2.Inteligência artificial 3.Manutenção 4.Método dos elementos finitos 5.Modelagem dinâmica I.Universidade de São Paulo. Escola Politécnica. Departamento de Engenharia Mecânica II.t.

Name: Michalski, Miguel Angelo de Carvalho

Title: Rotating Machinery Fault Identification Using Model-Based and Data-Based Techniques Integration

Thesis presented to the Escola Politécnica of the University of São Paulo to obtain the title of Doctor of Sciences.

Approved in:

Examination Board

Prof. Dr. _____

Institution: _____

Judgment: _____

Prof. Dr. _____

Institution: _____

Judgment: _____

Prof. Dra. _____

Institution: _____

Judgment: _____

Prof. Dr. _____

Institution: _____

Judgment: _____

Prof. Dr. _____

Institution: _____

Judgment: _____

To my sons, Natan and Otto, my
wife, Ranny, and my father in
law, Renato (*in memoriam*)

ACKNOWLEDGMENTS

I would like to thank my wife, Ranny, for all the motivation and support and to my sons, Natan and Otto, for being such special and wonderful boys. They remind me, every single day, about the priorities of my life.

I also thank my advisor, Prof. Dr. Gilberto Francisco Martha de Souza, for all his dedication, confidence, help, support, and guidance in this journey.

Thanks to the professors of Poli-USP and Poli-UFRJ (where this journey actually started) for all their shared knowledge. Without exception, they were all important to me and my work.

I appreciate and thank the friendship of all my colleagues at the Poli-USP Reliability Laboratory, without exception. Special thanks to Arthur Melani, Renan Favarão, and Italo de Melo, with whom I shared great experiences. Their collaborations were extremely important in the elaboration of this work.

Special thanks to Mrs. Lucia, for all the help she gave whenever needed.

I finally thank CNPq and FDTE for the financial support granted during this work.

*Tu ne quaesieris, scire nefas, quem mihi, quem tibi
finem di dederint, Leuconoe, nec Babylonios
temptaris numeros. ut melius, quidquid erit, pati.
seu pluris hiemes seu tribuit Iuppiter ultimam,
quae nunc oppositis debilitat pumicibus mare
Tyrrhenum: sapias, vina liques et spatio brevi
spem longam reseces. dum loquimur, fugerit invida
aetas: carpe diem quam minimum credula postero.*

Odes (I, 11.8)

Horácio

ABSTRACT

The use of modern maintenance techniques in rotating machinery has changed the scenario in energy companies, both concerning generation, such as in hydroelectric, thermoelectric, and wind power plants, and the exploitation of resources such as oil and natural gas. The quest for excellence makes new sophisticated and refined tools more necessary and, in this way, academic research is increasingly approaching industrial reality. Wishing to contribute to the answer to such demand, so that in the future new integration and asset management tools can be developed for industrial applications, this work proposes a hybrid methodology in which already recognized techniques are applied and integrated to highlight their qualities and overcome their weaknesses. Applying model-based techniques, inverse methods, Bayesian inference, and data-driven statistical methods, the proposed methodology enables machines and faults modeling and simulation, providing information that would allow the identification, detection, and diagnosis of malfunctions in real machines. To illustrate the methodology, three examples were developed, in which different machines with mechanical unbalance were considered.

Key-words: Fault Detection and Diagnosis. Data-based Techniques. Model-based Techniques. Rotating Machinery. Unbalance.

RESUMO

O uso de técnicas modernas de manutenção em máquinas rotativas mudou o cenário nas empresas de energia, tanto em relação à geração, como em usinas hidrelétricas, termoelétricas e eólicas, quanto na exploração de recursos como petróleo e gás natural. A busca pela excelência faz com que novas ferramentas, mais sofisticadas e refinadas sejam necessárias e, com isso, a pesquisa acadêmica está cada vez mais próxima da realidade industrial. Desejando contribuir com a resposta a tal demanda e vislumbrando que em um futuro próximo novas ferramentas de integração e gestão de ativos possam ser desenvolvidas e aplicadas em ambientes industriais, este trabalho apresenta a proposta de uma metodologia híbrida na qual são utilizadas técnicas já reconhecidas, integrando-as de tal forma que suas qualidades possam ser destacadas e suas fraquezas superadas. Aplicando técnicas baseadas em modelos, métodos inversos, inferência Bayesiana e métodos estatísticos para análise de dados, a metodologia proposta possibilita a modelagem e simulação de máquinas e falhas, fornecendo informações que permitiriam identificar, detectar e diagnosticar defeitos em máquinas reais. Para ilustrar a metodologia, três exemplos foram desenvolvidos, nos quais diferentes máquinas com desbalanceamento mecânico foram consideradas.

Palavras-chave: Detecção e Diagnóstico de Falhas. Técnicas baseadas em Dados. Técnicas baseadas em Modelos. Máquinas Rotativas. Desbalanceamento.

LIST OF FIGURES

Figure 1 – Finite Element Models for Several Rotating Machinery	13
Figure 2 – System performance over time	18
Figure 3 – Failure mode stages	18
Figure 4 – FDD process	20
Figure 5 – Vibration modes influence on system observability	23
Figure 6 – Influence of the number of sensors on system observability	23
Figure 7 – Comparison of shaft bend and unbalance response	37
Figure 8 – Oil whirl and oil whip vibration response	41
Figure 9 – Fault Detection and Diagnose Methods	48
Figure 10 – Generic forward model	58
Figure 11 – Deterministic inverse modeling	58
Figure 12 – Least-squares solution to inverse modeling	59
Figure 13 – SA and MCM framework	69
Figure 14 – SA and MCM interface	69
Figure 15 – SA and MCM interface	70
Figure 16 – The Kalman Filter family tree	72
Figure 17 – Forward model structure assumed by discrete Kalman filter	73
Figure 18 – First Variable (V_1) Sample Values	88
Figure 19 – Second Variable (V_2) Sample Values	88
Figure 20 – Third Variable (V_3) Sample Values	88
Figure 21 – Concatenated Variables	97
Figure 22 – Fixed-length window sliding process	98
Figure 23 – PCw results without the reference data sample	100
Figure 24 – PCw results with the reference data sample	100
Figure 25 – Comparison between PCw results with and without reference data sample	101
Figure 26 – RMPCA implementation process framework	102
Figure 27 – Simplified Framework	104
Figure 28 – Proposed framework	106
Figure 29 – Jeffcott model	109
Figure 30 – Test rig	110

Figure 31 – Jeffcott rotor system equivalence	112
Figure 32 – Exact model simulation FRF	114
Figure 33 – System FRF variation due to the bearings damping.....	117
Figure 34 – System equivalent stiffness and bearings' stiffness correlation.....	119
Figure 35 – FRF simulations with the rejection criteria	120
Figure 36 – Maximum amplitude distribution	121
Figure 37 – Critical speed distribution	121
Figure 38 – Bearings' stiffness distribution	122
Figure 39 – Damping proportionality coefficient distribution	122
Figure 40 – Unbalance distribution.....	123
Figure 41 – MCM frequency response	124
Figure 42 – Comparison between the exact solution and the MCM solution FRF ...	125
Figure 43 – Amplitude convergence in mean	126
Figure 44 – Critical speed convergence in mean	126
Figure 45 – Bearings' stiffness convergence in mean	127
Figure 46 – Damping proportionality coefficient convergence in mean	127
Figure 47 – Unbalance convergence in mean.....	128
Figure 48 – Amplitude and critical speed vs. bearings' stiffness	129
Figure 49 – Amplitude and critical speed vs. damping proportionality coefficient....	130
Figure 50 – Amplitude and critical speed vs. unbalance	130
Figure 51 – Simulated Annealing temperature variation.....	132
Figure 52 – Comparison between the FRF exact solution and the SA solution.....	133
Figure 53 – Jeffcott rotor FRF for several unbalance conditions	136
Figure 54 – Jeffcott rotor steady-state analysis reference – example A	137
Figure 55 – Jeffcott rotor steady-state continuous signal – example A	138
Figure 56 – Jeffcott rotor RMPCA results – example A	139
Figure 57 – Jeffcott rotor RMPCA results with normalized weights – example A	139
Figure 58 – Jeffcott rotor unbalance mapping – example A	141
Figure 59 – Jeffcott rotor steady-state analysis reference – example B1	144
Figure 60 – Jeffcott rotor RMPCA results with normalized weights – example B1 ..	144
Figure 61 – Jeffcott rotor unbalance mapping – example B1	145
Figure 62 – Jeffcott rotor steady-state analysis reference – example B2	147
Figure 63 – Jeffcott rotor RMPCA results with normalized weights – example B2 ..	147
Figure 64 – Jeffcott rotor unbalance mapping – example B2	148

Figure 65 – Unbalance mapping comparison – Reference data influence	150
Figure 66 – Jeffcott rotor steady-state analysis reference – example C1	151
Figure 67 – Jeffcott rotor steady-state continuous signal – example C1	152
Figure 68 – Jeffcott rotor RMPCA results – example C1	152
Figure 69 – Jeffcott rotor RMPCA results with normalized weights – example C1 ..	153
Figure 70 – Jeffcott rotor unbalance mapping – example C1	154
Figure 71 – Jeffcott rotor unbalance mapping – example C2	156
Source: Author Figure 72 – Jeffcott rotor unbalance mapping – example C3	157
Figure 73 – Unbalance mapping comparison – Noise level data influence	159
Figure 74 – Jeffcott rotor steady-state analysis reference – example D1	160
Figure 75 – Jeffcott rotor RMPCA results for– example D1	161
Figure 76 – Jeffcott rotor RMPCA results with normalized weights – example D1 ..	161
Figure 77 – Jeffcott rotor unbalance mapping – example D1	162
Figure 78 – Jeffcott rotor steady-state analysis reference – example D2	163
Figure 79 – Jeffcott rotor RMPCA results for– example D2	164
Figure 80 – Jeffcott rotor RMPCA results with normalized weights – example D2 ..	164
Figure 81 – Jeffcott rotor unbalance mapping – example D2	165
Figure 82 – Unbalance mapping comparison – Analysis window influence	167
Figure 83 – Test rig finite element model	171
Figure 84 – Test rig experimental data	172
Figure 85 – Test rig merged experimental data	173
Figure 86 – Test rig displacement estimation	174
Figure 87 – Test rig unbalance estimation	175
Figure 88 – Test rig displacement estimation error	175
Figure 89 – Test rig unbalance estimation with unbalance initial value variation	177
Figure 90 – Test rig rotor FRF for several unbalance conditions	178
Figure 91 – Test rig trend line experimental data	179
Figure 92 – Test rig noise data	179
Figure 93 – Noise level histogram	180
Figure 94 – Noise level probability density function	180
Figure 95 – Test rig rotor steady-state analysis reference	182
Figure 96 – Test rig rotor steady-state continuous signal	182
Figure 97 – Test rig rotor RMPCA results	183
Figure 98 – Test rig rotor RMPCA results with normalized weights	183

Figure 99 – Test rig rotor unbalance mapping	184
Figure 100 – Centrifugal compressor finite element model	187
Figure 101 – Drive end (left) and non-drive end (right) radial vibration probes	188
Figure 102 – FPSO compressor experimental data	189
Figure 103 – Centrifugal compressor merged experimental data	190
Figure 104 – Centrifugal compressor displacement estimation	191
Figure 105 – Centrifugal compressor unbalance estimation	191
Figure 106 – Centrifugal compressor displacement estimation error	192
Figure 107 – Centrifugal compressor FRF for several unbalance conditions – DE	194
Figure 108 – Centrifugal compressor FRF for several unbalance conditions – NDE	195
Figure 109 – Centrifugal compressor trend line experimental data	196
Figure 110 – Centrifugal compressor noise data	196
Figure 111 – Noise level histogram – DE	197
Figure 112 – Noise level histogram – NDE	197
Figure 113 – Noise level probability density function – DE	198
Figure 114 – Noise level probability density function – NDE	198
Figure 115 – Centrifugal compressor steady-state analysis reference	200
Figure 116 – Centrifugal compressor steady-state continuous signal	200
Figure 117 – Centrifugal compressor RMPCA results	201
Figure 118 – Centrifugal compressor RMPCA results with normalized weights	201
Figure 119 – Centrifugal compressor unbalance mapping	202
Figure 120 – Steady-state experimental data samples	204
Figure 121 – Steady-state simulated data samples	205
Figure 122 – Steady-state experimental reference data	206
Figure 123 – Steady-state simulated reference data	206
Figure 124 – RPCA results – Simulated analyzed data and simulated reference ...	207
Figure 125 – RPCA results – Experimental analyzed data and simulated reference	207
Figure 126 – RPCA results comparison with simulated reference data	208
Figure 127 – RPCA results – Simulated analyzed data and experimental reference	209
Figure 128 – RPCA results – Experimental analyzed data and experimental reference	210

Figure 129 – RPCA results comparison with experimental reference data	211
Figure 130 – RPCA results comparison with both reference data	213

LIST OF TABLES

Table 1 – Maintenance evolution.....	3
Table 2 – Characteristics that distinguish unbalance and misalignment	33
Table 3 – Input Data Sets.....	87
Table 4 – Basic Statistics	87
Table 5 – Correlation coefficients between Input Data Sets 1, 2, and 3 and the Reference Data	89
Table 6 – Standard PCA Recentered Data Sets	89
Table 7 – Standard PCA Covariance Matrices	90
Table 8 – Standard PCA Eigenvalues	90
Table 9 – Standard Normalized PCA PCw	90
Table 10 – Euclidean distance between the Reference Data and each Input Data Set	90
Table 11 – RPCA Input and Recentered Data Sets	92
Table 12 – RPCA Covariance Matrices.....	93
Table 13 – RPCA Eigenvalues and PCw	94
Table 14 – Euclidean distance between the Reference Data and each Input Data Set considering the RPCA algorithm	94
Table 14 – Concatenated Data.....	96
Table 15 – PCw Results for RMPCA.....	99
Table 17 – Exact model parameters.....	114
Table 18 – Exact model results for maximum amplitude and critical speed	115
Table 19 – Parameter a priori limit values with literature information	118
Table 20 – Parameter's limit values considered in Monte Carlo simulations	119
Table 21 – Rejection criteria values	120
Table 22 – Mathematical expectation and Error for the MMC results.....	123
Table 23 – A priori correlation	128
Table 24 – Posteriori correlation.....	129
Table 25 – Posteriori correlation of the system parameters and responses.....	129
Table 26 – Mathematical expectation and Error for SA results.....	132
Table 27 – Mathematical expectation and Error for MCM and SA results	134
Table 28 – Unbalance conditions time windows and number of samples	137

Table 29 – PC weights’ means and standard deviations (sd) vs. unbalance level – example A	142
Table 30 – Jeffcott simulated system test examples	143
Table 31 – PC weights’ means and standard deviations (sd) vs. unbalance level – example B1	146
Table 32 – PC weights’ means and standard deviations (sd) vs. unbalance level – example B2	149
Table 33 – PC weights’ means and standard deviations (sd) vs. unbalance level – example C1	155
Table 34 – PC weights’ means and standard deviations (sd) vs. unbalance level – example C2	158
Table 35 – PC weights’ means and standard deviations (sd) vs. unbalance level – example C3	158
Table 36 – PC weights’ means and standard deviations (sd) vs. unbalance level – example D1	163
Table 37 – PC weights’ means and standard deviations (sd) vs. unbalance level – example D2	166
Table 38 – Unbalance conditions time windows and number of samples	181
Table 39 – PC weights’ means and standard deviations (sd) vs. unbalance level – Test rig example	185
Table 40 – Unbalance conditions time windows and number of samples	199
Table 41 – PC weights’ means and standard deviations (sd) vs. unbalance level – Test rig example	203
Table 42 – RPCA results comparison with simulated reference data	209
Table 43 – RPCA results comparison with experimental reference data	212
Table 44 – Case studies summary	215

SUMMARY

ACKNOWLEDGMENTS	5
ABSTRACT.....	1
RESUMO.....	2
LIST OF FIGURES.....	3
LIST OF TABLES	8
SUMMARY.....	10
1 INTRODUCTION	1
1.1. Context, Relevance, and Justification	1
1.2. Objective	9
1.3. Outline of the Thesis	10
2 FUNDAMENTAL CONCEPTS	12
2.1. Rotordynamic Modeling and Analysis	12
2.2. The Process of Fault Detection and Diagnosis	16
2.3. Data Acquisition, Excitability, and Observability	20
2.4. Mechanical Faults in Rotating Machinery	26
2.4.1. Unbalance	27
2.4.2. Misalignment and Rotor bow	31
2.4.3. Other Mechanical Faults in Rotating Machines	37
3 FAULTS DETECTION AND DIAGNOSIS METHODS	47
4 PARAMETER ESTIMATION AND INVERSE PROBLEMS	57
4.1. Simulated Annealing combined with Monte Carlo Method	65
4.2. Kalman Filter	70
5 PRINCIPAL COMPONENT ANALYSIS	78
5.1. Principal Component Analysis Fundamentals	80
5.2. A Novel FDD Strategy Based on PCA.....	83

5.2.1.	RPCA application – static example	87
5.2.2.	RMPCA application – dynamic example	95
5.2.3.	RMPCA implementation	101
6	PROPOSED FRAMEWORK	103
7	APPLICATIONS AND RESULTS.....	108
7.1.	Theoretical Jeffcott Rotor	108
7.1.1.	Rotor modeling	109
7.1.2.	The model transient exact solution	113
7.1.3.	Parameter’s estimation	115
7.1.4.	Steady-state simulation and PCA analysis	134
7.1.5.	Method’s sensitivity regarding the analyzed data parameters	142
7.2.	Jeffcott Rotor Test Rig.....	168
7.2.1.	Rotor modeling	169
7.2.2.	Test rig measurements experimental data.....	172
7.2.3.	Unbalance estimation.....	173
7.2.4.	Steady-state simulation and PCA analysis	177
7.3.	FPSO Centrifugal Compressor	185
7.3.1.	Rotor modeling	186
7.3.2.	Compressor measurements and experimental data	187
7.3.3.	Unbalance estimation.....	189
7.3.4.	Steady-state simulation and PCA analysis	193
7.4.	Validating the Method with Real Data.....	203
7.5.	Results Discussion	214
8	CONCLUSIONS AND PROPOSAL OF FUTURE STUDIES.....	217
9	BIBLIOGRAPHIC REFERENCES.....	224

1 INTRODUCTION

1.1. Context, Relevance, and Justification

Rotating machinery is a type of equipment found in virtually every industrial segment. These pieces of equipment include, but are not limited to, engines, compressors, turbines, pumps, generators, blowers, and gearboxes. In fact, from very small dental drills to large hydro generators, the importance of rotating machines is unquestionable today.

According to Rao (2011), it can be said that the history of rotating machines dates to the Mesolithic period when man began to use tree trunk sections as a means of moving large loads because of their ability to roll. It was probably Archimedes, in ancient Greece, who created a special screw used to move water, named in his honor. To Hero, from the Alexandria School of Engineers, is attributed the creation of the *aeolipile*, the first known reaction turbine.

All these creations are examples of such an ancient type of machine and many studies have been carried out on virtually every aspect of its operation, modeling, applications, and maintenance. Even so, research on rotating machines will not seem to be over anytime soon.

Having a key role in strategic sectors, such as power generation and petrochemical industries, rotating machinery is a topic of great academic and industrial interest. This interest becomes even more evident considering the changes these industries currently undergo, with the introduction of alternative power sources, the increasing electrification, the reducing use of fossil fuels, and the social, economic, political, and environmental issues that increasingly restrict and regulate the expansion of these segments.

Considering the power generation sector as an example, it is evident how in several emerging industrialized countries, including Brazil, the opening of the electricity generation markets and environmental issues brought profound changes in many aspects, as presented by Lizarraga and Sinha (2016), Queiroz et al. (2016), Falcetta

(2015), Andrușcă et al. (2012), Araújo, Cullen, and Tsamenyi (2011), Neves (2009), Sioshansi and Pfaffenberger (2006), and Farias (2006).

Due to all these changes, the availability, reliability, and maintainability of rotating machinery have become increasingly significant in power generation and petrochemical industries. To meet these needs, as an important part of asset management, maintenance planning becomes a key point.

Anyone who has ever worked or had some experience in these sectors in the last decade realizes that maintenance is no longer considered as a secondary activity, necessary just to keep an equipment or component integrity. This change is lined up with the principles of Reliability Centered Maintenance (RCM), which points to maintenance focused on the system functions, and not on the system hardware (RAUSAND, 1998).

From this new perspective, maintenance can be actually understood as the process used to determine what must be done to ensure that any physical component continues to do whatever it was designed to do under the existing circumstances and operational conditions (DEEPAK PRABHAKAR; JAGATHY RAJ, 2014), maximizing their availability and minimizing production losses.

Driven by several factors, maintenance planning has been in constant evolution since the 1940s. According to Moubray (1997), before World War II, the need for production lines allowed significant machinery downtimes, without major consequences. The low mechanization and simplicity of the equipment made maintenance a secondary activity and the strategies adopted until then were completely corrective. Table 1 presents the maintenance generations over the years and their major aspects, according to Kardec and Nassif (2012).

Table 1 – Maintenance evolution

Maintenance Evolution					
Generation Years	First Generation 1940 - 1950	Second Generation 1960 - 1970	Third Generation 1980 - 1990	Fourth Generation 2000 - 2005	Fifth Generation 2010 - ...
Raising expectations about maintenance	1. Repair after failure	1. Increasing availability 2. Longer equipment life cycle	1. Greater reliability and availability; 2. Best value for money; 3. Environment preservation	1. Greater reliability and availability 2. Environment preservation 3. Safety 4. Asset manager 5. Influencing business results	1. Asset management 2. Optimization of asset life cycles 3. Influencing business results
Asset Failure View	1. All equipment wears out with age and therefore fails	1. All equipment behaves according to the classical bathtub curve	1. Six failure patterns (bathtub failure pattern, wear-out failure pattern, fatigue failure pattern, initial break-in period pattern, random failure pattern, and infant mortality failure pattern)	1. Dramatically reduce premature failures of the bathtub and infant mortality failure patterns	1. Life cycle planning from the project phase to reduce failures
Change in maintenance techniques	1. Repair-oriented skills	1. Manual maintenance planning 2. Large and slow computers 3. Preventive maintenance (by time)	1. Condition monitoring 2. Predictive maintenance 3. Risk analysis 4. Fast and small computers 5. Powerful software 6. Disciplinary workgroups 7. Reliability-oriented design	1. Increased predictive maintenance and condition monitoring 2. Reduction in preventive and unplanned corrective maintenance 3. Failure analysis 4. Reliability techniques 5. Maintainability 6. Projects focused on reliability, maintainability, and availability 7. Hiring by results	1. Increased predictive maintenance and condition monitoring applications 2. Effective participation in the design, acquisition, installation, commissioning, operation, and maintenance of assets 3. Ensure maximum assets operational efficiency 4. Implement improvements to reduce failures 5. Excellence in maintenance engineering 6. Hiring by results consolidation

Source: Adapted from Kardec and Nassif (2012)

However, following the needs imposed by the Second Industrial Revolution, brought by the postwar high industrial development, new maintenance practices are introduced, starting the second generation of maintenance. Due to increased productivity, the industrial sector was faced with the need to increase mechanization and reduce downtime, thereby increasing availability and a longer equipment life cycle.

With the Third Industrial Revolution, in the 1970s, the demand for technology and skilled labor has increased. Computerization, biotechnology, microelectronics, and computing have become the pillars of industrial production. In response to these changes, the third generation of maintenance begins. The main characteristics of this phase are the pursuit of higher plant availability and reliability, greater safety in operations, a better quality of products, a concern for reducing damage to the environment, ensuring a longer equipment life, as well as greater cost-effectiveness (MOUBRAY, 1997).

Along with the new 21st century, the fourth-generation maintenance cycle starts. According to Kardec and Nassif (2012), the new maintenance organizational structure focuses on increasing the availability, reliability, and maintainability of equipment and systems.

Ten years later, with the inclusion of asset management principles, which has become a very popular topic, the fifth generation of maintenance begins, with a focus on monitoring, reliability, maintainability, hazard study, and in the use of faster computers, systems integration, and interdisciplinary works (SOUZA, 2018).

The good practices introduced thereafter made clear that it would be economically advantageous to extract the maximum from the already installed machines associated with the need to achieve sustainability and environmental preservation goals. Reliability became even more relevant and the reduction in the number of shutdowns with a longer interval between scheduled maintenance stops turned into a necessity for almost every production line.

As important tools to obtain a full understanding of machinery behavior and supporting the predictions of the operational condition and capabilities of each production unit, therefore helping in maintenance planning, commercial condition monitoring systems began to be used by many companies. These are essential tools

to Condition Based Maintenance (CBM), used by RCM as a primary fault management strategy (NIU, YANG, and PECHT, 2010)

Condition monitoring has progressed for many years, with significant, but gradual improvements to algorithms for data analysis. Pattern recognition methods for condition monitoring are well established and can successfully detect and classify many faults.

Condition monitoring has a wide variety of interpretations, ranging from a subjective judgment from relatively raw measurements to the use of advanced signal processing and history data to form the basis of a maintenance schedule. Significant effort has been aimed at the detection and diagnosis of incipient faults and the minimization of false alarms, and the increase in computing power has played an important role in this case.

Yet, many operational parameters play a role in condition monitoring (ISO STANDARDS, 2012), still, there is some difficulty in merging information with the variations of parameters amplitudes under nominally steady-state conditions, as discussed by Lees, Friswell, and Jennions (2006).

The adoption of scheduled maintenance considering the results obtained from the monitoring and diagnosis systems, together with the natural resources availability evaluation, clients demand and the best opportunities in the market, among other important considerations, seems to be the companies' business managements desire.

However, turning such a wish into reality requires several adjustments in the operational structure in plant maintenance and, mostly, a certain degree of investment in knowledge, technology, and personal training. Knowledge may be the fundamental aspect of asset management and it is not difficult to understand that there is a gap between maintenance practices and theory considering modern maintenance management strategies. Furthermore, because of the current changes in the global scenario regarding Industry 4.0, this gap becomes even more evident.

Nowadays, the world is in a new process of change, in the middle of the fourth industrial revolution, or Industry 4.0. According to Schwab (2016), the key point is the industrial convergence, that is the merger between the physical, digital, and biological worlds. This integration is made possible by the development of new technologies such

as robotization, nanotechnology, biotechnology, 3D printing, cloud computing, edge computing, big data, virtual reality (VR), augmented reality (AR), and the Internet of Things (IoT).

From the maintenance point of view, as highlighted by Cachada et al. (2018), the latest trends lean towards the predictive approach, incorporating techniques such as Prognosis and Health Management (PHM) and CBM. The implementation of such approaches demands a well-structured framework and can be pushed using the previously mentioned technologies, shaping the so-called Maintenance 4.0.

The integration of information and knowledge seems to be the key to solve many issues. Walker, Perinpanayagam, and Jennions (2013), for example, considered that in the future it will be possible to join machine diagnostics and prognostics algorithms to Integrated System Health Management (ISHM).

Integrated System Health Management (ISHM), or Integrated Vehicle Health Management (IVHM), is the capability to develop and unify validated tools, technologies, and techniques for automated detection, diagnosis, and prognosis of adverse events during systems or vehicles operation (BENEDETTINI et al., 2009 and SRIVASTAVA, MAH and MEYER, 2009). ISHM may be the key point to the structured architecture mentioned by Cachada et al. (2018).

However, with these algorithms, a large amount of data should be analyzed. In this case, it is important to have tools that can perform such analysis and, especially, reducing the number of variables to be analyzed without losing relevant information to the problem understanding. The answer to this issue can be found in data-based techniques.

According to Yin et al. (2015), data-based techniques have been developed over the past two decades and are widely used in numerous industrial sectors. The central idea of data-based techniques is to take full advantage of huge levels of available operational data, looking to apply the information in a useful way.

Data-driven models built based on such historical data can be used for monitoring, fault diagnosis, optimization, and control. Latent variable models are used because they provide reduced dimensional models for high dimensional processes (MACGREGOR and CINAR, 2012). Compared with model-based approaches, data-

based techniques provide efficient alternative solutions for different industrial systems operating under several operating conditions, especially when the development of a model faithful to the analyzed system is difficult or even impossible to be carried out. Zhou et al. (2010) presented a comparative study of data-driven and model-based approaches for Fault Detection and Diagnosis (FDD) of rotating machinery.

Nevertheless, physics-based modeling has provided significant advances in specific faults, such as shaft and blade cracks, where techniques like Finite Element Analysis (FEA) can provide easier, faster, and cheaper data trials when compared to seeding faults into real machinery (MICHALSKI and SOUZA, 2018).

In fact, the model-based approaches involve the rigorous development of a process model based on first principles (ALAUDDIN et al., 2018). Because these models reflect physical laws or device implementation knowledge, whether they are engineering design quantitative models or qualitative models such as causal fault propagation models or state transition diagrams, they bring the solution of problems closer to engineering knowledge, facilitating their understanding. The same cannot be said when pure data approaches or empirical models are applied, when data derived from tests or from the output of more detailed and exact simulation models are used such as curve fits and regression models, or even neural networks.

Also, locating and distinguishing faults with just condition monitoring and data-driven techniques may be difficult, requiring many field tests that can be expensive or even impossible in real situations. Seeding faults into real operational machinery to carry out tests and analyze faults and failures is not a feasible option under virtually any condition. In this way, computational modeling simulations become an extremely important tool and a machine spatial model may be successfully used.

Through simulation, it may be possible to distinguish small changes in response due to the presence of different faults. However, the model may contain uncertainties and the measurements will be contaminated by noise. To robustly detect and locate faults the change in response must be sufficiently significant to reduce the influence of these aspects. Also, a good physical understanding of the machine's dynamics is of crucial importance, allowing an improved model estimation by reducing its uncertainties, and leading to improved fault diagnosis.

It must be also considered that the simulated dynamic response belongs to a single unit, which has its characteristics, such as stiffness and damping. In these cases, an accurate model representation of the machine can be built from model updating and parameter estimation. That is, the mathematical model, that can be built from the general characteristics of a given machine project, must be individually adapted to each analyzed rotating unit through these techniques.

Model updating in structural dynamics, as presented by Friswell and Mottershead (1995), considers, predominantly, Finite Element Models (FEM) with a small number of uncertain physical parameters. On the other hand, experimental modal analysis of structures or rotating machines, as described by Bucher and Ewins (2001), consider a model-based on the rotor modes' properties.

The unknown model parameters must be estimated using measured data. Usually, the measured response will be a nonlinear function of the parameters. In these cases, minimizing the error between the measured and predicted response will produce a nonlinear optimization problem, with the usual question about convergence and local minima. As the complexity of models increases, the number of parameters to be estimated can exceed the available data, being a major issue especially when the data are noisy or strongly correlated (KIM and LEE, 2018). In the worst case, this means that there is no unique solution to the estimation problem, and many sets of parameters can be fitted to the available data, with great variability. In these cases, to overcome the ill-conditioned problem many optimization procedures can result in the solution of linear equations for the unknown parameters.

In conclusion, as presented in Dai and Gao (2013), FDD in a complex system, from the perspective of data processing, is done through modeling, signal processing, and intelligence computation. On the other hand, Walker, Perinpanayagam, and Jennions (2013) considered, from the PHM perspective, that future research in the rotordynamic area may provide the connection between recent studies and real systems by combining physics-based simulations with data-driven techniques and validation against experimental data.

Considering the demands of complex systems maintenance, the modern maintenance techniques developed and applied globally, and the tools currently available for machine monitoring and diagnosis, especially with the advent of industry

4.0, the present work proposes a framework integrating model-based and data-driven techniques that could be replicated in the near future in intelligent asset monitoring and fault diagnosis of rotating machines such as turbines and generators.

In this work two horizontal rotary machines are considered: a Jeffcott rotor from a laboratory test rig and a centrifugal compressor used in FPSO (Floating Production Storage & Offloading). The Rayleigh-Ritz method and FEM are used for the units' modeling, and parameters estimation is made using different approaches: Kalman Filter (KF), and an innovative combination of the Monte Carlo Method (MCM) and the Simulated Annealing (SA), in which the latter is applied as an iterative refinement (or iterative improvement) method to approximate the result obtained from the former to a more satisfactory solution. The objective of these modeling and updating methods is to develop a reliable virtual representation for each analyzed unit. The application of different techniques and approaches demonstrates the versatility of the proposed framework.

Therefore, based on simulated data from the updated models previously obtained, a data-based technique is used for the analysis and comparison of the rotary machines under different operating conditions. In this case, the fundamental chosen method is the Principal Component Analysis (PCA). However, a new modification of the original PCA algorithm is proposed to improve the performance of the method, especially by increasing its sensitivity to variations in the dynamics of the analyzed systems. In all cases, the analyzed fault is the mechanical unbalance. The results are discussed and compared at the end of this work, validating the feasibility and applicability of the proposed method. In addition, the results demonstrate that the application of analytical models of the machines and the use of monitored signals for the detection and identification of faults offers speed in the analysis and an immediate understanding of the physical condition of the fault.

1.2. Objective

Considering the new approaches for rotating machines maintenance, especially those related to strategic sectors, such as power generation and petrochemical industry, and the expected evolution for monitoring and diagnostic systems due to the

adoption of Integrated Health Management (IHM) methodologies in a near future, the main objective of this work is to present a hybrid method for FDD based on the dynamic response of rotating machinery using model-based and data-based techniques integration. The heart of the matter is to combine in the form of a framework the capacity to identify and quantify faults, characteristic of model-based methods, with the ability to detect real-time variations in the behavior of a system, inherent to data-based methods.

The proposed framework, main innovation and contribution of the thesis, is applied as follows: considering a rotary unit and the chosen model-based approach, a mathematical model that represents the machine dynamic behavior is developed and its unknown parameters are estimated, with special attention to those related to possible pre-existing faults. In this way, a numerical model that represents the equipment's current operating condition is obtained. From this model, new operational conditions, considering, e.g., the development of the analyzed fault and the consequent system degradation, can be simulated as well. From the obtained simulated data, a data-based technique can be applied to detect the changes in the machinery behavior under these different conditions. This allows a correlation between the equipment's expected behavior and the different fault degradation levels. Continuously monitored data from the actual equipment is also processed using the same data-based technique, providing a comparison between simulated conditions and real steady-state operating conditions, supporting fault diagnosis. This approach allows the real-time identification and quantification of the fault present in the analyzed equipment without the need to run the numerical model due to variations in the operational condition.

Additionally, the development of the new methods proposed, both for updating models (combining MCM and SA), and for data analysis (modified PCA), is also one of the objectives of the thesis, as well as demonstrating the applicability and innovation of the proposed methodology based on the results presented.

1.3. Outline of the Thesis

To promote a better understanding of this work, this thesis is organized into several chapters, as follows:

Chapter 1 covers the thesis introduction, with the contextualization, relevance, and objectives of the work, as presented before. Chapter 2, in turn, presents some fundamental concepts for this work development, such as Rotordynamic Modeling and Analysis, Fault Detection and Diagnosis, and Mechanical Faults in Rotating Machinery. Then, Chapter 3 presents a bibliographic review regarding Fault Detection and Diagnosis Methods.

The next chapter, Chapter 4, present a review considering the model-based methods applied in this thesis, while Chapter 5 present Principal Component Analysis fundamentals and a novel approach, proposed in this work, to the application of such technique.

In Chapter 6 the proposed methodology is addressed based on a framework that integrates the main tools discussed in the literature review. Chapter 7 presents the framework application and the results obtained to demonstrate the proposed methodology viability.

In Chapter 8 the thesis conclusions, as well as some proposals for future work that could continue the research, are presented. Lastly, Chapter 9 presents bibliographic references.

2 FUNDAMENTAL CONCEPTS

Continuing the introductory part of the thesis, this chapter covers some fundamental concepts related to rotating machines, rotordynamics, FDD as well as definitions and terminologies used throughout this work.

2.1. Rotordynamic Modeling and Analysis

Considering the purpose of this thesis, a key point that needs to be addressed is rotordynamic modeling and analysis.

According to Lees (2016), with the increasing complexity and sophistication of rotating machinery architecture, modeling turns out to be a way to better understand the machines' behavior. The comparison between model results and monitored data brings more information, increases the machine behavior understanding, and allows the obtained knowledge to be used in guiding maintenance and operation planning.

Essentially, the purpose of using models is prediction and transforming a complex physical system or phenomenon into a representative and desirably simple mathematical model. The actual models required for condition monitoring fall into two categories: faults modeling and machine modeling.

The first category, faults modeling, will be addressed later, in the “Mechanical Faults in Rotating Machinery” section.

Regarding the latter category, machine modeling, there are several ways to represent and to predict the dynamic behavior using models, from simple two degrees of freedom models to complex three-dimensional FEMs. The chosen resolution method can also vary, as presented by Rao (2011).

Generally, rotordynamic models are described using three basic elements: shaft, discs, and bearings. In more complex and recent models, foundations also play an important role (LEES, SINHA, and FRISWELL, 2009). The model complexity will depend on its application, however, the analytical prediction of the dynamic behavior

of the rotor and its components is deeply dependent on the physical system modeling accuracy and the understanding of the assumptions and limitations applied in the analytical and modeling tools employed (CHEN, 2015). Figure 1 presents some examples of FEM for several rotating machinery.

Figure 1 – Finite Element Models for Several Rotating Machinery

Source: Adapted from Chen (2015)

Lalanne and Ferraris (1998) considered that the general rotor equations are provided through the following steps:

- The kinetic energy, T , the strain energy, U , and the virtual work δW of external forces are calculated for the system's elements.
- A numerical method for the problem numerical solution must be chosen: the Rayleigh-Ritz, in which global functions are formulated over the entire domain of the structure, for a small number of degrees of freedom; and the FEM, in which the concept of dividing the structural domain into many small elements are applied, using functions defined only for these localized domains, for engineering applications with Multiple Degrees of Freedom (MDOF).

- Lagrange's equations are applied in the following form, presented by Eq. 1, where N ($1 \leq i \leq N$) is the number of degrees of freedom, q_i are the generalized independent coordinates, and F_i are the generalized forces.

$$\frac{d}{dt} \left(\frac{\partial T}{\partial \dot{q}_i(t)} \right) - \frac{\partial T}{\partial q_i(t)} + \frac{\partial U}{\partial q_i(t)} = F_i(t) \quad (1)$$

Genta (2005) remarks that methods based on transfer matrices, as the Myklestad-Prohl method, were very usual in the past, since they allowed the use of tabular manual computations or the implementation on very small computers. Due to their limitations and increasing computational capacity over the years, however, such methods have been replaced by FEM. Nelson (1979) presented a key work in FEM application to rotating machinery modeling with MDOF, considering one dimensional Timoshenko beam elements.

In this case, where MDOF modeling is necessary, according to Less (2016), some choices on how to represent the system must be taken. The main decision to be made are the following:

- Is a beam model adequate?
- Depending on the rotor's aspect ratio and the modes considered, is shear deformation and/or rotary inertia important?
- Is the number of elements used appropriately?
- Other factors such as stiffness and damping of bearings and seals, or the mass distribution must be considered?

As described by Vance, Zeidan, and Murphy (2010), rotordynamics modeling using beam elements models are generally adequate for modeling rotors. Beam elements are defined with geometrical and material characteristics and applying the theory of finite element formulations, the stiffness and inertia matrices are calculated. The main objective is to estimate the beam deflection to verify the internal clearances between the rotor and static parts and the rotor stability.

Nelson (1979) is also the basis for several works in this researching area, including Childs (1993), who also presented modeling approaches to important rotordynamic

components, such as bearings, squeeze-film dampers, seals, turbines, and pumps impellers.

Considering bearings modeling, it should be characterized by their dynamic properties at a limited number of connection degrees of freedom between the rotor and the bearing housing. In actual test conditions, obtaining reliable estimates of the bearing operating conditions is difficult, and this leads to inaccuracies in the well-established theoretical bearing models. To reduce the discrepancy between response measurements and predictions, physically meaningful and accurate parameter identification is required in actual test conditions. Such experiments may also be used to validate bearing models.

Regarding the bearings' stiffness and damping parameters estimation, two approaches stand out: a simpler and more direct one, in which the parameters are considered independent of the rotor rotation speed, as proposed by Lalanne and Ferraris (1998), and a more complex and precise one, in which the stiffness and damping properties are not considered constant, varying according to the rotor speed, and being evaluated by solving Reynold's equations, as presented by He, Cloud and Byrne (2005).

Tiwari, Lees, and Friswell (2002) highlighted that the equations used to estimate speed-dependent bearing parameters become an ill-conditioned problem in the presence of circular orbits and suggested that assuming isotropic bearing may be a way to regularizing the solution.

Chen (2015) presented a modern and, yet, complete approach to rotordynamic modeling and analysis, based on real machines, considering the importance of flexible supports and soft foundation when necessary.

In the most trivial sense, a general equation of motion can mathematically describe a rotor system as shown in Eq. 2 (MICHALSKI, 2004). The equation is presented in a generalized matrix form and considers a constant rotational speed (spin) for a symmetrical rotor about the axis of rotation. In linear cases, it is assumed also that the rotor has a small imbalance and displacement (WALKER, 2013).

$$\mathbf{M}\ddot{\mathbf{q}}(t) + [\mathbf{D} + \Omega\mathbf{G}]\dot{\mathbf{q}}(t) + \mathbf{K}\mathbf{q}(t) = \mathbf{F}_{exc}(t) \quad (2)$$

In this equation, $\mathbf{M}$ is the inertial matrix, $\mathbf{D}$ is the damping matrix, $\mathbf{G}$ is the gyroscopic matrix, Ω is the rotor rotational speed, $\mathbf{K}$ is the stiffness matrix, $\mathbf{F}_{exc}$ is the excitation forces vector and $\mathbf{q}$ is the generalized coordinators' vector.

There is a commitment between the chosen model to represent the machine dynamics and the considered fault model since the accuracy of the fault identification can be significantly influenced by the adequacy of the fault model as well as the accuracy of the rotating machine model (PENNACCHI and VANIA, 2004b), as will be presented in the next section.

2.2. The Process of Fault Detection and Diagnosis

Once the basic concepts regarding the dynamics of rotating machines were previously addressed, this section will present the connection between these themes with the principal mechanical faults that can affect such equipment behavior, which will be further presented.

The question one wants to explore is how the variations in the dynamic response of a rotary machine caused by the presence of faults can be observed, leading to its detection. The instrumentation available on the equipment and the data processing and acquisition process are key parts in this context and will be covered in the next section. However, it is rather interesting to present first the process of arising and evolution of a fault as well as the main steps of an FDD process in this scenario.

To present this process, inevitably some concepts and definitions need to be introduced. However, there is no consensus among authors, or even standards, for the definition of some terms that will be used such as fault, defect, and failure (RAUSAND, 2014; SARTORI ET AL., 2012). Although Sartori et al. (2012) can be considered a good reference for the subject when presenting a consistent proposition of definitions and terminology regarding detection, diagnosis, and fault correction, understanding the meaning of these terms is more important than their simple definition.

Equipment faults arise from root causes, usually understood as one or more events that may cause perturbations or disturbances to normal equipment operation (SARTORI ET AL., 2012). Human error, both in operation and prior maintenance, as well as the natural wear-and-tear process, can be included among these root causes. If a root cause exists, the fault condition also exists. Thus, a fault (or abnormal behavior condition) can be defined as a condition that leads to any deviation from a characteristic or equipment requirement, which may or may not affect the evaluated equipment's ability to perform its function, thus causing a failure or malfunction event.

The fault condition is the starting point for the development of a failure mode, leading to the degradation of an equipment or system. The point from which such degradation is detectable can be known as the potential failure point. In its turn, a failure event (also known as functional failure) can be characterized by the end of the ability of an equipment or component to perform its function under specific conditions. That is, a failure may not be noticed under all operating conditions of the equipment. In the case of rotating machines, this would mean that a failure could be noticed only under some specific load or speed conditions, for example. On the other hand, a malfunction event is characterized by the partial lost and/or irregular capacity of a system or component to perform, intermittently or not, one or more functions.

When the fault condition leads to a failure event, the system or equipment can undergo a functional incapacity state or even a complete shutdown. However, when the fault condition leads to a malfunction event, a defect state can be developed, in which the equipment remains operational within the limits of performance deviation, but without being able to perform at its maximum capacity.

Figure 2 presents a diagram with the system performance over time highlighting the events and states related to a fault condition, based on the RCM P-F curve (MOUBRAY, 1997).

Figure 2 – System performance over time

Figure 3 presents the five stages of a failure mode, from root cause to symptoms, according to Sartori et al. (2012).

Figure 3 – Failure mode stages

Source: Adapted from Sartori et al. (2012)

To maximize the potential-to-functional failure interval (time interval between a malfunction and a failure event) is quite important to maintenance since, given the assumptions of RCM (MOUBRAY, 1997), the sooner the fault detection is performed,

the more efficient maintenance planning can be done. However, fault detection is related to the ability to observe pieces of evidence (or symptoms), which in turn will depend on the chosen fault detection method (model-based, data-based, knowledge-based, or a hybrid method), as will be discussed in this thesis.

The FDD process is subdivided into two phases: detection and diagnosis. From the detection phase, it is determined the existence of a fault in the analyzed system and the time in which such a fault was detected.

On the other hand, the diagnostic phase is subdivided into two stages: classification and identification. In the fault classification (or isolation) stage, the objective is to classify the existing fault by type, location, and timing of its occurrence. The fault identification (or analysis) phase is defined as any further detail of the fault such as the definition of size, cause, behavior over time (directly related to prognosis and remaining useful life – RUL), among others (SARTORI et al., 2012).

Some authors prefer to subdivide the fault diagnosis by the type of analysis (qualitative or quantitative) that can be performed once the fault is detected. The qualitative analysis would be related to the fault diagnosis step and the quantitative analysis would be related to the fault identification step. Pennacchi, Vania, and Chatterton (2010) presented a subtle difference between fault diagnosis and fault identification, from this perspective: while fault diagnosis would mean the simple task to classify the fault type, fault identification means a more complete solution, in which the fault is not just classified but also localized in a specific position of the machine and its quantitative evaluation is given.

As mentioned in the introductory chapter of this thesis, depending on the FDD method adopted, quantitative fault analysis may not be completely performed. This issue will be addressed in detail in the next chapter.

Figure 4 presents the FDD process, from symptoms to fault identification, and the outputs obtained from the performed analysis that will feed the maintenance planning and actions.

Figure 4 – FDD process

Source: Adapted from Sartori et al. (2012)

2.3. Data Acquisition, Excitability, and Observability

The previous introduction of the FDD process highlights how perturbations in the dynamic behavior of a rotary machine caused by faults will be translated into a diagnosis. However, there are still two open questions: which are the methods that can be used in the FDD process, which will have a chapter entirely devoted to them, and how the fault symptoms are "obtained", which will be covered within this section.

Considering the principles of CBM, a management philosophy introduced to carry out the correct maintenance of the correct equipment at the right time (NIU, YANG, and PECHT, 2010), the use of real-time data to prioritize and optimize maintenance resources is a basic premise. In this way, data acquisition is fundamental to observe the system state, determining the equipment health, and indicating actions only when it is necessary. In fact, without reliable data, it is not possible to predict the machine behavior and condition, and, therefore, any predictive methodology is no longer valid or relevant under this situation.

Condition monitoring measurements are primarily centered on the critical components of a machine. In the case of rotary machines, the basic instrumentation consists of proximity probes (used for relative vibration measurements such as bearing clearance and air gap), accelerometers (used for absolute vibration measurement), temperature probes, oil level probes, and speed indicators.

Oak Ridge National Laboratory (2012) presented a best practice catalog for machine condition monitoring, with special attention to the instrumentation aspects, while Eisenmann and Eisenmann (1998) presented rotary machine instrumentation in detail. According to the former, for the fault addressed in this thesis, the mechanical unbalance, the vibration sensors signals (bearing clearance and absolute vibration) must be considered. The variations in these signal readings indicate the fault symptoms.

Besides the type of sensor, its position in the monitored equipment is fundamental for the success of its signal analysis. Accelerometers, sensors that collect absolute vibration measurements, are generally installed in stationary parts of rotating machines, such as bearing housings, reading their vibrations. On the other hand, proximity probes, relative vibration measuring sensors, are generally installed to collect signals from rotating parts such as shafts, discs, gears, and vanes. Usually, they are installed inside the equipment housing or in nearby regions where the rotating parts of the equipment are exposed.

There are advantages and disadvantages to use accelerometers and proximity probes to measure vibration on rotary machines, as presented by Eisenmann and Eisenmann (1998). In practice, it is recommended the use of such sensors in a complementary way. Regarding mechanical fault detection and the type of sensor, in the author's understanding and experience, proximity probes would be more sensitive to incipient mechanical faults since they measure the shaft dynamic motion directly, which cannot be done with the use of accelerometers, which actually measures the effects of the dynamics of the rotating parts of the equipment on its stationary components. Thus, when the fault effects on the shaft dynamics are noticed in the accelerometers' signals, it would mean that the fault would already be very developed, reducing maintenance planning and action times.

However, it is necessary to highlight the fact that in a real machine, the number, position, and type of probes and sensors are not a free choice, being dependent on equipment design, geometry, and operation issues. The sensors' arrangement may be different in each case and the analysis approach must be adapted to each scenario found.

Furthermore, the ability to infer the state of a system (observability) is not only related to the position and type of sensors used for data acquisition (monitoring) but also to the system's response to the introduction of a fault condition (excitability). Even if the system is correctly monitored (with the quantity, position, and type of sensors appropriate to the quantities to be observed), if the failure mode does not bring variations to the operating status of the system, it cannot be detected.

Generally, the small number and position of proximity probes usually applied to rotating machinery monitoring in industrial conditions do not guarantee total observability of the system (GOLFIERI, 2018). This situation gets worse for machines with flexible shafts, high operating rotation speed, or multiple couplings (multirotor machines), which generally operate above the first critical speed, that is, in a modal composition beyond the first bending mode.

Considering, for example, proximity probes location: in industrial applications, these probes are usually inside the bearings housing or positioned as close as possible to them. In the case of a machine operating in a bending mode condition (case 1, in Figure 5), its observability will be worse than in a machine working in a rigid body mode condition (case 2, in Figure 5), since rigid body modes produce large amplitudes in the bearings while bending modes tend to produce smaller amplitudes in the bearings (BENTLY and HATCH, 2003).

Several factors define the probes' location in this case, such as the difficulty of positioning these sensors along the shaft and the need to monitor the shaft vibration amplitude inside the bearings (to avoid metal to metal contact during machine operation, especially in transient conditions).

Regarding the number of sensors, considering a machine, as presented in Figure 6, with its actual mode shape shown in red (case 1) and just one transducer installed per bearing, on the inboard sides (case 2), more than one possible mode shape could fit the observed data from these probes. If additional probes were installed outboard of the bearings (case 3), for instance, the additional information would help to identify the actual mode shape and the nodal points, improving the observability of the system.

Figure 5 – Vibration modes influence on system observability

Source: Adapted from Bently and Hatch (2003)

Figure 6 – Influence of the number of sensors on system observability

Source: Adapted from Bently and Hatch (2003)

On the other hand, the system excitability is a function of its operating condition (rotating speed and load) and the faults presented. The measure of excitability indicates which position of the system for a given critical mode is most easily excited to detriment of the others (BOTTURA, 2019).

In the current analysis, the critical mode is, in fact, the forced mode shape (BENTLY and HATCH, 2003), and the position with the highest excitability for a mode is also the one with the highest observability for the same mode (MOHAJERPOOR, ADBI and NAHAVANDI, 2015 and XU et al., 2005).

This position will depend on the forced mode shape adopted by the equipment, which is a function of the excitation forces acting on the system, that is, the amplitude and number of harmonics introduced by the faults present in the machine, as well as the rotation speed itself (since unbalance is directly related to it and is always present in any rotating equipment).

Therefore, depending on the operating conditions and faults present in a rotary machine, the system's forced mode shape changes and the most observable points may simply not be monitored in an industrial situation.

Considering, for example, Figure 6, in which the position with the highest excitability is the shaft mid-span (or the mode antinode), without any probe. The positions with the lowest excitability (and observability), on the other hand, are the bearings (or the mode node) where the probes are positioned.

Whereas the two cases presented in Figure 6 represent the operating condition (steady-state condition) of two rotary machines and both are unbalanced, that is, in a fault condition, the fault location is probably the mid-span of the shafts, considering the observed vibration modes. However, due to the differences in the systems' state observability, in case 1 it will be much more difficult to identify the fault and the defect evolution (equipment degradation) than in case 2.

This problem could be mitigated by varying the equipment operating condition, such as the rotational speed, especially in the case of unbalance, whose amplitude is a function of the square of the machine speed.

Indeed, the practice in data acquisition, for many years, has been to collect data during machine run-downs or on-load steady-state conditions. In the first case, the data set is rich in information as the number of resonances of the machine, which may be excited during a run-down. In the second case, the data set is not rich in information, although a large quantity of data is available.

The differences between the two approaches can be found by comparing the works of Bachschmid and Pennacchi (2006), Sinha, Lees, and Friswell (2004a), and Bachschmid, Pennacchi, and Vania (2002). All these works used a single model-based method and the conclusions of a joint analysis point to the fact that single speed fault identification (during on-load steady-state condition) can be successful, but does not allow to discriminate between different malfunctions that generate similar symptoms. Nevertheless, the identification results can be used to define corrective balancing masses in real machine applications.

For better results and the correct identification and differentiation of simultaneous faults, especially when similar symptoms are observed, the use of data acquisition during a machine run-down or startup seems to be more effective, since it improves the system's excitability and observability conditions by varying the harmonics' amplitude of the systems' excitation forces, related to the faults present in the equipment.

However, it should be noted that in real industrial applications, the idea of stopping a machine to test it and evidence a possible fault is not the most productive approach from the economic point of view. Thus, the fault detection in industrial rotating machines should be done under on-load steady-state conditions.

In this context, the question that arises is which FDD method can detect and diagnose a fault, including its quantification, under steady-state conditions data acquisition. To help answer this question next is presented a review of the different methods of FDD.

2.4. Mechanical Faults in Rotating Machinery

One of the fundamental aspects in the development of a methodology that aims to detect, diagnose, and identify faults in a specific type of machine is to know and understand the major aspects of the failure modes associated with its components. Thus, this section presents a review considering the most usual faults in rotating machinery and its main features.

According to Silva (2013), faults with mechanical origin are the most common problems found in rotating machinery. Although some authors present studies seeking to define which failures more frequently occur in the industry, Walker, Perinpanayagam, Jennions (2013) emphasize that due to the lack of (commercial) information, it is very difficult to quantify the rate of each failure mode in a general way. This analysis must be done individually for each unit based on its own failures database.

However, there is a consensus that among all failure modes, unbalance will always be present at some level in any rotating machinery, since in practice it is virtually impossible to assemble a perfectly balanced rotor. For this reason, unbalance will be the considered fault in the examples that will be developed in this work, but other mechanical faults will be presented as well.

Based on the fundamental works of Muszynska (2005) and Bently and Hatch (2003), Walker, Perinpanayagam, and Jennions (2013) described seven more key faults, besides unbalance: misalignment, rub and looseness, fluid-induced instability (oil whirl and oil whip), bearing faults, shaft and blade cracks and rotor bow.

Freire (2006) and Mechefske (2005) mentioned other important faults. The former present a more direct approach for hydro generators, as the latter present a more general approach for rotating machinery.

Considering these contributions, among others, in the sequence of the present text a total of eleven mechanical faults will be addressed: unbalance, misalignment, rotor (shaft) bow, shaft cracks, blades and vanes cracks, bearing faults, oil whirl and oil whip, rub and looseness, fretting, resonances, and foundations problems.

Regarding modeling, each one of these eleven faults can be distinguished into two groups: those that modify the machine behavior due to external excitations and those that change the physical properties of the equipment.

Considering the general equation of motion for rotating machinery, presented in Eq. 2, faults that belong to the first group will change the excitation forces vector, in the right side of the equation, and faults that belong to the second group will change any physical parameter, such as mass, stiffness or damping, in the left side of the equation.

According to Vania, Pennacchi, and Chatterton (2013a), the most important faults of rotating machines can be modeled employing proper sets of equivalent excitations having a suitable harmonic content, that is, modifying the vector of external loads on the right side of the equation of motion.

Unbalance, misalignment, and rotor bend, for example, are faults primally modeled changing the excitation forces vector. On the other hand, cracks are generally modeled changing the stiffness matrix, especially considering the breathing mechanism.

Oil whirl and oil whip, however, are phenomena caused by self-excited vibrations due to changes in stiffness and damping in journal bearings, being modeled adequately with the addition of a term related to the hydrodynamic loads on the right side of the equation (DE CASTRO, CAVALCA, and NORDMANN, 2008).

Lees (2016) presented in detail the modeling for the most usual mechanical faults found in rotating machinery, such as mass imbalance, rotor bends, and misalignment. These faults have in common the same symptoms, especially in their initial evolution phase.

Next, a brief review of each of the eleven above-mentioned faults will be presented.

2.4.1. Unbalance

Unbalance is defined by the International Standards Organization (ISO) as the "condition that exists in the rotor when vibration, force or motion is transmitted to the bearings as a result of centrifugal forces" (SILVA, 2013). Simply, unbalance (also

known as imbalance) exists when the center of mass of a rotating component is not coincident with the center of rotation. The rotor will be balanced when the rotor center of mass axis coincides with the rotor's physical axis (geometric axis) or rotation axis. According to the position of these axes in the rotor, three types of imbalance can be highlighted: static, coupled, and dynamic unbalance (MECHEFSKE, 2005).

As presented in Walker, Perinpanayagam, and Jennions (2013), unbalance is one of the most common faults found in rotors, since every rotating machine has an inherent degree of unbalance. It is practically impossible to manufacture a perfectly balanced component. Hence, the unbalance is a relatively usual condition in a rotor or other rotating component as flywheels, fans, and gears.

The degree to which an unbalance affects the machining operation determines the problem (MECHEFSKE, 2005). If kept uncorrected, unbalance can result in excessive bearing wear, fatigue in support structures, decreased production quality, power losses, and adjacent machinery disturbance.

According to Silva (2013), the main sources of mechanical unbalance are:

- Eccentric components in the rotor;
- Eccentricity due to shaft manufacturing processes;
- Reduce manufacturing quality;
- Nonsymmetrical design;
- Accumulation of material in turbine blades during machine operation;
- Non-homogeneity of the rotor material;
- Stiffness variation in different parts of the rotor;
- Breakage of turbine blades.

In some cases, as noted from the presented unbalance main sources, this failure mode can be a secondary consequence of a primary fault. However, in most cases, even when unbalance is the primary fault of a rotating machine, this is not necessarily the factor that leads to machine failure. The consequences and side effects of unbalance, such as excessive vibrations, loosening of fastening elements, or rubbing between the rotating and static parts of the machine, are generally the major issues that lead to machine failure. This combination of failure modes makes the location and

prognosis of imbalance an area of research still under development since the remaining life predictions are made based on a specific failure mode.

Freire (2006) highlighted that the major characteristics used to identify unbalance-caused vibrations are: a predominantly radial rotating vector, periodical in the frequency of rotation of the machine, and directly proportional to the rotation speed magnitude. The vibration spectrum presents a narrow band at the rotation frequency, with stable amplitude and phase. On the other hand, the unfiltered trajectory of the shaft centerline tends to be circular. A high magnitude radial vibration at the fundamental frequency is the classic characteristic diagnostic symptom. Moreover, if the rotor is bent or has some angular misalignment, there will also be a strong axial vibration at the same frequency.

As the response amplitude is related to the square of the rotational speed, unbalance is a dangerous condition in machinery that runs at high rotational speeds, such as centrifugal compressors used in Floating Production Storage & Offloading (FPSO), as presented in Souza, Melo, and Michalski (2018).

In variable speed machines, the effects of unbalance will vary with the shaft rotational speed. In low-speed machines, as hydro generators, the high spot (location of maximum displacement of the shaft) will be at the same location as the unbalance. At increased speeds, the high spot will lag behind the unbalance location, as in super high-pressure compressors.

Regarding fault modeling, according to Lees (2016), the general equation of motion, represented by Eq. 2, could be rewritten to give the system response to unbalance, at a rotating speed corresponding to Ω radian per second, presented in Eq. 3, considering complex coordinates.

$$\mathbf{q}(t) = [\mathbf{K} + i(\mathbf{D} + \Omega\mathbf{G})\Omega - \mathbf{M}\Omega^2]^{-1} \mathbf{M}\Omega^2 \boldsymbol{\xi} e^{i\Omega t} \quad (3)$$

In this case, $\boldsymbol{\xi}$ is usually a vector giving the mass eccentricity at each point along with the rotor. This eccentricity represents the difference in location between the center of mass and the center of rotation. The implication is related to the fact that, considering the inertial term, the relevant acceleration is that of the rotor center of mass, instead of

its geometric or rotation center. Thus, there is an acceleration imposed on the center of mass by the shaft rotation.

Without any detailed analysis of the solution of Eq. 3, it is immediately noticeable the response synchronism and the dependence of the dynamic response amplitude concerning the square of the rotation speed. This last aspect is probably the most important to differentiate the unbalance of the other faults analyzed in this section.

Mathematically, the sum of the vectors relative to all the different sources of unbalance can be combined into a single vector. This vector represents an imaginary heavy spot on the rotor. If this heavy spot is located and the unbalance force quantified, the placement of an appropriate weight 180° opposite to the heavy spot will counteract the original unbalance.

According to Lees, Friswell, and Jennions (2006), in general, the use of measurement data from multiple transducers allows the unbalance estimation and the subsequent rotor balancing in several planes, simultaneously, through the addition of correction masses. Even in cases where the stator or foundation is flexible and their properties are unknown, as considered by Sinha, Lees, and Friswell (2004a, 2004b), Sinha, Friswell, and Lees (2002) and Edwards, Lees and Friswell (2000), the unbalance estimation is feasible.

The same idea applies when bearing parameters are unknown and need to be estimated, as detailed in Lees, Sinha, and Friswell (2004), in which the short bearing theory was used to obtain values for the bearing stiffness and damping, and Tiwari, Lees, and Friswell (2002), in which methods to estimate bearing models from measured data were employed. Although both methods have some limitations, as presented in the respective articles, it can be considered that the unbalance estimation is still possible in both cases, with good results.

It can be concluded from these works that the estimation of the unbalance of a rotating machine is possible considering measurement data even when some structural parameters of the equipment have uncertainties or are unknown.

2.4.2. Misalignment and Rotor bow

Due to their characteristics, the way they affect the dynamic behavior of a rotating machine and its symptoms, both shaft misalignment and rotor bow are failure modes that can be easily mistaken by unbalance, especially in the early stages of development of the defect. Such failure modes are also relatively common in some types of rotating machines and, although they are not the focus of this work, they will be a little more detailed below.

In rotating machines, as presented in Sudhakar and Sekhar (2009), shaft coupling misalignment is the most usual fault found behind unbalance. And, as in the case of unbalance, secondary faults can also follow misalignment.

Walker, Perinpanayagam, and Jennions (2013) list some good references that show how the combination of different faults and misalignment can happen. El-Shafei et al. (2009a), for example, present an experimental study considering the misalignment effects on the instability of plain journal bearings.

Misalignment can arise in several different places, depending on the machine design, as between shafts and bearings or between gears. In the case of multiple rotor machines, constant synchronous forces and moments are generated at the couplings depending upon the extent of the offset between the two rotors and independent of the machine rotating speed, as presented by Gibbons (1976).

There are two main categories of misalignment: parallel misalignment, also known as offset, and angular misalignment. Parallel misalignment occurs when shaft centerlines are parallel, but offset from one another in the horizontal or vertical direction. It can also be a combination of both cases. Angular misalignment occurs when the shaft's centerlines meet at an angle. The intersection may be at the driver or driven end, between the coupled units, or behind one of the coupled units. In practice, the misalignment found in rotating machines is usually a combination of both types described above (MECHEFSKE, 2005).

Flexible coupling machines can tolerate some shaft misalignment, but misalignment should always be minimized (MECHEFSKE, 2005). The resultant

vibration from misalignment increases bearings' excessive radial loads, which can cause premature bearing failure.

In multi-coupled rotors is observed that misalignment generates 2X component in the machine response, as presented by Dewell and Mitchell (1984) and Ehrich (1992), and the effect on the 1X component is assumed to be small. However, Jordan (1993) confirms that the misalignment initially affects the 1X response component, resulting in an elliptical orbit. Therefore, incipient misalignments would have symptoms like unbalance, making it difficult to distinguish each other (SINHA, LEES, and FRISWELL, 2004a). In practice, both the 1X and the 2X components will be affected by misalignment, and the physical source of these effects may be modeled as a rotor bend and rotor asymmetry, respectively.

A banana-shaped orbit can also be found, indicating that the rotor loads are not the same in all radial directions. Besides misalignment, this symptom can be related to radial bearing stiffness asymmetry. Significant differences between the vibration amplitude in the two measured directions may also indicate misalignment (FREIRE, 2006).

In the case of severe misalignment, the orbit would become like the shape of an eight (8), due to the appearance of a frequency component twice the rotation speed in the response. In extremely severe cases, the observed frequencies in the frequency spectrum are primarily the rotor rotation frequency and several harmonics (usually up to the third, but sometimes up to the fifth or sixth). These are the usual diagnostic signatures and, in these cases, the harmonics allow misalignment to be distinguished from mechanical unbalance (MATSUO, 2017).

However, since unbalance and misalignment are probably the two most common causes of excessive machinery vibrations and have similar characteristics when the first symptoms appear, Table 2 is presented to help to distinguish these two faults.

Table 2 – Characteristics that distinguish unbalance and misalignment

Unbalance	Misalignment
High magnitude at 1X response in frequency spectra	High magnitude at 1X and harmonics response in frequency spectra
Measurements at different locations are in phase	Measurements at different locations are 180° out of phase
Vibration levels are independent of temperature	Vibration levels are dependent on temperature (changing during warm-up)
Vibration level at 1X increases with rotation speed. Centrifugal force increases as the square of the shaft rotational speed	Vibration level does not change with rotational speed. Forces due to misalignment remain relatively constant with changes in the shaft rotational speed

Source: Mechefske (2005)

One interesting note regarding misalignment, highlighted by Mechefske (2005), is that the heat generated during machine operation causes the metal to expand resulting in thermal expansion. Considering that, vibration data acquisition should be taken when the equipment is cold and, once again, after the normal operating temperature has been reached. The changes in alignment due to thermal v may be minimal, but should always be measured since they can lead to significant vibration levels.

Misalignment may become a major problem in machines with many bearings, where alignment is critical for smooth operation but is difficult to measure. In this case, the machine model must have MDOF to be able to represent the fault correctly, since it is assumed that the misalignment sources are the multi-rotor system couplings.

According to Sinha, Lees, and Friswell (2004a), considering flexible coupled machines, misalignment is assumed to affect only the rotor. For systems with hydrodynamic journal bearings and rigidly coupled shafts, misalignment will also affect the static loads' distribution in the bearings, altering the load supported by individual bearings.

In these cases, and once the hydrodynamic journal bearing clearances are small, even small changes in alignment can lead to significant differences in load. The static load on a bearing alters its stiffness and damping and this effect may be predicted by a simplified bearing model, for example, short bearing theory, as presented in Hamrock, Schmid, and Jacobson (2004).

Lees (2016) presented a new and interesting approach to misalignment modeling. Considering a rigid coupling, usually find in large machines, and an unbalance on the rotor, a rotating bending moment vector will be associated with the coupling. From this approach, the bending moments in the elements immediately before and after the coupling can be defined, as well as the shear force.

The bending moment imposes a gradient on the interfacial pressure distribution on the coupling flanges and has the effect of displacing the center of rotation by some distance, Δ , whose magnitude depends on both the degree of misalignment and the unbalance force. Due to this last assumption, it is not considered a response in which misalignment occurs without the presence of unbalance. The system response is presented by Eq. 4, considering both unbalance and misalignment influences.

$$\mathbf{q}(t) = \left[\mathbf{K} + i(\mathbf{D} + \Omega \mathbf{G})\Omega - \mathbf{M}\Omega^2 \right]^{-1} \mathbf{M}(\Omega^2 \boldsymbol{\xi} + \ddot{\Delta}) e^{i\Omega t} \quad (4)$$

Besides being strongly time-dependent, according to Lees (2016), since Δ has arisen from the interaction between unbalance and misalignment, the system response will often have the previously mentioned harmonics of the rotation speed Ω .

Although some references to support prognosis can be found in the literature, misalignment prognosis has the same problems as unbalance since other faults can follow it. Also, the misalignment localization and faulty component determination can be difficult in real applications due to the number of potential locations.

On the other hand, as presented by Walker, Perinpanayagam, and Jennions (2013), rotor bows are also a usual fault find especially in rotating thermal machines, such as gas turbines, generally caused by thermal differences induced by operational conditions and being a primary source of undesired vibration. Also, this non-symmetrical thermal distribution can cause excessive unbalance in turbomachinery (DOMES, 2008).

In jet engines and aero-derivative turbines, thermal bows generally occur due to imperfect cooling after the unit shutdown in its last operating cycle (SMITH, NEEL, and PALFREY-SNEDDON, 2017). In hydro generators, thermal effects can also cause shaft bows. In this case, as presented in Morgan (2015), mechanical friction between

rotating and stationary parts or asymmetric heating in the generator rotor can be the major cause.

Shaft bows, like unbalance and misalignment, are related to synchronous vibration, but there is some significant difference in the characteristics of an unbalanced and a bent rotor, although a real rotor may be unbalanced and bent at the same time (LEES, 2016).

Any bow in the shaft system will produce synchronous shaft motion, introducing vibrations or run-outs in the same way as a mechanical unbalance. If the bow is present in the run-up, the machine will behave roughly as if an unbalance were present: the vibration amplitude will increase with the machine speed at a constant (or slightly increasing) phase angle. If the bow is due to a shaft rub or other non-uniform heating effect, for example, the vibration amplitude and phase will quite change over time.

If a thermally distorted rotor machine is tripped and the rotor does not have time to cool down significantly during the time that it takes for the machine to slow down and stop running, the vibration amplitude will reduce as the square of the speed at a constant phase angle during the shut down. When the machine is allowed to cool before restarting, it will behave in a normal way with the vibration increasing again with time as the thermal effects become dominant.

According to Mechefske (2005), a bent shaft or bowed rotor can cause a special form of unbalance. These two conditions are essentially the same and only the location distinguishes them. While a bent shaft is located outside the machine housing, a bowed rotor is found inside the machine housing. This condition can be found on large horizontal machines, with heavy rotors, that have been out of operation for a long time. Gravity and time cause the natural bow in the rotor to become permanent.

As highlighted before, the vibration spectrum from a machine with a bent shaft or bowed rotor is identical to unbalance, and in some cases, could be mistaken by an unbalanced condition. Bent shafts and bowed rotors are difficult to correct, so in industrial applications, to overcome the problem and prevent loss of equipment functions for long periods, the machine needs to be balanced by adding counterweights in the same way done to correct unbalance (BACHSCHMID and

PENNACCHI, 2006). In these cases, the best way to avoid this condition is to keep the shaft or rotor slowly rotating when the machine is not in use.

As presented in Sanches and Pederiva (2018, 2016), considering that a piece of rotating machinery could be virtually perfectly balanced, a residual shaft bow would cause a mass offset in the shaft center from the straight line joining the center of the bearings. As the rotor rotates, there is an additional elastic deformation of the rotor and the shaft bow can be modeled as an elastic restoring force acting at the equilibrium position.

Considering Lagrange's equation, the changes due to a shaft bow will be noticed in the potential energy terms. If the bending vector is $\mathbf{b}$, according to Lees (2016), a rotor with steady rotation speed Ω , the system response may be obtained considering Eq. 5.

$$\mathbf{q}(t) = [\mathbf{K} + i(\mathbf{D} + \Omega\mathbf{G})\Omega - \mathbf{M}\Omega^2]^{-1} \mathbf{K}\mathbf{b}e^{i\Omega t} \quad (5)$$

In this way, the presence of this fault in a rotor is related to a 1X excitation, but the vibration amplitude is fundamentally different from that caused by rotor unbalance. While the proportionality term of unbalance force is related to the square of the rotation speed, in the case of shaft bows, the term is linearly related to the machine rotation.

Qualitatively, to exemplify the differences between unbalance and shaft bows, considering that in a given Jeffcott rotor can be found, in different moments, both a single mass unbalance and a shaft bend in the midspan, the expected response when passing through a critical speed, considering the maximum load due to both faults is the same, will be given by Figure 7.

Figure 7 – Comparison of shaft bend and unbalance response

Source: Adapted from Lees (2016)

2.4.3. Other Mechanical Faults in Rotating Machines

The following is an overview of other failure modes that can occur on rotating machines. Such failure modes are not the object of study in this work and their presentation has a complementary character in this thesis.

Shaft Cracks

Shaft cracks are a potentially serious fault in rotating machines. Bachschmid, Pennacchi, and Tanzi (2010) presented an interesting survey on cracked rotors' static and dynamic behavior, including modeling and diagnosis.

Crack formation and propagation methods can be diverse, ranging from high and low-cycle fatigue to stress corrosion, as in the case presented in Halipchuk, Penner, and Smith (2011). It is interesting to note that, unlike unbalance, misalignment and even some cases of rotor bow, cracks represent, in fact, permanent damage to the equipment structure.

Considering Eq. 2 and the work of Morais et al. (2019), the differential equation that represents the dynamic behavior of a rotating system with a cracked shaft can be given by Eq. 6, presented next., where besides the previously presented terms, $\mathbf{K}_c$ is the time-variant stiffness matrix due to the presence of cracks in the rotor shaft.

$$\mathbf{M}\ddot{\mathbf{q}}(t) + [\mathbf{D} + \Omega\mathbf{G}]\dot{\mathbf{q}}(t) + [\mathbf{K} + \mathbf{K}_c(t)]\mathbf{q}(t) = \mathbf{F}_{exc}(t) \quad (6)$$

Trebuña et al. (2017) present the analysis of the causes of a rotor shaft failure in a steam turbine due to crack propagation considering the chemical composition and microstructure of the shaft material, the mechanical properties of the shaft material under static and fatigue loading, as well as operational load in the crack location on the shaft, using numerical and analytical methods.

The crack propagation can lead to catastrophic events. Momčilović et al. (2012), for example, describe the analysis of a major failure of a horizontal hydro turbine shaft caused by the occurrence of corrosion fatigue cracks. Special emphasis is given to the metallurgical failure analysis of in-service crack start.

Blades and Vanes Cracks

Turbine blade failure is considered a recurrent problem in thermal units, such as gas and steam turbines. According to Rani, Agrawal, and Rastogi (2017), the most usual failure mechanisms found in gas turbine blades include fatigue, creep, oxidation, coating degradation, corrosion, erosion, and surface degradation due to overheating.

In steam turbine blades, pitting corrosion is a frequent starting point of growing fatigue cracks (PLESIUTSCHNIG et al. 2016). On the other hand, compressor blades are subjected to many kinds of operational problems that lead to cracks, especially high-cycle fatigue (WITEK 2015).

In hydro generators, blade cracks have, in general, hydraulic origins, although they still are purely mechanical faults. In this case, blade cracks refer to cracks in the runner, wicket gate, and distributor.

The number of blades and vanes involved in the rotary machine operating process determines the harmonics frequencies that characterize the crack presence in each component. The number of moving components, the number of fixed components, and the product between both values are multiplied by the rotational speed of the unit to characterize such harmonics (MATSUO, 2017).

Bearing Faults

According to Mohanta et al. (2017), defects in bearings are generally caused due to normal wear during use. Machine speed influences the process of bearing faults identification using vibration signals when the bearing condition is progressively degraded. When failure is approaching, vibration may decrease.

The journal bearings wear become more severe especially in cases in which the machine stops and starts more frequently. But this phenomenon can be worsened by deficient lubrication. The poor lubrication can be caused by several factors, but the main ones are:

- Incorrect selection of lubricating oil;
- Insufficient oil pumping capacity;
- Inadequate piping diameters of the lubrication system;
- Accidental oil flow interruption.

This poor lubrication can cause excessive friction (dry friction or dry whirl) between the shaft and the bearing pads. In addition to vibrations, dry friction causes severe bearing wear. In axial bearings (thrust bearings) with tilting pads, the irregularities in surface contact induce vibrations with a frequency equal to the number of pads multiplied by the shaft rotation speed. If the contact is partial or intermittent, the stiffness will vary in time, meaning that the system stiffness increases during contact. In this case, system vibration becomes non-linear with sub-harmonics and inter-harmonics frequency components. The radial vibrational spectrum presents excitations in harmonics of one, two, three, and four times (or even higher) the shaft rotation frequency (ALMEIDA, 2008). The direct contact friction results in a resonant response of the entire structure in the form of frequencies scattered throughout the spectrum, with wide bands, as noise.

Another journal bearing problem, usually found in hydro generators, is excessive clearance. The primary cause for this fault is often related to break or wear on components responsible for regulating bearing clearances (FREIRE, 2006). Excessive clearances in radial journal bearings increase the vibration amplitude with greater intensity in the fault bearing, since excessive clearance bearings have their capacity reduced for dynamic force absorption because of the bearing stiffness reduction. As a

result, oil whirl and even oil whip may occur, as also rub. These faults will be discussed in the next topic.

Oil Whip and Oil Whirl

Fluid-induced instabilities in journal bearings, also known as oil whirl and oil whip, could be discussed as journal bearing faults, as well. However, due to their particularities, it is interesting to address such issues separately.

Oil whirl occurs when the fluid in a lightly loaded journal bearing does not exert a constant force on the shaft that is being supported and a stable operating position is not maintained. On the other hand, the oil whip occurs when a subsynchronous instability caused by oil whirl excites a critical speed, causing a resonance, which then remains at a constant frequency regardless of speed changes. Oil whip often occurs at two times the critical speed since, at that speed, oil whirl matches the critical speed (MECHEFSKE, 2005).

Muszynska (1986) is a classic reference for a better understanding of oil whirl and oil whip phenomena. Figure 8 presents a cascade spectrum of rotor vibration response measured at a hydrodynamic bearing. The spectrum indicates regions of synchronous vibrations (1X the rotation speed) due to unbalance, subsynchronous vibrations (42% to 48% of the rotating speed) due to oil whirl (MATSUO, 2017), and close to the first balance resonance (with constant frequency) due to oil whip. In addition, the image emphasizes the pulse of the key phasor, indicating the relationship with the frequency of the rotation speed and the non-linearity inherent to the phenomena of oil whirl and oil whip (MICHALSKI, 2004).

- (a) Orbit display of synchronous vibrations;
- (b) Oil whirl orbit;
- (c) Oil whip orbit;
- (K) Key phasor pulse indicating the relationship with the rotation speed frequency.

Figure 8 – Oil whirl and oil whip vibration response

Source: Adapted from Muszynska (1986)

Still, according to Mechefske (2005), in most journal bearing designs, the oil instability situation is prevented by using pressure dams or tilt pads to ensure that the shaft rides on an oil pressure gradient that is enough to support it. In Michalski, Zindeluk, and Rocha (2006), the influence of journal bearing axial grooves on the dynamic behavior of horizontal rotors has been experimentally studied and the Poincaré map analysis was used as an alternative tool to complement the classical orbit and FFT analysis applied in the characterization of this fault.

During oil whirl, the shaft pushes a wedge of oil in front of it and then migrates in a circular path within the bearing clearance at just less than one half the shaft rotational speed; the rotor is revolving around inside the bearing in the opposite direction of the shaft rotation. Because of the inherent instability of oil whirl, in many situations where the phenomenon occurs, the time waveform will show intermittent whirl events. This “beating” effect is often evident in the time waveform and can be used as a diagnostic indicator.

Persistent oil whirl usually requires a replacement of the bearing. However, temporary measures to mitigate the detrimental effects include changing the oil viscosity (changing the operating temperature or the oil itself), running the machine in a more heavily loaded condition, or introducing a misalignment that will load the bearing asymmetrically. This last course of action is of course not recommended for more than a relative short-term relief.

From the perspective of aero-engine turbines, Fan (2011) used a full Hilbert spectrum to study startup conditions and predict oil whip and dry whip. However, fluid-induced instability prognosis is a topic little explored in specific research, given the difficulty to induce such faults into real systems.

Rub and Looseness

Although acting in opposite ways, rub and looseness have much in common. According to Walker, Perinpanayagam, and Jennions (2013), rub and looseness between mechanical parts can create complex vibration signals which are difficult to diagnose using traditional methods.

Rub is usually a secondary fault, and its effects can be linked to other primary problems such as unbalance and misalignment, as presented in Lu et al. (2007). Rubs vibration signal generated may be like that of looseness, but is usually clouded with high levels of wideband noise. This noise is due to the impacts. If the impacts are repetitive, such as occurring each time a blade passes, there may be strong spectral responses at the striking frequency.

Considering hydro generators, in Kaplan turbines there is a specific case of rub between the blades and the Kaplan rotor hub, as presented by Freire (2006), causing an adhesive wearing process. Usually due to lack of lubrication between these two parts, this type of rub causes high-frequency vibrations during the blade movement. The wear process is very slow but, over time, ends up raising the friction torque for the blade movement, as well as introducing pressure pulses into the blade drive servo motor and causing fatigue to several components related to the Kaplan mechanism.

A simple way to diagnose mechanical looseness is by tracking the changes in the vibration signal as the condition worsens. In the early stages, mechanical looseness generates a strong response synchronous to the rotational speed in the frequency spectrum along with some harmonics. According to Matsuo (2017), these subharmonics and interharmonics are $1/3$, $1/2$, $3/2$, $5/2$, $7/2$, $9/2$ times the rotating speed.

At this initial stage, the looseness condition could be mistaken for unbalance. As the looseness worsens, the amplitude of the harmonics will increase relative to the fundamental response, which may decrease. The overall RMS value may also decrease. Further deterioration of the condition results in fractional harmonics increasing in amplitude. These harmonics are most visible in signals taken when the machine is only lightly loaded.

Another condition that is a type of mechanical looseness, but often mistaken as misalignment, unbalance, or rotor bow, is the so-called soft foot. Soft foot occurs especially in horizontal rotors when one of the machinery hold-down points is not capable to resist the dynamic forces exerted by the equipment. That part of the machine will move up and down as a function of the cyclical forces acting on it. All the diagnostic signs associated with mechanical looseness will be present in the vibration signal.

If the foundation (hold-down points) of a machine does not form a plane, then tightening the hold-down bolts will cause the casing or rotor to be distorted. This distortion is what leads to the misalignment, unbalance, and rotor bow vibration signatures. To check for a soft foot, the vibration level must be monitored while each hold-down bolt is loosened and then re-tightened.

The appearance or disappearance of the diagnostic indicators mentioned before will determine if the soft foot is the problem. When a horizontal machine's vibration level cannot be reduced by realignment or balancing, the soft foot could well be the cause (MECHEFSKE, 2005).

Fretting

Fretting is a slow evolution phenomenon that causes wear without relative movement between two contact surfaces, assembled together, and subject to relative vibration with extremely low amplitudes. Visible signs of fretting existence can be seen through in situ formations of iron oxide in the form of red powder (FREIRE 2006).

The maintenance prevention against this phenomenon is to protect the surfaces with grease based on molybdenum sulfite. With the passing years of operation, gaps may arise between keys and keyways, capable of raising significantly the vibration.

Typically, shafts and hubs couplings are subject to this phenomenon. The vibration resulting from these gaps occurs intermittently, following the operating condition of the generating unit. In the case of a magnetic crown keyed to the rotor spider, considering hydro generators, the accuracy loss can lead to inaccuracies in the rotor circularity and concentricity, also causing problems with the unit's magnetic balance. The final solution consists of the recomposition of the rotor shape and interfering mounting adjustments with the correct replacement of the keys. Also, re-machining the key features may be needed.

Resonances

Resonances in rotating machinery it is not a novel problem, as can be noticed from Püst (1967). But even today it is not an easy task to predict all the vibration characteristics of complex structures during the design stage. In this way, problems related to resonances continue to be found in industry and rotating machinery is not an exception.

Resonance is the so-called “natural frequency” at which all things tend to vibrate. A machine’s natural resonant frequency is dictated by the relationship between the stiffness and the mass. Most systems will have more than one resonant frequency and these resonances (also called modes) can be excited by any forcing function that is at or close to that frequency. The response amplitude can be much greater than the forcing function amplitude. The term “critical speed” is also used to refer to resonances when the machine rotating speed equals the natural frequency.

The level of response amplification depends on the system damping. A highly damped system will not show signs of resonance excitation. However, a lightly damped system will be subject to resonance excitations. Resonances can be diagnosed by monitoring the vibration level while the speed of rotation of the machine is changed. A resonance will cause a significant increase in the 1X vibration levels as the speed is slowly changed. Most machines are designed to operate well away from known resonance frequencies, but changes of the machine parameters as stiffness and damping, or proximity to other machines, may excite a resonance.

Foundation problems

According to MECHEFSKE (2005), machine foundations provide stiffness and inertia to keep, primarily, the machine alignment. The energy generated by a machine in the form of vibrations is transmitted, reflected, or absorbed by the foundation. Especially on heavy rotating machines, the foundation is fundamental to provide support to proper dynamic behavior. In fact, in heavy turbogenerators and hydro generators, the foundations can be dynamically analyzed as a machine component.

Lees, Sinha, and Friswell (2009) point out how, in the last half-century, the influence of foundations on machine dynamics has become important. This behavior change can be associate with the increase of turbo generators units’ size and the newer steel foundations. Compared to the massive concrete foundations used in the past, low tuned with several natural frequencies below the machine’s operation speed, the new foundations have higher natural frequencies, closer to the machine's operating speed.

Maximum energy can be transmitted through the foundation to an inertial reference when the mechanical impedance of the foundation is well matched to that of the vibration source, so, the machine and the foundation should have the same natural frequency. If this is the case, all frequencies of vibration below the natural frequency will be transmitted by the foundation to the ground. A poor match will mean that more energy is reflected or absorbed by the foundation, which could affect machine operation. Changes in foundation parameters and properties can directly affect amplitude and phase measurements, which means that vibration measurements can be used to easily detect anomalies in foundations.

3 FAULTS DETECTION AND DIAGNOSIS METHODS

Once the fundamental concepts for rotating machinery FDD have been introduced, this chapter presents a review of FDD methods found in the literature. FDD is an active research field that has encouraged the development of a wide range of methods and heuristics. Several authors have been addressing the subject by presenting review articles and comparative studies regarding FDD methods.

Habibi, Howard, and Simani (2019), for example, presented a review about FDD applied to wind turbines. Chen et al. (2018) presented a review of recent research and development trends in four main aspects, including intelligent diagnostics, among which FDD methods are included. Alauddin et al. (2018) present a bibliometric review and analysis of Data-Driven FDD methods for process systems.

Krichen et al. (2017) presented a review of FDD, classifying the methods from the perspective of electrical faults in permanent magnet synchronous machines. Tidriri et al. (2016) present an investigation about the features of different model-based and data-driven in individual and integrated approaches.

Gao, Cecati, and Ding (2015a, 2015b) presented a survey of Fault Diagnosis and Fault-Tolerant Techniques regarding model-based, signal-based, knowledge-based, and hybrid approaches. Yin et al. (2015, 2014) provided an overview of recent developments in data-based techniques focused on modern industrial applications, while Yin et al. (2012) presented a comparison study of basic data-driven fault diagnosis and process monitoring methods.

Alzghoul et al. (2014) presented a comparison of a knowledge-based and a data-driven method to query data streams produced from hydraulic drive systems. Sartori et al. (2012) included in their work a review of some Fault Detection, Diagnosis, and Correction (FDDC) techniques.

MacGregor and Cinar (2012) presented recent advances in the use of data-driven models built from historical data for monitoring, fault diagnosis, optimization, and control. Zhang and Jiang (2008) presented in their work a review about FDD methods,

which supported several other works, as well as the works of Isermann (2011, 2004, 1995, 1994).

Yang (2004), Venkatasubramanian (2003a, 2003b), and Venkatasubramanian, Rengaswamy, and Kavuri (2003) presented an extensive review of model-based and data-based methods.

Considering the aforementioned studies, a summary with several FDD methods was developed and presented in Figure 9.

Figure 9 – Fault Detection and Diagnose Methods

The similarities and differences between the two major families of methods presented in Figure 9, model-based, and data-based methods, are well summarized by Khorasgani et al. (2018).

Both model-based and data-driven solutions employ system measurements for FDD. However, data-driven methods generally apply a feature selection or feature extraction technique to collect a set of relevant attributes from the measurement data or select a subset of measurements that are sensitive to the faults (clusters). On the other hand, model-based techniques use inconsistency among the measurements and the model simulation predictions (residuals) for FDD.

Knowledge-based methods can also play an important role in feature selection. These methods can identify important attributes for detecting and isolating each fault. Moreover, they can help to define new features by providing critical information about the nominal behavior of each measurement regarding the set.

Signal-based methods, for example, are well developed and widely used in practice, especially considering faults such as rotor unbalance, rotor bent, crack, rub, misalignment, and fluid-induced instability, as shown in Adams (2001) and Muszynska (2005).

According to Walker, Perinpanayagam, and Jennions (2013), in the case of rolling element bearings, signal-based techniques are the basis of most research, providing an accurate bearing diagnostic and prognostic. Borghesani et al. (2013) use several signal-based techniques in many bearing types, emphasizing real-world applications for FDD. Michalski et al. (2007) consider the oil whirl and oil whip non-linearity to identify oil instability phenomena in journal bearings using signal-based nonlinear techniques analysis.

Jesus (2010) presented an interesting work correlating vibration signal and statoric current for unbalance monitoring and diagnosis in electrical machines while Sinou (2009) presented a complete study providing a review of the state of art in shaft cracks diagnosis techniques based on structural dynamic changes and the linear and non-linear vibration measurements, giving a broad view of the most efficient and well know damage assessment techniques.

However, the quantification part, which means to identify faults extents and locations, has been an active research field in the last years for model-based approaches. According to Lees, Friswell, and Jennions (2006), over the past half-century, theoretical models have played an increasing role in the rapid resolution of rotating machinery problems. The importance of model-based condition monitoring will increase as machines run faster and the need to minimize downtime increases.

Sinha (2009) detailed the diagnosis and quantifications of several faults, showing the advantages of mathematical modeling (including simplified models) over traditional vibration-based approaches. Hong et al. (2009) combined grade life and mathematical modeling to develop prognostic models for aero-engine bearings.

Regarding shaft cracks, model-based techniques can have significant advantages over signal-based and data-driven methods. The development and comparison of simple and complex crack models regarding the breathing mechanisms and the effect of the crack propagation are considered an interesting development in the future, as the improvement of correlations between experimental and numerical analysis for linear and non-linear assessment techniques with the inclusions of modeling errors and uncertainties.

Sudhakar et al. (2011) described a model-based method for unbalance identification using a minimal sensor suite, while El-Shafei et al. (2009b) constructed mathematical models to evaluate different misalignment cases severity. Another reference is the work of Villa et al. (2012), in which diagnostic and prognosis of statistical misalignment are discussed.

Bachschnid and Pennacchi (2006), Sinha, Lees, and Friswell (2004a), Bachschnid, Pennacchi, and Vania (2004a), and Pennacchi and Vania (2002), for example, presented some techniques that have been developed using model-based methods to diagnose mechanical faults in rotating machines.

In the fault identification field, Pennacchi and Vania (2005) applied two different diagnostic techniques (the orbit shape analysis and the model-based identification in the frequency domain) to an experimental case study considering a gas turbine-generator unit of a small power plant affected by an angular misalignment in a flexible coupling.

Mathematical modeling techniques have been used to diagnose residual rotor bows and differentiate these faults from other sources of unbalance, as presented in Vania, Pennacchi, and Chatterton (2013a, 2013b), Meagher et al. (2008), and Vania (2006). Sanches (2015) presented a complete work dedicated to simultaneous unbalance and shaft bow identification in rotors using mathematical models for both the rotor and the studied faults.

Pennacchi and Vania (2010) used data collected from a combined cycle power plant to analyse a shaft crack propagation in a steam turbine. However, due to an unusual problem presentation, this paper shows the results obtained with an uncommon fault symptom analysis along with some preliminary investigations carried out employing mathematical models.

Pennacchi and Vania (2004b) also presented some methods, based on modeling and basic statistics, which enable the accuracy of a generator thermal bow identification to be evaluated. Shen et al. (2008) and Lees, Sinha, and Friswell (2009) presented rotor bows modeling, being the latter considered a good reference paper for more research on this topic.

Bachschmid, Pennacchi, and Tanzi (2011) studied a wide range of vibration phenomena and developed a model-based identification and severity procedure. Previously, Pennacchi, Bachschmid, and Vania (2006) had already presented a model-based transverse crack identification method, based in the frequency domain, and applied in a test rig, suitable for industrial machines.

Other examples of studies considering localization and prognosis include Inoue, Nagata, and Ishida (2009), who detailed crack localization using forced response modeling, and Sonnichsen (2000), who described finite element modeling for crack propagation.

Pennacchi and Vania (2008) described a model-based diagnostic methodology that identified a crack in a load coupling of a gas turbine before a catastrophic failure. The shaft vibration analysis under operating conditions and rated speed was used and the authors have been able to identify the root problem, even with a shaft bow due to the propagation of a crack in the stub shaft of the coupling.

Sawicki et al. (2008) used an active magnetic bearing system for early detection, localization, and prognosis of blade cracks. FEA methods are also applied to support blade cracks prognostic tools, as in Xiang et al. (2007). Green and Casey (2005) presented mathematical modeling for blade cracks simulation, while Sonnichsen (2000) demonstrated high-fidelity modeling using FEA to model crack growth.

Kappaganthu and Nataraj (2011) and Gupta et al. (2011) used nonlinear models to study instability and chaos in bearings. De Castro, Cavalca, and Nordmann (2008) presented a rotor-bearing system nonlinear mathematical models, in which unbalance faults causing whirl and whip phenomena are also considered.

On the other hand, according to Yin et al. (2015), data-based techniques have been developed over the past two decades and are widely used in numerous industrial sectors these days. The central idea of data-based techniques is to take full advantage of huge levels of available data, looking for information applications in a useful way. Data-driven models built from historical data can be used for monitoring, fault diagnosis, optimization, and control. Compared to model-based approaches, data-based techniques can provide an alternative and efficient solution for different industrial systems that operate under several conditions, especially when an accurate model of the analyzed system is difficult or even impossible to be developed. Besides, the analysis of multiple operational conditions from models generally requires significant computational cost and requires a response time that can prevent the use of this approach in real-time applications.

Regarding statistical data-based approaches, according to Alauddin et al. (2018), multivariate methods have received more attention than univariate methods in recent years. Techniques such as PCA and Partial Least-Squares – or Projection to Latent Structure – (PLS) have been well established and, besides, many new techniques are emerging such as Independent Component Analysis (ICA) and Bayesian network (BN).

In fact, in the past 30 years, PCA, Artificial Neural Networks (ANN), Fuzzy Logic (FL), Bayesian Network (BN), and PLS were the most usual methods find in FDD literature. On the other hand, BN, Hidden Markov's Methods (HMM), Gaussian Mixture

Model (GMM), ICA, and Support Vector Machine (SVM) have gained more attention in the last 5 years.

Ngolah et al. (2011), for example, detailed the monitoring and diagnosis of common faults, such as rub and looseness, using ANN. In this case, the proposed system was tested not just in lab conditions, but also stressed into industrial applications.

On the other hand, according to MacGregor and Yoon (2001), multivariate statistical approaches, as PCA and its variations, have been found very useful in processes with many measured variables and when causal models are unavailable to fault detection based on historical operating data.

Michalski, Melo, and Souza (2019) presented a work comparing PCA and Mahalanobis-Taguchi System (MTS) to detect unbalance in a centrifugal compressor in an FPSO.

Yin et al. (2012) provided a comparison study considering some multivariate methods: PCA, Dynamic Principal Component Analysis (DPCA), Fisher Discriminant Analysis (FDA), PLS, Total Projection to Latent Structure (TPLS), Modified Partial Least Squares (MPLS), ICA, Modified Independent Component Analysis (MICA), and Subspace Aided Approach (SAP), while Russel, Chiang, and Braatz (2000) compared PCA to Dynamic Principal Component Analysis (DPCA) and Canonical Variate Analysis (CVA).

MacGregor and Cinar (2012) presented Latent Variable Models (LVM) as an interesting and usable technique since it provides reduced dimensional models for high dimensional processes.

Canonical Variate Analysis (CVA), as DPCA, is also a data dimensionality technique that considers serial correlations, but its effectiveness in detecting faults in industrial processes has not been extensively tested, according to Russel, Chiang, and Braatz (2000).

Ganeriwala et al. (2009), developed a method to detect unbalancing that considers the Operating Detection Shapes (ODS) measurements using a machine fault simulator and 14 accelerometers, which is not easy to reply in a complex system. In the

localization field, the work of Yang and Hsu (2009) used trending data and reasoning systems to locate unbalance and shaft bow across a system.

In the fault detection field, as presented by Maalouf (2007), traditional data-driven techniques for rotor bow detection can combine slow roll and vibration data. However, few works that try to localize rotor bows in large systems are based on data-driven techniques, as Gaka and Tabaszewski (2011).

Concerning hybrid methods, Alauddin et al. (2018) presented the status of some of the most successful combinations of data-based FDD techniques in the literature. ANN-FL, ANNPCA, PCA-ICA, PCA-BN, PCA-SVM, and ICA-SVM were the most frequently used combinations. It also appears that BN is emerging as a preferred algorithm in combination with other algorithms. Tidriri et al. (2016), however, points out that there are few studies found in the literature regarding hybrid methods, compared to the number of studies that address the application of simple methods.

Amin, Imtiaz, and Khan (2018) presented a hybrid technique for FDD using PCA and BN, while Khorasgani et al. (2018) present a unifying model-based and data-driven fault diagnosis proposal, assuming that data-driven and model-based diagnosis methods follow a similar procedure and can be represented by a general unifying framework.

Han, Zhang, and Wen (2008) present a hybrid method considering modeling and simulation applications to help data-driven techniques for rub prognosis and condition-based monitoring.

Khorasgani et al. (2018) and Tidriri et al. (2016) also categorized the diagnosis methods into two main groups: supervised and unsupervised. Both groups use historical data to perform the classification. The former group uses training data to establish normal and fault classes, which requires some prior knowledge about the data and their classification. These methods typically apply classification methods such as ANN or BN to map the features to the operating modes. The latter group, in contrast, typically use hypothesis tests or clustering approaches to divide up the data points into normal and fault conditions, assuming that normal conditions are much more frequent than anomalies in the test dataset. In these cases, no prior knowledge is needed.

With such a wide range of single and hybrid methods and so many successful applications, it is virtually impossible to cover in a single paper all possibilities regarding FDD methods and, even more, compare all these methods to choose the best one. No publication was found that provides any evidence in this regard. Even the works of Alauddin et al. (2018), Venkatasubramanian (2003a, 2003b), and Venkatasubramanian, Rengaswamy, and Kavuri (2003), with a complete overview of data-driven and model-based FDD methods, do not come to a definitive conclusion.

Venkatasubramanian (2003a, 2003b) and Venkatasubramanian, Rengaswamy, and Kavuri (2003), indeed, proposed a list of ten desirable characteristics (quick detection and diagnosis, isolability, robustness, novelty identifiability, classification error estimate, adaptability, explanation facility, modeling requirements, storage, and computational requirements, and multiple fault identifiability) to a diagnostic system and compared and evaluated several methods in terms of these characteristics. The relative strengths and weaknesses of the different approaches have been identified and the authors concluded that no single method has all the desirable features stipulated for a diagnostic system.

Thus, future developments of FDD methods point to hybrid solutions, in which two or more methods could be integrated and would complement each other, overcoming the limitations of individual solution strategies. Following precisely this research line, the present work proposes the use of two different methods in a complementary way: a qualitative model-based method and a qualitative data-driven method.

On the model-based side, the proposal pursues a method that could estimate unknown parameters of the proposed model, especially regarding pre-existing equipment faults. In this case, data collection can be done under transient conditions, such as a scheduled trial or equipment commissioning, both plausible situations in industrial environments.

On the data-based side, the method must be able to detect variations in the monitored or simulated parameters as a function of the defect degradation in the rotating machine under study. In this case, data collection would be done on a steady-state condition, allowing the identification of previously known failures and with predefined responses by the equipment modeling, performed *a priori*. Unexpected

variations would lead to a model review without, however, impairing a malfunction identification.

In the next two chapters, the specific methods used in this thesis will be addressed.

4 PARAMETER ESTIMATION AND INVERSE PROBLEMS

This chapter presents a brief overview of parameter estimation and inverse problems applied to FDD model-based methods in rotordynamics. Special attention will be given to the methods applied in this work: Simulated Annealing (SA) and Kalman Filter (KF) methods.

The basic idea in using models is to predict equipment behavior, especially when physics-based models are used. In the case of industrial applications considering rotating machinery, almost invariably these models are FE models. The remaining question is their accuracy to represent the real machine and how accurate can important details in the machine's behavior be represented by the model. In many cases, for a more accurate representation of the real machine, it is necessary to estimate some model parameters from the monitored data.

As presented by Assis and Steffen (2003), the determination of unknown parameters in rotating machinery is a difficult task and optimization techniques represent an alternative approach for parameter identification.

To fulfill this requirement, inverse problems may be an interesting strategy, that can be classified in direct and inverse methods in the first place. As the terminology suggests, inverse problems deal with unknown causes and known consequences, while forward problems deal with unknown consequences and known causes, being the exact opposite of the former (KAPIO and SOMERSALO, 2005).

In forwarding modeling, a set of known parameters and external inputs are used to predict the measured output of a system, while in inverse modeling a set of measured values are used to estimate the model states and parameters that best approximate the observed behavior of the true system (GIBBS, 2011). Figure 10 shows a generic time-dependent forward model, while Figure 11 shows the inverse modeling problem for a deterministic model.

Figure 10 – Generic forward model

Source: Gibbs (2011)

Figure 11 – Deterministic inverse modeling

Source: Gibbs (2011)

The presence of the random inputs, $\mathbf{w}(t)$, defines if the inverse problem is deterministic or not. When the term is not present, the problem is deterministic; when the term is present, is stochastic.

In practice, the forward model must be primarily known. Its determination will define the complexity of the problem and it is interesting to have some perception about the sensitivity to the variation of the parameters that define the quantities of interest that will be estimated when applying the inverse problem.

Inverse problems have been always close-banded to estimation theory. Estimation theory started with the least-squares method in early applications related to astronomy

in the 17th century. Figure 12 shows the general structure of the least-squares method devised by Gauss.

Figure 12 – Least-squares solution to inverse modeling

Source: Gibbs (2011)

Improvements in the least-squares computational approach, statistical and probability foundations, as well as extensions to other applications, were made in the 19th century, while at the beginning of the 20th century the maximum likelihood and analysis of variance methods for parameter estimation were developed. However, until the 1940s, applications were generally related to deterministic models (GIBBS, 2011).

When dealing with forwarding problems, the model parameters are previously known and what is desired is to determine the measurable quantities, which should be as close as possible to the data collected from observations of the real problem. In this way, forward problems are usually well-posed, as causes determine consequences uniquely and stably.

On the other hand, considering inverse problems, the model parameters magnitudes are usually the question that one wishes to answer. Thus, the collected response data may be insufficient to identify the parameter without ambiguities and an exact solution may not exist, especially when there is some linear dependence between the parameters (ZHAO et al., 2019).

Inverse problems are usually ill-posed and to determine the causes from some of the possible consequences observations without extra information tend to be highly sensitive to measurement noise and modeling errors (CALVETTI and SOMERSALO, 2018).

As presented in Kaipio and Somersalo (2005), assuming that the vector of observed data, $\mathbf{y} \in \mathbf{Y}$, relate to the vector of unknown parameters (states), $\mathbf{x} \in \mathbf{X}$ by an operator, $\mathbf{H}: \mathbf{X} \rightarrow \mathbf{Y}$, being $\mathbf{X}$ and $\mathbf{Y}$ distinct Hilbert spaces, and considering the problem of finding $\mathbf{x} \in \mathbf{X}$, where $\mathbf{y} \in \mathbf{Y}$ is given, the Fredholm equation of the first kind must be satisfied, as presented in Eq. 7, below:

$$\mathbf{y} = \mathbf{H}\mathbf{x} \quad (7)$$

Two major issues probably will arise and must be addressed. First, in general, it is very difficult to obtain a mathematical model as refined as necessary to respond to all different parameters that affect the response. In this way, it must be always assumed that the model contains errors and is incomplete. The second issue is the fact that the vector $\mathbf{y}$ usually represents measured data and, so, is also contaminated by noise.

However, it is possible to consider a general relation, where Θ is the model parameter vector, representing a finite set of unknown parameters. In this case, considering linear models, Eq. 7 becomes Eq. 8, where $\boldsymbol{\varepsilon}$ represents all the errors, such as measurement noise, discretization errors, and other errors and uncertainties related to the mathematical model.

$$\mathbf{y} = \mathbf{H}_\Theta \mathbf{x} + \boldsymbol{\varepsilon} \quad (8)$$

The simple deterministic inverse problem is obtained if the model parameters are considered perfect known, that is, Θ is completely defined previously, otherwise the problem becomes a blind inverse problem. In the case of this work, Θ it is defined by the bearings' stiffness and damping coefficients, as well as the parameters related to the system unbalance.

Even so, three conditions must be satisfied for an inverse problem be considered well-posed:

- Existence: for each data $\mathbf{y} \in \mathbf{Y}$, there is a solution $\mathbf{x} \in \mathbf{X}$, i.e., $\exists H^{-1}$;
- Uniqueness: the solution $\mathbf{x}$ is unique in $\mathbf{X}$;
- Continuity (stability): the dependence of $\mathbf{x}$ on $\mathbf{y}$ is continuous, i.e., when small errors in $\mathbf{y}$ tend to zero, the same can be said about $\mathbf{x}$.

These are the Hadamard necessary conditions and they explain why even in some simple cases, many methods based on generalized inversion or least-squares may not give satisfactory results (ECHEVERRÍA et al. 2019).

To treat ill-posed inverse problems, some regularization methods are traditionally used. Kaipio and Somersalo (2005) present some classical methods, although the literature on the regularization of inverse problems is extensive.

During the process of regularization, the ill-posed problem is replaced by an almost well-posed one. However, due to the nature of inverse problems, without extra information, the results tend to be very sensitive to measurement noise and modeling errors. Considering that, it should be interesting to apply a methodology that could incorporate extra information, supplementing the noise data and the model inaccuracies and inadequacies.

Bayesian methodology, as presented by Calvetti and Somersalo (2018), can provide a versatile and natural way to answer this request, presenting the solution in the form of a posteriori distribution, providing many possibilities to compute useful estimates.

Many regularization techniques can be reviewed considering the Bayesian approach through prior design. However, Bayesian formalism brings new techniques to deal with inverse problems. As the natural stability finds in forward problems turns into instability when going against causality in inverse problems, the regularization strategies are ways to add information, explicitly or implicitly, to find the unknown solution. On the other hand, Bayesian inference provides a different approach: the unknown solution is modeled as a random variable and described using its distribution, rather than a single value. That is, the distribution of values of the quantity $\mathbf{x}$ can be found given observations of the dependent quantity $\mathbf{y}$, with a description of its uncertainty (noise), a forward model, and possible additional (*a priori*) information.

Summarizing, the statistical inversion approach is based on the following principles:

1. All variables included in the model are modeled as random variables.

2. The randomness describes the degree of information concerning their realizations.
3. The degree of information concerning these values is coded in the probability distributions.
4. The solution of the inverse problem is the posterior probability distribution.

Considering $\mathbf{X}$ a random variable representing the unknown solution $\mathbf{x} \in \mathbb{R}^n$, and $\mathbf{Y}$ a probabilistic model of the observed quantity $\mathbf{y} \in \mathbb{R}^m$, being $\mathbb{R}^n$ and $\mathbb{R}^m$ distinct Euclidian spaces, with solutions and observations belonging to spaces of finite dimension, the model presented in Eq. 8 can be replaced by a stochastic model, presented in Eq. 9. In this case, the mapping between observations and solutions is represented by a function and not by an operator, ensuring uniqueness.

$$\mathbf{Y} = f(\mathbf{X}) + \mathbf{E} \quad (9)$$

It is also assumed that $\mathbf{E}$ represents the random variable modeling the additive noise in the observation and has a probability distribution belonging to $\mathbb{R}^m$ that is continuous for the Lebesgue measure (CALVETTI and SOMERSALO, 2018), that is, the probability density of $\mathbf{E}$ is denoted by Eq. 10, $\mathbf{E} \sim \pi_{\mathbf{E}}(\boldsymbol{\epsilon})$.

$$\pi_{\mathbf{E}}: \mathbb{R}^m \rightarrow \mathbb{R}_+ = \{t \in \mathbb{R} \mid t \geq 0\} \quad (10)$$

Considering $\mathbf{E}$ and $\mathbf{X}$ mutually independent and the probability density of $\mathbf{Y}$ conditional on $\mathbf{X} = \mathbf{x} \in \mathbb{R}^n$, that is, fixing $\mathbf{X} = \mathbf{x} \in \mathbb{R}^n$ there is no change in the probability distribution of $\mathbf{E}$, as presented in Eq. 11, and the only randomness in $\mathbf{Y}$ is due to $\mathbf{E}$, as presented in Eq. 12, the randomness of the noise can be translated by $f(\mathbf{x})$, leading to the likelihood density.

$$\pi(\boldsymbol{\varepsilon} | \mathbf{x}) = \pi(\boldsymbol{\varepsilon}) = \pi_{\mathbf{E}}(\boldsymbol{\varepsilon}) \quad (11)$$

$$\pi_{\mathbf{Y}|\mathbf{X}}(\mathbf{y} | \mathbf{x}) = \pi_{\mathbf{E}}(\mathbf{y} - f(\mathbf{x})) \quad (12)$$

Letting Eq. 13 denoted the prior probability density of $\mathbf{X}$, expressing the subjective expectation regarding the distribution of the value of $\mathbf{X}$ prior the measurements, through Bayes theorem application formula (CALVETTI and SOMERSALO, 2007; MALINVERNO, 2000), Eq. 14 can be obtained, updating the expectation with the information provided through measuring $\mathbf{Y} = \mathbf{y}_{observed}$.

$$\pi_{\mathbf{X}} : \mathbb{R}^n \rightarrow \mathbb{R}_+ \quad (13)$$

$$\pi_{\mathbf{X}|\mathbf{Y}}(\mathbf{x} | \mathbf{y}) = \frac{\pi_{\mathbf{X},prior}(\mathbf{x}) \pi_{\mathbf{Y}|\mathbf{X}}(\mathbf{y} | \mathbf{x})}{\pi_{\mathbf{Y}}(\mathbf{y})}, \quad \mathbf{y} = \mathbf{y}_{observed} \quad (14)$$

The conditional density, $\pi_{\mathbf{X}|\mathbf{Y}}(\mathbf{x} | \mathbf{y})$, called the posterior density, expresses the probability of an unknown quantity, given the likelihood, the observed data, and the prior expectation. In the Bayesian statistical inverse problem approach, the posterior density is the searched solution.

The remaining problem is how to extract information from the posterior density in a suitable form for each application. This distribution can be used to compute several estimates for $\mathbf{X}$ as well as posterior uncertainties for these estimates. A usual estimate is the maximum of a posterior estimate, which leads typically to an optimization problem. Another usual estimate is the conditional expectation, which leads to an integration problem (KAPIO et al., 2000).

However, due to practical difficulties in computing the integrals involved in the equations provided by Bayesian inference, to obtain the estimates and their confidences can rarely be performed analytically and numerical methods may be necessary, especially if the dimension of the parameter space $\mathbb{R}^n$ is large. Some of these methods, such as Gaussian approximations, multi-dimensional quadratures (or cubature integration methods), Monte Carlo (MC) methods, and importance sampling are described in Särkkä (2013).

A very well-known example of Gaussian approximation method, and extensively found in the literature, is the Kalman Filter. This method will be covered in more detail in this work.

Although in many filtering problems Gaussian approximations work well, sometimes the filtering distributions can be, for example, multi-modal, or some of the state components might be discrete, in which case Gaussian approximations are not appropriate. In such cases, Sequential Importance Resampling (SIR) based Particle Filters (PF) can be a better alternative, which are methods for forming MC approximations to the solutions of the Bayesian filtering equations.

The particle filter has some variations, as the Unscented Particle Filter (UPF), the Gauss-Hermite Particle Filter (GHPF), the Cubature Particle Filter (CPF), the bootstrap filter, the Rao-Blackwellized Particle Filter (RBPF), to mention some examples.

Although widely used for parameter estimation, the most powerful application of the Bayesian methods presented so far is to estimate only the system state, considering that the parameters of the state-space model are previously known.

However, in practical models, it is very usual that the parameters are unknown as well. In these cases, three types of method for parameter estimation can be considered most relevant in the literature: optimization-based methods for computing Maximum a Posteriori (MAP) or Maximum Likelihood (ML) estimates, Expectation-Maximization (EM) algorithms for computing the MAP or ML estimates, and Markov Chain Monte Carlo (MCMC) methods for generating MC approximations of the posterior distributions.

MCMC techniques have been considered a very effective class. These methods are relatively simple to implement, at least on the conceptual level and are extensively found in the literature with many applications. Metropolis-Hastings's algorithm (HASTING, 1970; METROPOLIS et al., 1957) and Simulated Annealing (CHIBANTE, 2010; VAN LAARHOVEN and AARTS, 1987; ČERNÝ, 1985; KIRKPATRICK, GELATT, and VECCHI, 1983) are some examples.

In the current work, two different situations will be considered: in the first case the parameters related to the unbalance force and the bearings' stiffness and damping will

be considered unknown variables to be estimated and, in the second case, only the unbalance force related parameters will be estimated. In the next sections, the two algorithms used in this work are presented in more detail.

4.1. Simulated Annealing combined with Monte Carlo Method

Like many combinatorial optimization problems, parameter estimation in dynamic equipment, especially rotating machinery, can belong to the class of NP-hard (non-deterministic polynomial-time) problems, that is, problems for which no algorithm is known to provide an exact solution using a computation time that is polynomial in the size of the input of the problem (AARTS and VAN LAARHOVEN, 1987).

In this problem's category, exact solutions require prohibitive computational efforts to come to a solution. As an alternative, less time-consuming optimization algorithms can be constructed by applying tailored heuristics striving for near-optimal solutions, often, however, depending strongly on the structure of the problem to be solved, which can be a major drawback since it denies fast and flexible implementations and applications. Considering that, a generally applicable and flexible optimization method, such as Simulated Annealing (SA), can be applied to this task.

As presented by Lobato, Steffen, and Neto (2010), the SA algorithm belongs to the same class of methods such as ANN and Genetic Algorithms (GA), being a general optimization technique providing solutions to combinatorial problems by mimicking nature's abilities. Aarts and Van Laarhoven (1987) present a trivial review of SA theory, including the algorithm mathematical model and some applications.

The method is a local search metaheuristic, inspired by the thermodynamic process of cooling of molten metals to reach the lowest free energy state. In fact, this metaheuristic is a metaphor for the thermodynamic process, called annealing, used in metallurgy to obtain low energy states in a solid. In this way, the method uses a direct analogy to the metal's cooling temperature. Thus, the parameter that indicates the approach of the algorithm's response to a minimum value is the annealing temperature. When the variation of this temperature between two consecutive interactions (steps)

of the algorithm tends to zero, it means that the method has reached a minimum value (local or global).

The SA is used to address discrete and continuous optimization problems and can be considered one of the most classical metaheuristics and perhaps the first to find alternatives to escape from local minima, allowing uphill moves. The technique is based on the Metropolis simulation, exploring the feasible solutions of a problem, aiming to converge to an optimal solution (INGBER, 1993; KIRKPATRICK, GELATT, and VECCHI, 1983).

Its simplicity and good results in numerous problems have made it a very popular tool, with hundreds of applications within the most varied fields, which encouraged the application of this technique in this work. However, despite being a simple implementation method, because it is not exactly an algorithm, but a heuristic strategy that depends on several decisions to be fully designed, the quality of its solutions is strongly influenced by such decisions (DOWSLAND and DÍAZ, 2003).

Another pitfall regarding SA application is the local energy minimum trapping (SILVA JÚNIOR, CAMPOS, and MARTINS, 2017), especially when the global minimum search is performed under a large-scale neighborhood (GENDREAU and POTVIN, 2019). In this case, reducing the size of the neighborhood a priori may be a good approach, leading to better results.

One of several alternatives to avoid such a problem is the application of Monte Carlo Simulated Annealing (MCSA) or the Sequential Monte Carlo Simulated Annealing (SMC-SA), as presented in Silva Júnior, Campos and Martins (2017) and Zhou and Chen (2013). In this method, successive Monte Carlo cycles with decreasing temperatures are performed, allowing this way to find the global minimum of the problem.

At each iteration, the standard SA essentially simulates a Markov chain whose stationary distribution is the Boltzmann distribution of the current temperature, and the current state becomes the initial state for a new chain at the next Monte Carlo cycle. Thus, the size of the Markov chain in each interaction is reduced and the global convergence occurs before the parameters freezing.

Considering the application proposed in this thesis, SA, in combination with the Monte Carlo Method (RUBINSTEIN and KROESE, 2017), will be used to estimate the full set of parameters previously mentioned, i.e., unbalance force parameters and bearings' stiffness and damping.

However, this application is made in a different way from the proposed MCSA method found in the literature. In this work, the Monte Carlo Method (MCM) and the SA are used in two separate stages. The purpose of this combined application is the same as mentioned above, that is, the search for the global minimum more effectively, avoiding that the algorithm freezes the results in a local minimum.

The first stage, in which the MCM is applied, aims to reduce the search neighborhood's scale dimension. In this case, each parameter to be estimated is considered a random variable in the forward problem. Following the principle of maximum entropy (JAYNES, 1957a and 1957b), such *a priori* distributions should allow the greatest uncertainty while obeying the constraints imposed by the prior information (MALINVERNO, 2000), enabling the set of results obtained from the MC simulations to cover the widest range of possibilities.

Considering an acceptance-rejection criterion for the MC simulation's results, the forward problem responses are filtered (from constraints imposed on the values obtained from the forward problem), thus creating distributions to the unknown inverse problem parameters. Such distributions are used as *a priori* distributions of the inverse problem solved with SA, additionally to the cooling schedule, that is, the chosen values for the parameters that control the convergence (VAN LAARHOVEN and AARTS, 1987).

Mathematically, the described MC process for parameter selection follows the fundamental formula in Bayesian parameter estimation, the Bayes' rule presented by Eq. 14, which for a vector of parameters Θ and a vector of observations Σ is given by Eq. 15.

$$\pi(\Theta/\Sigma) = \frac{\pi_{priori}(\Theta)\pi(\Sigma/\Theta)}{\pi(\Sigma)} \quad (15)$$

In this case, $\pi(\Theta/\Sigma)$ is the parameter distribution given the selected observation *a posteriori* (resulted from the acceptance-rejection criterion); $\pi_{priori}(\Theta)$ is the prior parameter distribution considering a large-scale neighborhood; $\pi(\Sigma/\Theta)$ is the likelihood function, that is, the distribution of observations considering the desired vector of parameters (defined by the acceptance-rejection criterion); and $\pi(\Sigma)$ is the distribution of the marginal observations, that is, the distribution of all the possible observations regardless the considered parameters.

As mentioned before, the MC stage output, $\pi(\Theta/\Sigma)_{MC}$, becomes the prior parameter distribution for the SA stage, $\pi_{priori}(\Theta)_{SA}$. Similarly, the likelihood function resulting from the selection criterion applied to the MC method, $\pi(\Sigma/\Theta)_{MC}$, becomes the distribution of the marginal observation of the SA, $\pi(\Sigma)_{SA}$. And in this way, from a new prior parameter distribution and a new marginal observations distribution, applying SA results in a new parameter distribution, $\pi(\Theta/\Sigma)_{SA}$, which is the expected parameter estimate, and a new likelihood function, $\pi(\Sigma/\Theta)_{SA}$. The initial temperature for each SA step can be obtained considering an estimation of the cost increase of strictly positive transitions and an acceptance ratio that is approximately equal to a given value χ_0 , as presented in Eq. 16 (BEN-AMEUR, 2004).

$$T_0 = -\frac{\overline{\Delta E}}{\ln(\chi_0)} \quad (16)$$

Where, in this case, the cost increase of strictly positive transitions is the expected value of the error vector considering the observations obtained with the MC simulations accepted by the rejection criteria and the experimental data observations values, ξ_0 , given by Eq. 17.

$$\overline{\Delta E} = E[(\Sigma - \xi_0)] \quad (17)$$

A framework with the complete process, considering both MCM and SA, is presented in Figure 13, and the interface between the two methods is shown below, in Figure 14.

Figure 13 – SA and MCM framework

Figure 14 – SA and MCM interface

It is interesting to note that there is a direct relationship between efficiency and computational cost in this combination of methods. While on the one hand, the SA has the advantage of converging at a low computational cost (compared to MCM), such convergence does not always occur properly, requiring a search neighborhood

restriction, made efficiently by MCM, but requiring more effort. Therefore, the narrower the search neighborhood dimension, most likely the method convergence (higher efficiency with higher cost), and vice-versa. At first, the optimal point for such a relationship should be adjusted empirically for each situation.

The MCM-SA combination algorithm is shown in Figure 15, where N is the number of simulations for the MCM and P the number of parameters to be estimated.

Figure 15 – SA and MCM interface

4.2. Kalman Filter

According to Fang et al. (2018) and Haug (2012), Kalman Filter belongs to a well-known methods family that represents the Bayesian analysis capacity to provide a powerful framework for state estimation, which revolutionized this field and opened many new theoretical and practical possibilities. This method is the closed-form solution to the Bayesian filtering equations for the filtered model, where the dynamic and measurement models are linear Gaussian.

The presence of random dynamic noise makes the stochastic problem significantly different from the least-squares parameter estimation. In the 1940s Andrey Kolmogorov and Norbert Wiener, concerned with modeling unknown stochastic signals corrupted by additive measurement noise, developed their work with an effective modeling concept: they both assumed that the dynamic system could be modeled as a shaping filter excited by white noise (SÄRKKÄ, 2013).

However, Kolmogorov's and Wiener's works had few practical applications due to the assumptions of stationary random processes and steady-state solutions. Many researchers have attempted to extend the theory to nonstationary random processes using time-domain methods. However, in 1960 and 1961 Rudolf Kalman published his papers on discrete and continuous filtering, with a focused design for non-stationary stochastic signals and resulting in a solution with time-varying gains (GIBBS, 2011).

Figure 16 presents the Kalman Filter family tree, according to Paluszek and Thomas (2019), and Figure 17 shows the generic model structure used as the basis of the Kalman filter design.

Figure 16 – The Kalman Filter family tree

Source: Adapted from Paluszek and Thomas (2019)

Figure 17 – Forward model structure assumed by discrete Kalman filter

Source: Gibbs (2011)

Therefore, there are two primary differences between least-squares estimators and the Kalman filter:

- Kalman filters model stochastic system while least squares are used for deterministic systems;
- Kalman filters process measurements recursively while most least-squares implementations use batch processing;

However, the Kalman filter is limited by its assumptions (GIBBS, 2011), and several nonlinear filtering methods along its line have been proposed and developed to overcome its limitations, such as the extended Kalman filter (EKF), unscented Kalman filter (UKF), and ensemble KF (EnKF), three primary members of the KF family, as presented by Fang et al. (2018).

As a linear quadratic estimator, Kalman filters are best designed for estimating linear systems with Gaussian noise. Although the computational requirements to implement Kalman filters are generally low, they are less flexible than other approaches in the Bayesian filtering family.

The generalized framework of a Gaussian filter also enables the use of several powerful Gaussian quadrature and cubature integration methods, enabling derivations such as the Gauss-Hermite Kalman filter (GHKF) and the cubature Kalman filter (CKF).

In this work, a nonlinear variable-gain variation of the Kalman filter is applied. In this case, the filter gain is inversely proportional to the analyzed system rotation speed (in radians per second), causing the parameter estimation to become more refined as the system speed increases.

As mentioned before, in this case, only parameters related to the unbalance force will be estimated. Also, as presented in Michalski (2004), the three fundamental elements of a rotor will be considered (the disk, the shaft, and the bearings), without considering the foundations' influence.

The general motion equation for rotors, in the matrix form, obtained from the Lagrange equations was presented in Eq. 2 (page 16), which can be described as Eq. 19, considering Eq. 18.

$$\mathbf{C} = \mathbf{D} + \Omega \mathbf{G} \quad (18)$$

$$\mathbf{M}\ddot{\mathbf{q}}(t) + \mathbf{C}\dot{\mathbf{q}}(t) + \mathbf{K}\mathbf{q}(t) = \mathbf{F}_{exc}(t) \quad (19)$$

In terms of a state-space problem, and considering Eq. 20, Eq. 19 can be presented in the form of a state system, as Eq. 21 shows.

$$\begin{Bmatrix} \mathbf{x}_2 \\ \mathbf{x}_1 \end{Bmatrix} = \begin{Bmatrix} \dot{\mathbf{q}} \\ \mathbf{q} \end{Bmatrix} \quad (20)$$

$$\begin{cases} \mathbf{M}\dot{\mathbf{x}}_2 + \mathbf{C}\mathbf{x}_2 + \mathbf{K}\mathbf{x}_1 = \mathbf{F}_{exc} \\ \dot{\mathbf{x}}_1 = \mathbf{x}_2 \end{cases} \quad (21)$$

However, as it is desired to estimate the system's external forces, the vector $\mathbf{F}_{exc}$ must be included in the state-vector, expanding the ordinary state-vector. Then, a state-space problem is formulated where the state is a vector containing the generalized coordinates, their derivatives, and the unknown forcing terms. Moreover, since the excitation forces vary in time, there is a derivative. The new state-space system is present by Eq. 22.

$$\begin{cases} \mathbf{M}\dot{\mathbf{x}}_2 + \mathbf{C}\mathbf{x}_2 + \mathbf{K}\mathbf{x}_1 = \mathbf{F}_{exc} \\ \dot{\mathbf{x}}_1 = \mathbf{x}_2 \\ \dot{\mathbf{F}}_{exc} = \mathbf{\Psi}\mathbf{F}_{exc} \end{cases} \quad (22)$$

The matrix $\mathbf{\Psi}$ is a square matrix with many terms equal to zero, excluding the ones related to the nodes where the system's external load acts.

With the forcing vector $\mathbf{F}_{exc}$ as part of the estimation problem, it is considered a new forcing vector, obtained from the output of a linear filter driven by zero-mean Gaussian white noise. Besides that, Eq. 22 can be presented in the matrix form, as shown in Eq. 23.

$$\begin{Bmatrix} \dot{\mathbf{x}}_2 \\ \dot{\mathbf{x}}_1 \\ \dot{\mathbf{F}}_{exc} \end{Bmatrix} = \begin{bmatrix} -\mathbf{C}\mathbf{M}^{-1} & -\mathbf{K}\mathbf{M}^{-1} & \mathbf{M}^{-1} \\ \mathbf{I}_{4n \times 4n} & \mathbf{0}_{4n \times 4n} & \mathbf{0}_{4n \times 4n} \\ \mathbf{0}_{4n \times 4n} & \mathbf{0}_{4n \times 4n} & \mathbf{\Psi}_{4n \times 4n} \end{bmatrix} \begin{Bmatrix} \mathbf{x}_2 \\ \mathbf{x}_1 \\ \mathbf{F}_{exc} \end{Bmatrix} + \begin{bmatrix} \mathbf{M}^{-1} \\ \mathbf{0}_{4n \times 4n} \\ \mathbf{0}_{4n \times 4n} \end{bmatrix} w \quad (23)$$

The Gaussian white noise, w , is defined by Eq. 24, with covariance matrix $\mathbf{Q}$.

$$w \in \mathbb{R}^{4n}, w \sim N(0, \mathbf{Q}) \quad (24)$$

Again, to simplify the presentation, Eq. 23 can be rewritten as equation Eq. 25.

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}w \quad (25)$$

On the other hand, the observation equation for the augmented model can be presented as Eq. 26, and the measurements' inherent errors, v , can be modeled as zero-mean Gaussian noise with covariance matrix $\mathbf{R}$, as defined by Eq. 27.

$$\mathbf{y} = \mathbf{H}\mathbf{x} + v \quad (26)$$

$$v \in \mathbb{R}^2, v \sim N(0, \mathbf{R}) \quad (27)$$

The matrix $\mathbf{H}$ is also a square matrix with most terms equal to zero, excluding the ones related to the node where the measurements are taken. In this way, the rotor dynamic system in the form of state-space equations is represented by Eq. 28.

$$\begin{cases} \dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}w \\ \mathbf{y} = \mathbf{H}\mathbf{x} + v \end{cases} \quad (28)$$

It is important to highlight that the noise sequences, w and v , are considered mutually independent and uncorrelated. The covariance matrices $\mathbf{Q}$, for the state variables, and $\mathbf{R}$, for the measurements, are admitted constant and diagonal.

As the states of the state-space evolve continuously, but the measurements are taken discretely, with a defined sampling rate, the state-space representation is hybrid (continuous-discrete). For computational purposes, the continuous process model can be discretized, using the same sampling rate as used in the measurements.

As mentioned before, this thesis proposes that the data used for the model updating and parameter estimation should be collected under transient conditions (during a machine start-up), increasing the system observability.

In this way, observations will not be made as a function of time, but as a function of each rotational speed to which the rotor is subjected and data collection is performed. Thus, for each rotational speed, Ω_k , the state must be estimated. The discrete state-space model is represented by Eq. 29, below.

$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}w_k \\ \mathbf{y}_k = \mathbf{H}\mathbf{x}_k + v_k \end{cases} \quad (29)$$

Thus, the estimated state $\hat{\mathbf{x}}$ propagation equation is given by Eq. 30, and the state covariance matrix $\mathbf{P}$ propagation is given by Eq. 31. In these cases, the notation $(-)$ represents the priori and the notation $(+)$, the posteriori.

$$\hat{\mathbf{x}}_k^- = \mathbf{A}\hat{\mathbf{x}}_{k-1}^+ \quad (30)$$

$$\mathbf{P}_k^- = \mathbf{A}\mathbf{P}_{k-1}^+\mathbf{A}^T + \mathbf{C}\mathbf{Q}\mathbf{C}^T \quad (31)$$

On other hand, the update equations are given next: the Kalman gain matrix $\mathbf{K}$, given by Eq. 32, the covariance matrix update, given by Eq. 33, and the state update, given by Eq. 34.

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H}\mathbf{P}_k^- \mathbf{H}^T + \mathbf{R})^{-1} \quad (32)$$

$$\mathbf{P}_k^+ = \mathbf{P}_k^- - \mathbf{K}_k \mathbf{H} \mathbf{P}_k^- \quad (33)$$

$$\hat{\mathbf{x}}_k^+ = \mathbf{A} \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{y}_k - \mathbf{H} \hat{\mathbf{x}}_k^-) \quad (34)$$

As mentioned before, the Kalman filter gain is variable, being defined for each step as inversely proportional to the rotation speed, that is, as the rotation increases, the gain decreases. This choice was made primarily to improve Kalman filter convergence. Since data acquisition is done at a machine start-up, at each filter step the rotational speed increases, making the next filter step closer and more refined. At the same time, when the equipment approaches the first critical speed, the unbalance becomes more evident and can be detected more easily (MICHALSKI, MELO, and SOUZA, 2019). Thus, with ever smoother steps and more noticeable unbalance, a better convergence is expected.

The effects of this choice will be evident in the results later presented in this work. In the next chapter, more details will be presented regarding the data-based method that will be used in conjunction with the modeling approach presented in this chapter.

5 PRINCIPAL COMPONENT ANALYSIS

Since an overview of FDD methods has been presented in chapter 3 and a more specific approach to the model-based methods that are applied in this thesis has been presented in chapter 4, this chapter is devoted to the presentation of the PCA, the data-driven method chosen to be applied in this work. The reasons for such a choice as well as a new approach derived from the traditional PCA algorithm are also presented.

As mentioned before, it would be very difficult to define among all FDD methods which one is the best in a general way. This idea applies equally to data-based methods, specifically with the increasing use of existing techniques and the development of new methods. Alauddin et al. (2018) concluded that data-based FDD is a growing research field, but still in the early stages of application in process systems, with potential for broader uses soon.

However, among all data-based techniques, PCA appears constantly in research works, being perhaps one of the earliest, most popular, and better-established data-based approach for the past two decades (YIN et al., 2015; ABDI and WILLIAMS, 2010). Besides being very versatile, PCA differs from other classical statistical approaches in some important aspects: the ability to reduce the proposed problem dimension and to consider correlations between the variables, rather than just the average value, which is essential in pattern analysis.

According to Kadlec, Gabrys, and Strandt (2009), the most popular methods for data-based FDD are the multivariate statistical techniques, i.e., PCA and PLS, which together cover 38% of the applications presented in this review paper.

Jiang, Yan, and Huang (2016) stated that among several multivariate statistical methods, PCA typically serves as the most fundamental technique because of its efficiency in dimension reduction and latent feature extraction.

PCA is a useful statistical technique that has found application in many fields, especially the ones in which finding patterns in multivariate data of high dimension

problems is needed (SARKAR, SAHA and AGRAWAL, 2014; SMITH, 2002), such as big data engineering, machine learning, medical diagnosis techniques, face recognition and image compression.

In cases where the analyzed system has a high complexity, PCA (and its variations) can be very useful to detect abnormal conditions (PINZÓN et al., 2017; MA and JIANG, 2012). The method's fundamental objective is the analysis of a set of data composed of many variables, through its reduction and overlaps elimination, preserving, as much as possible, the variation of the original data (JOLLIFFE, 2002). The idea is to use its synthesis capability, which analyzes monitored data in a more efficient process.

Even when there is a causal model well defined, PCA can be very useful. Nembhard et al. (2013) presented a study considering that current vibration-based maintenance methods can be improved considering further measurements, as bearings' temperature, and using PCA to identify fault patterns in rotating machinery.

A similar idea is considered in Plante et al. (2016), who applied PCA at vibration signals for rotating machine fault detection. Dong et al. (2014) presented a novel method applied to the rotating machinery fault diagnosis problem, based on PCA. Luwei, Yunusa-Kaltungo, and Sha'aban (2018) presented an integrated fault detection framework for classifying rotating machine faults using a hybrid methodology that includes PCA.

Ajami and Daneshvar (2012) presented a method for fault detection and diagnosis in rotating machinery, more specifically a turbine in a thermal power plant, based in PCA and ICA. More recently, Chrétien, Clarkson, and Garcia (2018) applied Robust PCA, a variation of the original method generally used when outliers corrupt the data, to estimate the topology in power grid networks.

PCA is also used as a clustering algorithm when in a scenario of many possible analysis results it is desired to group such responses into a smaller number of sets as shown in Ferraro et al. (2016) and Miranda Filho et al. (2016).

Considering the works of Tidriri et al. (2016), Yin et al. (2014), Yin et al. (2012), and Russel, Chiang, and Braatz (2000), in which PCA is compared to other data-driven

techniques, it is concluded that, in general, PCA presents good results when applied to the linear process that runs under stationary operating conditions.

Evaluating the fault detection rate (FDR) and the false alarm rate (FAR), PCA presents very similar results to other techniques, such as DPCA, FDA, PLS, TPLS, MPLS, ICA, MICA, and SAP, as presented by Yin et al. (2012).

Also, PCA generally preserves some great advantages: it is a stable and robust method, and, very likely, the one with the simplest computational implementation. This feature can be a great advantage in the case of automated implementations, as might be the case with IVHM systems.

Compared to artificial intelligence-based methods, such as ANN and BN, PCA may have a superior speed of detecting changes in a data set and less need for *a priori* requirements. On the other hand, the method has a lower ability to isolate and identify faults, although it is still more adaptable than ANN (and less than BN), as presented by Tidriri et al. (2016). However, these disadvantages can be overcome using models in a hybrid application, as proposed in this thesis.

That is, considering the premise that a system fault could be previously established and identified (using model-based techniques, for example), variations in the system's behavior in steady-state conditions due to defect degradation could be detected (at a low computational cost) with the use of PCA (or one of its variations, as will be presented later), making this method the most consistent choice for this application.

5.1. Principal Component Analysis Fundamentals

This section presents the PCA fundamentals as well as the basic algorithm for calculating the principal components. It should be mentioned that there are some basic mathematical concepts regarding statistics and linear algebra used in PCA, such as standard deviation, covariance, eigenvectors, and eigenvalues, easily found in the literature for further studies. Therefore, they will not be directly addressed in this work, although, it is important to keep in mind that knowing such concepts is fundamental to understanding PCA.

There are four major objectives when applying PCA to a data set: to get the most relevant information from the data set, to reduce the data set dimension keeping only the most relevant information, to clarify the data set characterization, and to measure the variables and observations structures, as presented in Bosisio et al. (2019).

Considering a data set of correlated variables in a matrix form, where lines are the observations and columns the variables, PCA uses an orthogonal transformation to convert this data set into a group of linearly uncorrelated values, the principal components. In other words, PCA transforms discrete variables into uncorrelated coefficients. These new uncorrelated coefficients can be interpreted geometrically as the projections of the observations toward the principal components (ABDI and WILLIAMS, 2010).

PCA is defined in such a way that the principal components are presented in order, as a function of its variance, from the component with the highest variance to the component with the lowest variance. The first component, with the greatest variation, contains most of the data set information. The second component, orthogonal to the first, holds most of the remaining information. The other components are estimated in the same way, successively.

Since PCA focuses on variances, not disregarding covariations and correlations (JOLLIFFE 2002), generally only the first two or three components, with the greatest variance, are considered in the subsequent analyzes.

According to Smith (2002), there are some steps needed to perform a principal components analysis on a data set:

- Step 1: get the data set, $\mathbf{X}_{n \times m}$, which means n samples of m variables.
- Step 2: calculate the mean of each variable in the data set, as presented in Eq. 35.

$$\bar{X}_j = \frac{1}{n} \sum_{i=1}^n X_{ij} \quad (35)$$

- Step 3: subtract the average from each of the data set dimensions. This leads to a new matrix, $\mathbf{B}$, composed of re-centered data with mean equals

to zero, whose element related to the i -th sample and j -th variable is presented in Eq. 36.

$$B_{ij} = X_{ij} - \bar{X}_j \quad (36)$$

- Step 4: calculate the covariance matrix, $\mathbf{S}_B$, presented in Eq. 37, of the new matrix $\mathbf{B}$. Since the data is m dimensional, the covariance matrix will have order m .

$$\mathbf{S}_B = \frac{1}{n-1} \mathbf{B}^T \mathbf{B} \quad (37)$$

- Step 5: calculate the eigenvectors, $\mathbf{v}_B$, and eigenvalues, λ_B , of the covariance matrix, $\mathbf{S}_B$, as presented in Eq. 38.

$$\mathbf{S}_B \mathbf{v}_B = \lambda_B \mathbf{v}_B \quad (38)$$

- Step 6: order the eigenvectors obtained from the covariance matrix by eigenvalues, highest to lowest, creating a new data set matrix arranged so that the first vector corresponds to the largest eigenvalue and the last vector corresponds to the lowest eigenvalue. This way, the components are given in order of significance.

It is important to highlight the role of eigenvalues and eigenvectors for the interpretation of results obtained with PCA. The eigenvalues represent the relative contribution of each component in the analysis of the total variation of the data set. There is an eigenvalue for each component, and its value is a direct indication of the component's importance in the global analysis of the data set variation. That is, the eigenvalue highlights the importance of the component on the total variation of the data.

On the other hand, the eigenvectors are sets of values that represent the relevance, or weight, of each original variable on each new principal component. For each main component, all variables have a set of corresponding eigenvectors, and the higher is the value in the eigenvector, the more important is the variable for the component.

The matrix of eigenvectors is also called the loading matrix. The product of the original data set, $\mathbf{X}_{n \times m}$, by the load matrix, $\mathbf{P}_{m \times m}$, originates the score matrix, $\mathbf{T}_{n \times m}$, which is the projection of the original data set into the principal component subspace (YANG, 2004). This linear transformation is presented in Eq. 39, next.

$$\mathbf{T} = \mathbf{X} \cdot \mathbf{P} \quad (39)$$

According to Yang (2004), a PCA model can be established based on the historical data collected when the process is at a steady-state condition. Then, two statistical measures are generally used to monitor the process: the T^2 score and the Squared Prediction Error (SPE, also known as the Q statistic).

The control limits of these two statistical measures are calculated based on the reference historical data and new observations can be compared to these control limits to detect any abnormal events. The detection by either one of these two methods (T^2 score or Q statistic) is enough to declare that a sample is possibly out-of-control. That is, in basic PCA applications, just monitoring these two values, rather than several process parameters, enables faults detection. However, the basic application of PCA may raise some issues that need to be addressed through variations of the method, as will be presented below.

5.2. A Novel FDD Strategy Based on PCA

Two fundamental statistical assumptions must be considered when applying PCA: measured variables are independent and identically normally distributed, and measured variables are uncorrelated in time (not auto-correlated). As in practice, measurements from dynamic processes generally do not satisfy these two assumptions, the T^2 score and Q statistic results may be affected.

To ensure consistency of PCA results over time, an adaptive process monitoring approach may be needed to accommodate the time-varying process condition, as presented by Yang (2004). Some examples of this type of adaptative process are the Adaptive PCA, whose algorithm updates the PCA model recursively, helping to reduce false alarms; the Moving Principal Component Analysis (MPCA), or Moving Window Principal Component Analysis (MWPCA), in which a moving fixed-length window is

defined, limiting the number of analyzed samples and following the data variation over time, having some advantages in adapting to damage detection (WANG, ZHOU, and CHEN, 2018; HARKAT et al., 2018; AYECH, CHAKOUR, and HARKAT, 2012; RYU, NODA and JUNG, 2011; YANG, 2004) and Multi-Scale Principal Component Analysis (MSPCA), that combines PCA and multiscale data processing techniques, such as wavelets, for Statistical Process Control (SPC) of processes containing parameters of different types, sizes, and scales, from uncorrelated or auto-correlated measurements (YANG, 2004).

Another of the few weaknesses of PCA is its sensitivity to outliers and corrupted values in the analyzed data set (XU, CARAMANIS, and SANGHAVI, 2012). To overcome this issue, Robust PCA can be applied, as presented in Chrétien, Clarkson, and Garcia (2018). Also, PCA is a linear technique while most real processes are nonlinear. Therefore, many extended methods have been developed to address this issue such as Nonlinear PCA based on auto-associative neural networks and Kernel PCA, which can efficiently compute principal components in a high-dimensional feature space using nonlinear kernel functions (TIDRIRI et al., 2016).

In the case of rotating machinery, some of these issues' aspects must be considered in PCA application: data collected in steady-state conditions can be correlated in time and do not follow a specific distribution. Also, changes occur in the equipment operating condition as a function of operating load and/or rotation speed, as well as data fluctuations over time under the same operating condition. Considering that, it is proposed in this work a PCA variation that may be more robust to data correlation, having a variable reference depending on the operating condition, and can follow signals changes over time under the same operating condition.

Thus, it is proposed in this work that the analyzed data matrix be delimited by a fixed-length window, as in MPCA. At the same time, a reference matrix, with the same number of parameters of the analyzed data and with the same number of measurements defined by the mentioned window length, must be included in the analysis process. This PCA-derived process proposal is referred to in this work as Referenced Moving Principal Component Analysis (RMPCA).

In this case, however, the matrix that will be used as input to the RMPCA algorithm must be composed of the data matrix to be evaluated together with the reference matrix, doubling the number of analyzed parameters, as presented in Eq. 40.

$$\mathbf{Z}_{n \times 2m} = [\mathbf{Y}_{n \times m} \mid \mathbf{X}_{n \times m}] \quad (40)$$

In this case, $\mathbf{X}_{n \times m}$ is the original analyzed data set, $\mathbf{Y}_{n \times m}$ is the reference data set, and $\mathbf{Z}_{n \times 2m}$ is the newly analyzed data set. Following the previously presented steps for the PCA algorithm, the mean of each variable in the data set should be calculated, as presented in Eq. 41.

$$\bar{Z}_j = \frac{1}{n} \sum_{i=1}^n Z_{ij} = \begin{cases} \bar{Y}_j = \frac{1}{n} \sum_{i=1}^n Y_{ij} & ; \text{ if } 1 \leq j \leq m \\ \bar{X}_j = \frac{1}{n} \sum_{i=1}^n X_{ij} & ; \text{ if } m+1 \leq j \leq 2m \end{cases} \quad (41)$$

Subtracting the average from each of the data set dimensions leads to a new matrix, $\mathbf{D}_{n \times 2m}$, composed of re-centered data with mean equals to zero, as presented in Eq. 42.

$$\mathbf{D}_{n \times 2m} = [\mathbf{R}_{n \times m} \mid \mathbf{B}_{n \times m}] \quad (42)$$

In this case, however, the new $\mathbf{D}_{n \times 2m}$ matrix represents the junction to matrix $\mathbf{R}_{n \times m}$, relative to the re-centered data reference matrix and matrix $\mathbf{B}_{n \times m}$, relative to the original data matrix in the same way. The element related to the i -th sample and j -th variable of matrix $\mathbf{D}_{n \times 2m}$ is presented in Eq. 43.

$$D_{ij} = \begin{cases} R_{ij} = Y_{ij} - \bar{Y}_j & ; \text{ for } 1 \leq j \leq m \\ B_{ij} = Z_{ij} - \bar{Z}_j & ; \text{ for } m+1 \leq j \leq 2m \end{cases} \quad (43)$$

The new covariance matrix, $\mathbf{S}_d$, is given by Eq. 44.

$$\mathbf{S}_d = \frac{1}{n-1} \begin{bmatrix} \mathbf{R}^T \mathbf{R} & \mathbf{R}^T \mathbf{B} \\ \mathbf{B}^T \mathbf{R} & \mathbf{B}^T \mathbf{B} \end{bmatrix} \quad (44)$$

Note that the covariance matrix can be divided into four quadrants. In the first quadrant is the covariance matrix of the reference data values, $\mathbf{S}_R$, while in the fourth

quadrant is the covariance matrix of the analyzed data, $\mathbf{S}_B$. In the other quadrants are the cross-covariance matrices of the combined data, $\mathbf{S}_C$ and $(\mathbf{S}_C)^T$. To simplify the notation, the covariance matrix, $\mathbf{S}_D$, can be represented by Eq. 45.

$$\mathbf{S}_D = \begin{bmatrix} \mathbf{S}_R & \mathbf{S}_C \\ \mathbf{S}_C^T & \mathbf{S}_B \end{bmatrix} \quad (45)$$

In this proposal, the chosen indexes to evaluate the data behavior are the normalized eigenvalues of the covariance matrix, $\mathbf{S}_D$. This approach is a way to simplify the detection process, without the use of a load or a score matrix. The eigenvalues are calculated in the same way as shown in Eq. 38, and the eigenvalue vector can be represented by Eq. 46, below.

$$\lambda_D = [\lambda_1 \dots \lambda_{2m}]^T \quad (46)$$

The eigenvalue normalization originates the principal component weights (PCw), so-called in this work, alluding to the contribution of each principal component of the data set $\mathbf{D}_{n \times 2m}$. The normalization process is given by Eq. 47, next.

$$PCW_i = \frac{100 \cdot \lambda_i}{\sum_{j=1}^{2m} \lambda_j} \quad (47)$$

As presented by Jolliffe, (2002), generally only the first two or three components are considered in the PCA analysis. Considering that, in this proposition, the first three PCw will be considered to evaluate the analyzed process.

To illustrate how the proposed process works, a data set is used as a reference and three groups of data that would represent different operational conditions of a process are used as analysis data in two examples: the first, in a "static" condition in that a single analysis is performed considering all the observations of the samples, and the second, in a "dynamic" condition in which the analyzed data vary over time with the application of a fixed length mobile window. Next, it is presented in a dedicated section how the proposed method can be implemented in a FDD process.

5.2.1. RPCA application – static example

In this first example of a PCA application, the objective is only to present how the introduction of a reference matrix modifies the results of the PCA analysis. In other words, a mere exercise in presenting the mechanism for modifying the original PCA algorithm and its consequences will be presented.

Considering four data sets, as presented in Table 3. For each data set there are seven samples (being *S1*, *S2*, *S3*, *S4*, *S5*, *S6*, and *S7*, ergo $n = 7$) and three variables (being *V1*, *V2*, and *V3*, ergo $m = 3$). These data sets were randomly generated, but selected in such a way that the behavior of one of the data sets stands out from the others.

Table 3 – Input Data Sets

	Reference Data Set			Input Data Set 1			Input Data Set 2			Input Data Set 3		
	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V1</i>	<i>V2</i>	<i>V3</i>
<i>S1</i>	0.11	0.94	2.07	2.18	1.95	2.17	6.72	-1.38	1.99	1.16	-0.32	0.62
<i>S2</i>	2.47	1.00	1.93	2.20	2.29	2.40	4.51	-1.94	9.18	-0.11	0.82	-1.74
<i>S3</i>	2.32	2.03	1.75	-0.06	2.15	-2.30	4.83	-0.96	10.14	1.16	0.64	0.73
<i>S4</i>	0.02	0.84	1.81	2.32	0.82	2.06	7.52	-0.32	10.63	0.04	0.07	0.80
<i>S5</i>	2.48	2.07	-2.39	0.14	2.29	-2.32	4.68	0.50	8.81	-0.02	0.51	0.84
<i>S6</i>	0.03	0.27	-2.76	-0.04	1.01	-3.04	8.25	2.00	5.79	0.94	0.87	-1.58
<i>S7</i>	2.31	0.49	-2.95	2.10	2.23	3.45	9.10	2.32	10.29	0.02	0.30	0.59

Source: Author

Table 4 below shows some basic statistical values (mean, variance – var, and peak to peak – pk-pk) of each parameter of the data sets presented in the previous table.

Table 4 – Basic Statistics

	Reference Data			Input Data Set 1			Input Data Set 2			Input Data Set 3		
	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V1</i>	<i>V2</i>	<i>V3</i>	<i>V1</i>	<i>V2</i>	<i>V3</i>
mean	1.39	1.09	-0.08	1.26	1.82	0.35	6.51	0.03	8.12	0.45	0.41	0.04
var	1.57	0.50	6.04	1.37	0.40	7.62	3.50	2.71	9.94	0.36	0.18	1.35
pk-pk	2.45	1.80	5.02	2.38	1.47	6.49	4.60	4.26	8.64	1.28	1.18	2.58

Source: Author

The behavior of each variable of the data sets presented in Table 3 can be verified by Figure 18 – for the first variable (first column of each data group, *V1*), Figure 19 –

for the second variable (second column of each data group, V2), and Figure 20 – for the third variable (third column of each data group, V3).

Figure 18 – First Variable (V1) Sample Values

Figure 19 – Second Variable (V2) Sample Values

Figure 20 – Third Variable (V3) Sample Values

It is noted, as mentioned earlier, that in fact one of the data sets stands out from the others from a visual point of view. In this case, data group 2 (in green) has a very different behavior. Besides, the data were selected in such a way that the first data set (in red) has the highest correlation with the reference group (in blue), as shown in Table 5, at the same time that it presents the peak-to-peak and variance values closest to

those of the reference data set (as presented in Table 4), while the second data set has a larger variation in the data (highest pk-pk and variance values in Table 4) and the third data set (in purple), the smaller variation (lowest pk-pk and variance values in Table 4).

Table 5 – Correlation coefficients between Input Data Sets 1, 2, and 3 and the Reference Data

	Input Data Set 1	Input Data Set 2	Input Data Set 3
Reference Data	0.3197	-0.2639	0.0788

Source: Author

To perform data evaluation using the standard PCA approach, primarily the analysis indices (the principal component weights), as defined in Eq. 27, will be calculated for each data set without the addition of a reference in the data matrix, resulting in four groups of PCw. The mean value of each variable should be subtracted from the values of its respective columns for each data group, giving the respective B matrices, zero-centered, as presented in Table 6, being $V1_{rec}$, $V2_{rec}$, and $V3_{rec}$, respectively, the recentered variables $V1$, $V2$, and $V3$ in each data set.

Table 6 – Standard PCA Recentered Data Sets

Reference Data Set			Input Data Set 1			Input Data Set 2			Input Data Set 3		
$V1_{rec}$	$V2_{rec}$	$V3_{rec}$	$V1_{rec}$	$V2_{rec}$	$V3_{rec}$	$V1_{rec}$	$V2_{rec}$	$V3_{rec}$	$V1_{rec}$	$V2_{rec}$	$V3_{rec}$
-1.28	-0.15	2.14	0.92	0.13	1.82	0.21	-1.41	-6.13	0.70	-0.73	0.58
1.08	-0.10	2.00	0.94	0.47	2.06	-2.01	-1.98	1.06	-0.57	0.41	-1.78
0.93	0.94	1.83	-1.32	0.33	-2.65	-1.69	-0.99	2.02	0.71	0.23	0.69
-1.37	-0.25	1.89	1.06	-1.00	1.72	1.00	-0.35	2.51	-0.41	-0.35	0.76
1.08	0.98	-2.31	-1.13	0.47	-2.67	-1.84	0.47	0.69	-0.48	0.10	0.81
-1.36	-0.82	-2.68	-1.30	-0.80	-3.38	1.73	1.97	-2.33	0.48	0.45	-1.62
0.92	-0.60	-2.87	0.83	0.41	3.11	2.59	2.28	2.17	-0.44	-0.11	0.55

Source: Author

Then, the covariance matrix is computed for each recentered data group, presented in Table 7. Next, the eigenvalues (λ_1 , λ_2 , and λ_3) of the covariance matrices are obtained, as presented in Table 8, and normalized according Eq. 47 to achieve the data set PCw (PCw 1, PCw 2, and PCw 3) results, presented in Table 9.

Table 7 – Standard PCA Covariance Matrices

Reference Data Set			Input Data Set 1			Input Data Set 2			Input Data Set 3		
1.57	0.49	-0.49	1.37	-0.01	3.15	3.50	2.24	-0.67	0.36	-0.04	0.03
0.49	0.50	0.40	-0.01	0.40	0.22	2.24	2.71	0.72	-0.04	0.18	-0.33
-0.49	0.40	6.04	3.15	0.22	7.62	-0.67	0.72	9.94	0.03	-0.33	1.35

Source: Author

Table 8 – Standard PCA Eigenvalues

Reference Data Set			Input Data Set 1			Input Data Set 2			Input Data Set 3		
λ_1	λ_2	λ_3	λ_1	λ_2	λ_3	λ_1	λ_2	λ_3	λ_1	λ_2	λ_3
6.12	1.74	0.25	8.94	0.42	0.03	10.05	5.39	0.72	1.44	0.36	0.09

Source: Author

Table 9 – Standard Normalized PCA PCw

Reference Data Set			Input Data Set 1			Input Data Set 2			Input Data Set 3		
PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3
75.45	21.42	3.13	95.19	4.46	0.35	62.18	33.33	4.48	76.15	18.88	4.96

Source: Author

Regarding the results presented in Table 9, it can be considered that the approximation or distancing of two groups of data occurs, in this case, from the distance of the weights found for each principal component. Thus, considering the Euclidean distance, d_j , given by Eq. 48, the distance between each data set, j , and the reference data can be found, as shown in Table 10.

$$d_j = \sqrt{\sum_{i=1}^3 \left[(\text{PCw } i)_{\text{reference data}} - (\text{PCw } i)_{\text{data set } j} \right]^2} \quad (48)$$

Table 10 – Euclidean distance between the Reference Data and each Input Data Set

	Input Data Set 1	Input Data Set 2	Input Data Set 3
Reference Data	26.1753	17.8830	3.2073

Source: Author

It is observed that the obtained results presented in Table 10 does not follow the same assumption predicted from the statistical data of the data groups presented in Table 4 and Table 5. From the former results, it could be concluded that data set 1 would have the greatest similarity with the reference data set (the differences between the peak-to-peak value and the variance for each variable are the smallest between data set 1 and the reference data).

On the other hand, Table 10 results show just the opposite, i.e., that the data in group 1 are further to the reference data than the others since the Euclidian distance between the results from this data set and the reference data set is the greatest among all. In this case, data set 3 becomes the data group closest to the reference data. That is, the results obtained with the original PCA algorithm have little adherence with the statistical observations and the data dynamics itself.

Now, considering the RPCA algorithm and the previous reference data, the new data sets and the recentered data are presented in Table 11. It must be said that both the input data matrix and the reference matrix are identified in each case following the presentation of Eq. 40 in which $\mathbf{X}$ refers to the analyzed data set and $\mathbf{Y}$ refers to the reference data set.

Table 11 – RPCA Input and Recentered Data Sets

	Input Data Set						Recentered Data Set					
	X			Y			X			Y		
X = Reference Y = Reference	0.11	0.94	2.07	0.11	0.94	2.07	-1.28	-0.15	2.14	-1.28	-0.15	2.14
	2.47	1.00	1.93	2.47	1.00	1.93	1.08	-0.10	2.00	1.08	-0.10	2.00
	2.32	2.03	1.75	2.32	2.03	1.75	0.93	0.94	1.83	0.93	0.94	1.83
	0.02	0.84	1.81	0.02	0.84	1.81	-1.37	-0.25	1.89	-1.37	-0.25	1.89
	2.48	2.07	-2.39	2.48	2.07	-2.39	1.08	0.98	-2.31	1.08	0.98	-2.31
	0.03	0.27	-2.76	0.03	0.27	-2.76	-1.36	-0.82	-2.68	-1.36	-0.82	-2.68
	2.31	0.49	-2.95	2.31	0.49	-2.95	0.92	-0.60	-2.87	0.92	-0.60	-2.87
X = Data Set 1 Y = Reference	0.11	0.94	2.07	2.18	1.95	2.17	-1.28	-0.15	2.14	0.92	0.13	1.82
	2.47	1.00	1.93	2.20	2.29	2.40	1.08	-0.10	2.00	0.94	0.47	2.06
	2.32	2.03	1.75	-0.06	2.15	-2.30	0.93	0.94	1.83	-1.32	0.33	-2.65
	0.02	0.84	1.81	2.32	0.82	2.06	-1.37	-0.25	1.89	1.06	-1.00	1.72
	2.48	2.07	-2.39	0.14	2.29	-2.32	1.08	0.98	-2.31	-1.13	0.47	-2.67
	0.03	0.27	-2.76	-0.04	1.01	-3.04	-1.36	-0.82	-2.68	-1.30	-0.80	-3.38
	2.31	0.49	-2.95	2.10	2.23	3.45	0.92	-0.60	-2.87	0.83	0.41	3.11
X = Data Set 2 Y = Reference	0.11	0.94	2.07	6.72	-1.38	1.99	-1.28	-0.15	2.14	0.21	-1.41	-6.13
	2.47	1.00	1.93	4.51	-1.94	9.18	1.08	-0.10	2.00	-2.01	-1.98	1.06
	2.32	2.03	1.75	4.83	-0.96	10.14	0.93	0.94	1.83	-1.69	-0.99	2.02
	0.02	0.84	1.81	7.52	-0.32	10.63	-1.37	-0.25	1.89	1.00	-0.35	2.51
	2.48	2.07	-2.39	4.68	0.50	8.81	1.08	0.98	-2.31	-1.84	0.47	0.69
	0.03	0.27	-2.76	8.25	2.00	5.79	-1.36	-0.82	-2.68	1.73	1.97	-2.33
	2.31	0.49	-2.95	9.10	2.32	10.29	0.92	-0.60	-2.87	2.59	2.28	2.17
X = Data Set 3 Y = Reference	0.11	0.94	2.07	1.16	-0.32	0.62	-1.28	-0.15	2.14	0.70	-0.73	0.58
	2.47	1.00	1.93	-0.11	0.82	-1.74	1.08	-0.10	2.00	-0.57	0.41	-1.78
	2.32	2.03	1.75	1.16	0.64	0.73	0.93	0.94	1.83	0.71	0.23	0.69
	0.02	0.84	1.81	0.04	0.07	0.80	-1.37	-0.25	1.89	-0.41	-0.35	0.76
	2.48	2.07	-2.39	-0.02	0.51	0.84	1.08	0.98	-2.31	-0.48	0.10	0.81
	0.03	0.27	-2.76	0.94	0.87	-1.58	-1.36	-0.82	-2.68	0.48	0.45	-1.62
	2.31	0.49	-2.95	0.02	0.30	0.59	0.92	-0.60	-2.87	-0.44	-0.11	0.55

Source: Author

From the recentered data, the covariance matrices are obtained and presented in Table 12 (following the same structure presented in Eq. 45, highlighting each quadrant to facilitate understanding of the origin of each value), followed by the eigenvalues, calculated and normalized to get the PCw of each data set, presented in Table 13.

Table 12 – RPCA Covariance Matrices

X = Reference Y = Reference	1.57	0.49	-0.49	1.57	0.49	-0.49
	0.49	0.50	0.40	0.49	0.50	0.40
	-0.49	0.40	6.04	-0.49	0.40	6.04
X = Data Set 1 Y = Reference	1.57	0.49	-0.49	1.57	0.49	-0.49
	0.49	0.50	0.40	0.49	0.50	0.40
	-0.49	0.40	6.04	-0.49	0.40	6.04
X = Data Set 2 Y = Reference	1.57	0.49	-0.49	-0.25	0.67	-0.06
	0.49	0.50	0.40	-0.38	0.23	-0.85
	-0.49	0.40	6.04	1.19	-0.03	2.12
X = Data Set 3 Y = Reference	-0.25	-0.38	1.19	1.37	-0.01	3.15
	0.67	0.23	-0.03	-0.01	0.40	0.22
	-0.06	-0.85	2.12	3.15	0.22	7.62
X = Data Set 1 Y = Data Set 1	1.57	0.49	-0.49	-1.22	-0.14	2.22
	0.49	0.50	0.40	-1.08	-0.50	0.56
	-0.49	0.40	6.04	-2.10	-3.72	-0.69
X = Data Set 1 Y = Data Set 2	-1.22	-1.08	-2.10	3.50	2.24	-0.67
	-0.14	-0.50	-3.72	2.24	2.71	0.72
	2.22	0.56	-0.69	-0.67	0.72	9.94
X = Data Set 1 Y = Data Set 3	1.57	0.49	-0.49	-0.31	0.24	0.09
	0.49	0.50	0.40	0.02	0.03	0.39
	-0.49	0.40	6.04	0.33	-0.35	0.21
X = Data Set 2 Y = Data Set 2	-0.31	0.02	0.33	0.36	-0.04	0.03
	0.24	0.03	-0.35	-0.04	0.18	-0.33
	0.09	0.39	0.21	0.03	-0.33	1.35

Source: Author

Table 13 – RPCA Eigenvalues and PCw

	Eigenvalues	PCw
X = Reference Y = Reference	12.23	75.45
	3.47	21.42
	0.51	3.13
	0.00	0.00
	0.00	0.00
	0.00	0.00
X = Data Set 1 Y = Reference	10.36	59.20
	4.87	27.81
	2.05	11.72
	0.12	0.70
	0.08	0.47
	0.02	0.11
X = Data Set 2 Y = Reference	10.95	45.14
	9.81	40.41
	2.93	12.06
	0.42	1.72
	0.15	0.60
	0.02	0.07
X = Data Set 3 Y = Reference	6.18	61.74
	1.89	18.94
	1.43	14.25
	0.35	3.45
	0.13	1.35
	0.03	0.27

Source: Author

Evaluating the Euclidean distance between the results, as shown in Table 10, and considering just the first three PCw, since the Cumulative Percentage of Total Variation (CPV) is greater than 95%, it is noted that the results obtained with the data set 2 become the farthest to the results obtained with the reference data, while the results of data set 1 and 3 have similar values and are closer to the results of the reference data, as presented in Table 14.

Table 14 – Euclidean distance between the Reference Data and each Input Data Set considering the RPCA algorithm

	X = Data Set 1 Y = Reference	X = Data Set 2 Y = Reference	X = Data Set 3 Y = Reference
X = Reference Y = Reference	19.4585	36.8693	17.8220

Source: Author

It must be said that the CPV is obtained from the sum of the weights of each principal component considered, or, in other words, the sum of the ordered and normalized eigenvalues. It represents the percentage of the variance of the original dataset carried by the new dataset, i.e., the PCA eigenvectors (JOLLIFFE, 2002).

As can be observed from the results presented in Table 14, obtained for each data set with the RPCA algorithm, with the inclusion of reference values there is a greater coherence between the PCA results and the data sets' behaviors and its statistical evaluation (presented in Table 4 and Table 5), that is, in spite of not showing the least correlation in absolute values with the reference data, the second group of data is the one that presents the biggest difference in terms of data variation. And, in fact, it is exactly such a difference that the results shown in Table 14 demonstrate.

Note that the PCw results obtained from the standard PCA for the reference data set are identical to those obtained with the modified algorithm (RPCA) for the same data. The eigenvalues, however, double in value in the second case. That is, by doubling the input dimension to the number of parameters of the reference matrix, the eigenvalues results have twice the value obtained with the standard algorithm, but the relationship between them is not changed, i.e., the weight of each principal component in the variance of the analyzed data variables.

Based on the previous analysis, it can be concluded that the application of a reference matrix in relation to itself, that is, the matrix of analyzed data is self-referenced, being composed of the duplicated reference matrix, does not change the original result of the proposed PCA algorithm evaluation, therefore having no practical effect. Thus, in future applications of this algorithm in this work, self-referencing will be avoided, that is, the analyzed data will not be equal to the reference data ($\mathbf{X}_{n \times m} \neq \mathbf{Y}_{n \times m}$).

5.2.2. RMPCA application – dynamic example

In the second example of PCA application, the objective is to present how the introduction of a moving fixed-length window and a reference matrix modifies the results from the standard PCA analysis.

The same data set previously used will be considered in this example. However, in this case, the four data sets will be concatenated into a single set for each variable, as presented in Table 14 and Figure 21. In this case, the data set has twenty-eight samples ($n = 28$) and three variables ($m = 3$).

Table 14 – Concatenated Data

Index	Variable 1 (V1)	Variable 2 (V2)	Variable 3 (V3)
1	0.11	0.94	2.07
2	2.47	1.00	1.93
3	2.32	2.03	1.75
4	0.02	0.84	1.81
5	2.48	2.07	-2.39
6	0.03	0.27	-2.76
7	2.31	0.49	-2.95
8	2.18	1.95	2.16
9	2.20	2.29	2.40
10	-0.06	2.15	-2.30
11	2.32	0.82	2.06
12	0.14	2.29	-2.32
13	-0.04	1.01	-3.04
14	2.10	2.23	3.45
15	6.72	-1.38	1.99
16	4.51	-1.94	9.18
17	4.83	-0.96	10.14
18	7.52	-0.32	10.63
19	4.68	0.50	8.81
20	8.25	2.00	5.79
21	9.10	2.32	10.29
22	1.16	-0.32	0.62
23	-0.11	0.82	-1.74
24	1.16	0.64	0.73
25	0.04	0.07	0.80
26	-0.02	0.51	0.84
27	0.94	0.87	-1.58
28	0.02	0.30	0.59

Source: Author

Figure 21 – Concatenated Variables

In this case, as in the first example, two approaches will be compared: the first in which a moving fixed-length window is considered, without the reference matrix being included in the algorithm and the second, in which, in addition to the sliding window, the reference matrix will be included in the PCA algorithm.

It is considered in these cases a window size equals seven, the same size as the number of samples from each original data set, and self-referenced data will be disregarded. Thus, for the first seven values of each variable, there will be no result for the PCw. Only from the eighth index value will there be a result for the RMPCA algorithm, allowing the data window to be completely considered without self-referenced data.

Thus, from the eighth to the twenty-eighth value, the window slides step by step, adding the next index in the row and removing the lowest index value (thus keeping the window size fixed), totalizing twenty-one data sets windows. A simplified representation of this process is given in Figure 22.

Figure 22 – Fixed-length window sliding process

Given the window sliding process over the considered data, two approaches, as mentioned before, will be taken: in the first, only the variant data samples as a function of the window sliding will be considered; in the second, in addition to each data sample from the above-mentioned moving window, the reference data sample is also considered. The obtained results from both processes are presented in Table 15.

Table 15 – PCw Results for RMPCA

Index	Results without Reference				Results with Reference			
	PCw 1	PCw 2	PCw 3	Sum	PCw 1	PCw 2	PCw 3	Sum
1	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-
6	-	-	-	-	-	-	-	-
7	-	-	-	-	-	-	-	-
8	77.99	18.78	3.23	100	54.00	26.59	15.07	96
9	80.12	18.28	1.60	100	49.71	32.26	9.52	91
10	75.91	18.02	6.07	100	55.74	24.63	9.50	90
11	81.60	10.96	7.44	100	56.40	23.93	12.63	93
12	83.90	12.29	3.81	100	47.90	35.12	10.09	93
13	85.95	11.96	2.09	100	56.01	33.39	6.36	96
14	95.19	4.46	0.35	100	59.20	27.81	11.72	99
15	76.99	21.89	1.12	100	56.47	25.81	12.66	95
16	85.71	12.04	2.25	100	79.89	12.67	4.77	97
17	87.74	10.44	1.82	100	82.35	12.71	3.10	98
18	89.54	8.13	2.33	100	85.65	8.08	2.71	96
19	86.30	10.63	3.07	100	78.20	9.63	6.40	94
20	64.42	23.51	12.07	100	50.03	29.22	16.56	96
21	62.18	33.33	4.48	100	45.14	40.41	12.06	98
22	74.32	23.83	1.85	100	60.21	30.88	6.18	97
23	88.48	10.60	0.93	100	79.65	11.04	6.11	97
24	92.92	6.20	0.88	100	89.35	5.29	3.52	98
25	93.56	6.02	0.42	100	85.14	7.54	5.16	98
26	96.66	2.82	0.52	100	82.39	11.69	4.11	98
27	96.80	2.63	0.57	100	79.52	13.89	3.73	97
28	76.15	18.88	4.96	100	61.74	18.94	14.25	95

Source: Author

Note that in the non-referenced case, the input data set has only three variables, and thus only three principal components are generated with PCA. In this way, the sum of the weights of these three components (CPV) is always equal to 100%. In the referenced case, the number of "variables" in the input data doubles, and so the result of the PCA has six principal components. Even so, the sum of the weights of the first

three components is always greater than 90%, that is, the first three components retain at least 90% of the variability of the data considered.

Figure 23 and Figure 24 show the graphic representation of the respective results for the PCw without and with the reference data sample. Note that with the application of the reference data and the moving fixed-length window the results of PCw over time travel more significantly, increasing the distance between the maximum value and the minimum value calculated for each PCw, which translates into greater sensitivity of the method.

Figure 23 – PCw results without the reference data sample

Figure 24 – PCw results with the reference data sample

Without the use of a data reference, the effect of data variation on calculated PCw is not noticed in the same way. In fact, in the example presented, the detection of variation in data from the fifteenth index is not noticed without the use of a reference.

The greatest difference between the results is in the transition between the first and second half of the concatenated signal when the three variables change variance and DC level. Without the use of a reference, the values found for PCw fluctuate without allowing an exact notion of when such a transition occurs, while with the use of a reference, beyond the sliding window, such a transition becomes evident, as presented in Figure 25.

Figure 25 – Comparison between PCw results with and without reference data sample

5.2.3. RMPCA implementation

Once the RMPCA mathematical foundation has been presented, as well as its operating mechanism, this section will present a framework for implementing the method focused on the systems FDD process.

Next, Figure 26 presents a framework with the RMPCA implementation process. The first step is to define the data parameters, that is, the observations' window size, the number of variables analyzed, and the reference date. The latter refers to the moment when it is known that the analyzed system is in a healthy condition. As the RMPCA method is unsupervised, this reference is necessary for it to detect variations in the monitored data and caused by possible failures in the analyzed system.

Then, from the definition of such parameters, the data can be acquired from a database, or even from real-time measurements, so that the original input matrices and the reference matrix can be selected, originating the data matrix to be analyzed, $\mathbf{Z}$, as presented in Eq. 40.

With the data set matrices assembled, they can be inserted in the PCA algorithm, originating the weights of the principal components over time. For the detection to be carried out in this case, it is only necessary to establish an evaluation criterion in relation to the weights of the main components considered, such as, for example, limit values that, if exceeded, would indicate the presence of a system failure.

Figure 26 – RMPCA implementation process framework

6 PROPOSED FRAMEWORK

This chapter presents the architecture that unifies model-based methods and data-based methods, proposing the hybrid method that is the major contribution of this thesis.

The increasing need to integrate more information and knowledge into contemporary rotating machinery FDD leads to the development of new techniques based on methods that are still underexplored by the reliability area, but there are often already consolidated in other areas of engineering.

This is the case of modeling and analysis approaches based on mathematical and numerical models, inverse problems, and parameter estimation to support model updating and data-driven statistical methods for fault detection and analysis. The major issue is to integrate these techniques in a convenient and applicable algorithm, considering a clear and concise framework.

From a general perspective, the proposed hybrid method can be divided into four steps: data acquisition, modeling, simulation, and detection. Figure 27 presents this simplified approach.

Figure 27 – Simplified Framework

Considering the first step, the data acquisition, as mentioned earlier two techniques are considered: steady-state data acquisition and transient data acquisition (in this work case, during a machine start-up). The data collected from the latter condition is used in the modeling phase to update the considered model, while data collected from the former condition is used to detect and diagnose faults in the analyzed equipment.

Concerning the second step, modeling, some general aspects deserve attention, regardless of the used method. Usually, geometrical and inertia parameters of the modeled equipment are previously known since they are directly related to the equipment design. Similarly, the shaft stiffness can be calculated from its geometry and material properties, also generally known as *a priori*. On the other hand, the bearings' stiffness and damping coefficients, as well as the foundation parameters, when applied, are not always previously known, and can become a great source of uncertainties in the machine model. The prior knowledge of such values is determinant

in the selection of the equipment modeling method. However, the most fundamental aspects of the modeling step are estimating previously existing faults in the analyzed equipment and developing a model that can simulate the machine behavior under both the initially observed degradation condition and future degradation condition estimates.

After the model development, follows the simulation step. In this phase, the equipment dynamic response is simulated in a steady-state condition. It is important to highlight that the simulated response of a mathematical model does not include the noise naturally present in the data collected from the real machine. Thus, for more realistic results, the noise observed in real data should be added to the simulated data.

Having the simulated data in hand, the framework proceeds to the detection step. Considering simulated data under different fault conditions, a theoretical fault mapping can be built in this phase, from the results of the considered data-based method. Applying the same data-based algorithm to real data, it is possible to compare the theoretical and real results in the same operational conditions. In this way, the considered fault can be detected in the analyzed equipment and its degradation state can be estimated by comparing the results from real data to the previously performed mapping. The diagnosis, in this case, is previously defined once the failure is already determined.

Figure 28 shows the proposed framework detailing each mentioned step and considering the previous methods already presented in this work. Note that the same color scheme used to identify the four steps shown in Figure 27 is used in this case.

Figure 28 – Proposed framework

In this case, the modeling-related step has two decision points, since two different methods for forwarding problem solving and other two different methods for parameter estimation and model update were considered. In the detection step case, however, only PCA (RMPCA) is considered, since this was the data-driven method chosen to be applied in this thesis. Still, regarding the detection step, the only fault mapped is the unbalance, chosen as the example of application in this thesis.

As presented in the proposed framework, the greatest novelty of this approach is the combination of the qualities and strengths of the modeling tools and an unsupervised multiparametric statistical method. In this way, the result is an FDD tool that can identify and quantify (in real-time) a pre-established fault in a rotating system. Since RMPCA is an unsupervised method, its application does not require prior knowledge about the monitored data behavior due to the presence of a fault in the analyzed equipment. With the changes made in the traditional PCA algorithm, the method has a dynamic response that allows the monitoring of variations in the data observed over time, while maintaining a reference of the machine in a healthy condition that allows, as the equipment degrades due to the considered fault, a better distinction between the healthy and unhealthy conditions.

In the next chapter are presented the results obtained from the application of this framework in three distinct situations, considering a theoretical Jeffcott rotor, a test rig Jeffcott rotor, and a centrifugal compressor used in FPSO.

7 APPLICATIONS AND RESULTS

To prove the viability of the proposed method, this chapter presents some applications considering the previous framework.

Three distinct situations were considered for the analysis:

- A theoretical Jeffcott rotor, for which is used the Rayleigh-Ritz method for the forward problem solution and the combined Monte Carlo and Simulated Annealing methods for the parameter's estimation (bearings' stiffness and damping coefficients, and unbalance level);
- A Jeffcott horizontal rotor of a laboratory test rig, in which FEM is used for forwarding problem solving and the Kalman filter for parameter estimation (in this case, just the level of unbalancing);
- A centrifugal compressor used in an FPSO, modeled as the previous case using the FEM and Kalman Filter to estimate the level of unbalancing.

In all cases, PCA is used as the data-based method for mapping unbalance from different hypothetical situations. The results are presented in sections 7.1, 7.2, and 7.3. In the test rig rotor case, a comparison of actual and simulated results can be made for which the level of unbalance is considered constant and the machine rotating speed varies, presented in section 7.4. At the end of the chapter, section 7.4, a discussion regarding the obtained results is presented.

7.1. Theoretical Jeffcott Rotor

The first application of the proposed framework in this thesis takes into account a theoretical horizontal rotating machinery, that is, only simulated data is considered.

The analyzed rotating machinery is a symmetrical Jeffcott rotor based on an experimental test rig with previously known behavior (MICHALSKI, 2004). The rotor consists of a disc, with more than 65% of the system inertia, a continuous and flexible shaft, which is supported by two hydrodynamic journal bearings. The only fault considered in the system is a residual mechanical unbalance.

Only the first flexible mode of vibration is considered in the system response, and the dynamics of the system can be simplified to just the disc dynamics, so few degrees of freedom are needed to describe it. Therefore, the rotor is modeled as a mass-spring-damper system with two degrees of freedom. The unbalance is modeled as a synchronous load and the bearings' stiffness and damping are considered *a priori* unknown parameters.

Considering the method framework presented in Figure 28, since the use of a few degrees of freedom is satisfactory for modeling, the Rayleigh-Ritz method is used for the forward problem solution. On the other hand, as more than one parameter will be estimated, the combination of Monte Carlo and Simulated Annealing methods is applied for model updating.

All analysis and simulations of model-based methods were performed using codes developed by the author in the Wolfram Mathematica 11 software while data-based methods analyses were developed using LabView software.

7.1.1. Rotor modeling

As previously mentioned, the rotor under analysis is a symmetrical Jeffcott rotor with a single central disc and supported by two hydrodynamic journal bearings. The schematic model is presented in Figure 29.

Figure 29 – Jeffcott model

In the presented schematic model k_{xx} and k_{yy} , are the bearings' stiffness coefficients respectively in the horizontal and vertical directions; c_{xx} and c_{yy} , are the bearings' damping coefficients, also in the horizontal and vertical directions; l_e and d_e are the shaft total length and diameter; l_m is the shaft span between bearings; d_d and e_d are the disk diameter and thickness, and u and v are the horizontal and vertical displacements considered in the generalized coordinators' vector.

This model is based on an experimental test rig located in the Vibration and Acoustic Laboratory (LAVI) of the Department of Mechanical Engineering at the Federal University of Rio de Janeiro. An image of the test rig is shown in Figure 30.

Figure 30 – Test rig

The system's equations of motion can be obtained from the Lagrange equations. The spatial portion of the chosen displacement is represented by the first vibration mode, according to Eq. 49. The first-order derivative, related to the shaft rotations, and the second-order derivative required for the potential energy expression are represented by Eq. 50 and Eq. 51, respectively.

$$f(z) = \sin\left(\frac{\pi z}{l_m}\right) \quad (49)$$

$$g(z) = \partial_z f(z) = \frac{\pi}{l_m} \cos\left(\frac{\pi z}{l_m}\right) \quad (50)$$

$$h(z) = \partial_z g(z) = -\left(\frac{\pi}{l_m}\right)^2 \sin\left(\frac{\pi z}{l_m}\right) \quad (51)$$

Developing the Lagrange equations and considering Eq. 49, Eq. 50, and Eq. 51, the inertia, gyroscopic, and shaft stiffness terms are defined, respectively represented by Eq. 52, Eq. 53, and Eq. 54, which will be used in the system's equations of motion.

$$m = m_d f^2\left(\frac{l_m}{2}\right) + I_d g^2\left(\frac{l_m}{2}\right) + \rho_e S_e \int_0^{l_t} f^2(z) dz + \rho_e I_e \int_0^{l_t} g^2(z) dz \quad (52)$$

$$a = J_d g^2\left(\frac{l_m}{2}\right) + 2\rho_e I_e \int_0^{l_t} g^2(z) dz \quad (53)$$

$$k_e = E_e I_e \int_0^{l_t} h^2(z) dz \quad (54)$$

On the other hand, the system's equations of motion regarding the horizontal and vertical directions are given by Eq. 2 (page 16), where each term is represented by Eq. 55 through Eq. 60.

$$\mathbf{M} = \begin{bmatrix} m & 0 \\ 0 & m \end{bmatrix} \quad (55)$$

$$\mathbf{G} = \begin{bmatrix} 0 & -a \\ -a & 0 \end{bmatrix} \quad (56)$$

$$\mathbf{C} = \begin{bmatrix} c_x & 0 \\ 0 & c_y \end{bmatrix} \quad (57)$$

$$\mathbf{K} = \begin{bmatrix} k_x & 0 \\ 0 & k_y \end{bmatrix} \quad (58)$$

$$\mathbf{q}(t) = \begin{bmatrix} u(t) \\ v(t) \end{bmatrix} \quad (59)$$

$$\mathbf{F}_{exc} = \begin{bmatrix} m_u \varepsilon \Omega^2 \sin(\Omega t) \\ m_v \varepsilon \Omega^2 \cos(\Omega t) \end{bmatrix} \quad (60)$$

Special attention must be given to Eq. 60, representing the external forces vector, which in this case consists exclusively of the unbalance force, described by two components, horizontal and vertical, where m_u is the unbalance mass, ε is the unbalance eccentricity, and Ω is the shaft rotation speed. The product $m_u \cdot \varepsilon$ is the unbalance rate, or just unbalance and is the major value to be estimated in this case, representing the analyzed fault quantification.

The terms of damping and stiffness presented in Eq. 57 and Eq. 58 are obtained from the equivalent stiffness and damping equations presented in Eq. 61 and Eq. 62 (considering the horizontal direction), being k_e the shaft stiffness. The same expressions can be obtained in the vertical direction replacing the "x" indices with "y" in each equation.

$$k_x = \frac{1}{\frac{1}{2k_{xx}} + \frac{1}{k_e}} \quad (61)$$

$$c_x = \frac{c_{xx}}{2} \quad (62)$$

The considered equivalent system is presented below, in Figure 31.

Figure 31 – Jeffcott rotor system equivalence

Considering the damped system, the solution of the equations is given by the forms presented in Eq. 63 and Eq. 64, next.

$$u(t) = A_x \sin(\Omega t) + B_x \cos(\Omega t) \quad (63)$$

$$v(t) = A_y \sin(\Omega t) + B_y \cos(\Omega t) \quad (64)$$

Substituting Eq. 63 and Eq. 64 in Eq. 2 (page 16), a system of linear equations is obtained, which can be presented by Eq. 65 in the matrix form.

$$\begin{bmatrix} k_x - m\Omega^2 & -c_x\Omega & 0 & a\Omega^2 \\ c_x\Omega & k_x - m\Omega^2 & -a\Omega^2 & 0 \\ 0 & -a\Omega^2 & k_y - m\Omega^2 & -c_y\Omega \\ a\Omega^2 & 0 & c_y\Omega & k_y - m\Omega^2 \end{bmatrix} \begin{bmatrix} A_x \\ B_x \\ A_y \\ B_y \end{bmatrix} = \begin{bmatrix} m_u \varepsilon \Omega^2 \\ 0 \\ 0 \\ m_u \varepsilon \Omega^2 \end{bmatrix} \quad (65)$$

For further simplification of the problem, the bearings' proportional damping premise is also considered. Thus, Eq. 66 defines the relationship between the bearings' stiffness and damping in each direction, where β is the proportional factor (SCHWARZ and RICHARDSON, 2013).

$$\begin{bmatrix} c_x & 0 \\ 0 & c_y \end{bmatrix} = \beta \begin{bmatrix} k_x & 0 \\ 0 & k_y \end{bmatrix} \quad (66)$$

The solution of Eq. 65 applied to Eq. 63 and Eq. 64 defines the rotor displacement as a function of the frequency in the two considered directions. The maximum displacement value occurs at the rotor critical speed and since these two pieces of information are previously known, they can be considered at the problem solution to determine the system unknown parameters, as will be better discussed.

7.1.2. The model transient exact solution

Considering the displacement solution as a function of the frequency in the two considered directions, Table 17 presents the parameters considered in the exact model simulation and Figure 32 shows the Frequency Response Function (FRF) obtained for the exact system (being $u(t)$ the horizontal displacement and $v(t)$ the vertical displacement).

Table 17 – Exact model parameters

Parameters	Values
d_d	110 mm
e_d	15 mm
l_e	540 mm
l_m	420 mm
d_e	12 mm
ρ	7800 kg/m ³
E	2.0 x 10 ¹¹ Pa
$m_{u,\varepsilon}$	0.000875 kg.m
k_{xx}	0.9 x 10 ⁷ N/m
k_{yy}	1.0 x 10 ⁷ N/m
β	4.0 x 10 ⁻⁵ s

Source: Author

Figure 32 – Exact model simulation FRF

Table 18 presents the maximum amplitude and critical speed values for each direction considered.

Table 18 – Exact model results for maximum amplitude and critical speed

Parameters	Values
U_{max}	1.44 mm
V_{max}	1.59 mm
Ω_x	53.26 Hz
Ω_y	53.94 Hz

Source: Author

7.1.3. Parameter's estimation

Once the system response is known, which in this case will be used instead of monitored data, the next step is to update the model estimating the unknown parameters.

Model updating

The chosen model is the same one previously used to estimate the system response. In making such a choice, the “inverse crime” is committed (KAIPLO and SOMERSALO, 2005). However, for a first application of the proposed method, where the main objective is to develop the method itself, such an issue is not considered a major problem.

The estimated parameters, as mentioned above, are those related to the unbalance force, and the bearings' stiffness and damping coefficients, that is, the bearing stiffness coefficients, the proportional damping factor, and the level of unbalance. On the other hand, the observed variables considered are the maximum amplitude and critical speed in each direction.

Considering the Bayes formula to the proposed problem, Eq. 15 (page 68), both unknown parameters, given by Eq. 67, and observable variables, given by Eq. 68, are considered random variables.

$$\Theta = (k_{xx}, k_{yy}, \beta, m_u, \varepsilon) \quad (67)$$

$$\Sigma = (u_{\max}, v_{\max}, \Omega_c) \quad (68)$$

The system unknown parameters can be considered *a priori* independent random variables, but the same cannot be said about the parameters obtained as a function of the system response, since the correlation between the parameters given the selected observation resulted from the acceptance-rejection criterion application is not zero, as will be verified later in this work. In this way, the terms relative to such parameters, presented in Eq. 15 (page 68), the prior parameters distribution considering a large-scale neighborhood, and the parameters distribution given the selected observation *a posteriori*, can be presented as Eq. 69 and Eq. 70, respectively.

$$\pi(\Theta) = \pi(k_{xx})\pi(k_{yy})\pi(\beta)\pi(m_u, \varepsilon) \quad (69)$$

$$\pi(\Theta/\Sigma) = \pi(k_{xx}, k_{yy}, \beta, m_u, \varepsilon / u_{\max}, v_{\max}, \Omega_c) \quad (70)$$

The simulations were made considering simultaneous draws for all parameters, treated as random variables from an *a priori* uniform distribution. The rotor was considered perfectly symmetrical and the properties of the bearing identical in the horizontal and vertical directions. Thus, Eq. 69 and Eq. 70 can be simplified considering Eq. 71 and Eq. 72, becoming Eq. 73 and Eq. 74. Note that, in the simplification process, k_{xx} and k_{yy} were replaced by k_m , as well as $u_{\max}$ and $v_{\max}$ were replaced by $A_{\max}$.

$$\Theta^* = (k_m, \beta, m_u, \varepsilon) \quad (71)$$

$$\Sigma^* = (A_{\max}, \Omega_c) \quad (72)$$

$$\pi(\Sigma^*) = \pi(A_{\max})\pi(\Omega_c) \quad (73)$$

$$\pi(\Sigma^*/\Theta^*) = \pi(A_{\max}, \Omega_c / k_m, \beta, m_u, \varepsilon) \quad (74)$$

The ambiguities issue

Initially, this example did not include the Monte Carlo Method application. The initial idea was to use only the Simulated Annealing in four steps to estimate the unbalance and, in the process, the bearings' stiffness and damping parameters. However, during the initial simulations of the Simulated Annealing, the method convergence was not satisfactory. This can be considered a typical ill-posed inverse problem case in which the collected data is insufficient to estimate the model parameters without ambiguities and an exact solution does not exist. With a very wide variation of the *a priori* data, the combination of the initial chosen values often converged to a result far from what was expected, running in a local minimum. Usually, the problem arises when the combination of stiffness and proportional damping coefficient turns the system overdamped and the response becomes different from the expected response.

Figure 33 presents four examples showing how the system response changes as a function of bearings' damping. The bearings' stiffness is known and constant for all cases, being equals to 10 MN/m. The bearings' damping varies for each case, as numbered, being equal to 750 N.s/m (1), 1000 N.s/m (2), 1500 N.s/m (3) and 2000 N.s/m (4).

Figure 33 – System FRF variation due to the bearings damping

All the cases presented demonstrate a behavior that can be considered physically impossible to be observed in real situations. In this way, new *a priori* distributions for each parameter can be obtained as an alternative to the problem. Considering the forward problem, using Monte Carlo simulations with a rejection criterion, just the candidate responses whose amplitude curves as a function of the frequency approaches the desired shape (Figure 32) were considered.

Monte Carlo Method with rejection criterion

The limit values initially considered for each parameter distribution were obtained from the literature for the parameters related to the bearings (LALANNE and FERRARIS, 1998) and based on the test rig rotor disk geometry and mass for the eccentricity and the unbalance mass (MICHALSKI, 2004). Table 19 presents the prior limit values considering this information.

Table 19 – Parameter *a priori* limit values with literature information

Parameters	Min. Values	Max. Values
k_{xx}	10^6	10^9
k_{yy}	10^6	10^9
β	0	2.0×10^{-4}
m_u	0	$0.05 m_d$
ε	0	$0.5 d_d$

Source: Author

Besides the previous information, before the Monte Carlo simulations, a sensitivity analysis was also performed for the bearing's parameters (equivalent system stiffness variation regarding the bearings' stiffness variation). As can be seen in Figure 34, regarding the bearings' stiffness and its influence on the system equivalent stiffness, it was observed that beyond 10^8 N.s/m their values did not affect the system equivalent stiffness anymore, so it does not make sense to use values above this limit in the simulations.

Figure 34 – System equivalent stiffness and bearings' stiffness correlation

Concerning the proportionality factor, it was assumed, considering the sensitivity analysis, that the system should always be even minimally damped. Thus, a value other than zero was stipulated for the damping proportionality factor minimum value.

Both in the stiffness and the damping proportionality factor cases, the objective of reducing the value window is to allow a better result from the simulations, since it would be done considering values closer to the expected ones. Such a search for information to better represents the prior distributions of the system parameters is entirely following the principle of maximum entropy (JAYNES, 1957a and 1957b).

Table 20 presents the updated *a priori* limit values considered in Monte Carlo simulations. These values were also used in the first simulations of the Simulated Annealing and, as previously mentioned, the results were not satisfactory.

Table 20 – Parameter's limit values considered in Monte Carlo simulations

Parameters	Min. Values	Max. Values
k_{xx}	10^6	10^8
k_{yy}	10^6	10^8
β	5.0×10^{-8}	2.0×10^{-4}
m_u	0	$0.05 m_d$
ε	0	$0.5 d_d$

Source: Author

Thus, a rejection criterion was applied in the Monte Carlo simulations so that new Simulated Annealing *a priori* parameters probability distributions could be obtained, following the framework presented in Figure 13 (page 69). A 20% acceptance window was used for the maximum and minimum values found from the exact model for the maximum amplitude ($A_{\max}$) and the critical speed (Ω_c) in the two considered directions.

Table 21 shows the values used for the rejection criteria. Initially, 150 thousand FRF simulations were performed and reduced to almost 3300 results with the rejection criteria application, presented in Figure 35.

Table 21 – Rejection criteria values

Parameters	Min. Values	Max. Values
$A_{\max}$	1.15 mm	1.90 mm
Ω_c	42.61 Hz	64.73 Hz

Source: Author

Figure 35 – FRF simulations with the rejection criteria

The distributions obtained with the simulations for the maximum amplitude and the critical speed are presented in Figure 36 and Figure 37. On the other hand, the obtained distributions for each considered parameter are shown in Figure 38, Figure 39, and Figure 40. The distributions presented below will be used as the *a priori* distributions for each parameter in the Simulated Annealing simulations.

Figure 36 – Maximum amplitude distribution

Figure 37 – Critical speed distribution

Figure 38 – Bearings' stiffness distribution

Figure 39 – Damping proportionality coefficient distribution

Figure 40 – Unbalance distribution

From the presented distributions, the mathematical expectation for each parameter can be evaluated, as well as the expected result for the rotor frequency response considering such values. Table 22 presents the values found for the mathematical expectation for each parameter as well as the error for each value when comparing the MCM results with the model exact values.

Table 22 – Mathematical expectation and Error for the MMC results

Parameters	Values	Error
$m_{u,\varepsilon}$	0.000879 kg.m	0.5%
k_{xx}	2.44×10^7 N/m	171.1%
k_{yy}	2.44×10^7 N/m	144.0%
β	4.63×10^{-5} s	15.8%
A_x	1.50 mm	5.7%
A_y	1.50 mm	4.2%
Ω_x	54.94 Hz	3.2%
Ω_y	54.94 Hz	1.9%

Source: Author

Figure 41 presents the rotor frequency response estimated from the MCM. In red is presented the mean FRF and in green the values obtained considering one standard deviation above and below the mean. For each value of “ Ω ”, several amplitudes are

estimated, forming a distribution from which the mean and standard deviation of “A” is calculated.

Figure 41 – MCM frequency response

Figure 42 presents a graphic comparison between the FRF exact solution (in blue) and the expected FRF solution obtained with the MCM application (in red), for each direction (horizontal, “a”, and vertical, “b”).

Figure 42 – Comparison between the exact solution and the MCM solution FRF

Note that there is a clear difference between the mathematical expectation of the maximum amplitude value in each direction and the maximum amplitude of the expected graphic solution obtained with the MCM. While the first is obtained by considering the maximum amplitude of each response, regardless of the critical velocity, the second is obtained by calculating the mean amplitude of all the graphical responses obtained.

To support the previous results, the parameter convergence and correlation were analyzed. Regarding convergence, the great question is whether the number of simulations resulting from the rejection criteria application is enough to achieve the parameters mean convergence. Figure 43 to Figure 47 show the convergence of the

parameter values due to the Monte Carlo simulations, where “p” is the number of Monte Carlo simulations.

Figure 43 – Amplitude convergence in mean

Figure 44 – Critical speed convergence in mean

Figure 45 – Bearings' stiffness convergence in mean

Figure 46 – Damping proportionality coefficient convergence in mean

Figure 47 – Unbalance convergence in mean

It is clear from such graphs that the number of simulations obtained with the application of the rejection criteria is enough to provide an excellent convergence in mean. On the other hand, the input parameters correlation and the correlation between the input parameters and the system response were also estimated. Correlation is used in the first case to verify the independence between the rotor parameters *a priori* and *posteriori*, and in the second case to order the Simulated Annealing stages.

Table 23 shows the *a priori* correlation and Table 24 the *posteriori* correlation. As previously mentioned, the parameters related to unbalance and the bearings can be considered as independent random variables *a priori*, since only in the main diagonal of the correlation matrix are found non-zero values. The same does not occur with the same parameters considering the system responses, since the values found outside the main diagonal are not null.

Table 23 – *A priori* correlation

	$m_{u,\varepsilon}$	k_m	β
$m_{u,\varepsilon}$	1	0	0
k_m	0	1	0
β	0	0	1

Source: Author

Table 24 – Posteriori correlation

	$m_{u,\varepsilon}$	k_m	β
$m_{u,\varepsilon}$	1	0.08	0.18
k_m	0.08	1	-0.61
β	0.18	-0.61	1

Source: Author

Table 25 shows the system responses with each estimated parameter correlation. It can be noted that the strongest correlation is found between the unbalance and the critical speed, and not with the maximum amplitude as could be expected. It is also remarkable how there is no correlation between the bearing's stiffness and amplitude.

Table 25 – Posteriori correlation of the system parameters and responses

	$m_{u,\varepsilon}$	k_m	β
A_{max}	0.27	0.00	-0.02
Ω_c	0.88	0.13	0.08

Source: Author

Figure 48, Figure 49, and Figure 50 show the correlations of each parameter with the amplitude and the critical speed. Graphically it is also possible to note how the correlation between the critical speed and the unbalance is stronger than the other correlations between the responses and the system parameters.

Figure 48 – Amplitude and critical speed vs. bearings' stiffness

Figure 49 – Amplitude and critical speed vs. damping proportionality coefficient

Figure 50 – Amplitude and critical speed vs. unbalance

Parameter estimation using Simulated Annealing

As previously mentioned, the obtained distributions for each unknown parameter (Figure 38, Figure 39, and Figure 40) are considered as prior distributions in a four steps SA, applied for the system's parameters estimation.

The four steps SA means, in this case, that instead of treating the parameters' estimation at the same time (in parallel), with four simultaneous draws for the initial values that result in four simultaneous convergences, the parameters' estimation is treated in series. In this way, the initial value of each parameter is drawn only after the convergence of the previously selected parameter, ensuring that the starting point of the algorithm is already a valid response, although not necessarily the ideal one. In each step, one of the system responses (maximum amplitude in the horizontal and vertical directions and the respective critical rotation speeds) was used to estimate one of the unknown parameters ($m_u \cdot \epsilon$, k_{xx} , k_{yy} , and β).

Such an approach also helps to reduce the dimension size of the analyzed neighborhood, allowing the SA to escape from local minimums that would most likely be reached if the search for the system solution considered the estimate of the four parameters simultaneously.

The correlations presented in Table 25 were used as a basis for ordering the SA steps and correlating each parameter to one of the system's response. The idea is to increasingly use the correlations in each step of the SA, that is, in the first step the weakest correlation is used and in the last step the strongest correlation is considered. In this way, the SA four steps were performed considering the following correlations:

- First step: bearings horizontal stiffness estimation considering the horizontal displacement measurement;
- Second step: bearings vertical stiffness estimation considering the vertical displacement measurement;
- Third step: bearings proportional damping factor estimation considering the critical speed in the vertical direction;
- Fourth step: unbalance level estimation considering the critical speed in the horizontal direction.

For all steps the maximum number of iterations is equal to 500, the maximum number of disturbances at each iteration equal to 50, and the maximum number of successes of the disturbances equal to 40. As previously mentioned in section 4.1, the initial temperature at each step was obtained considering Eq. 16 (with χ_0 equals to 0.8), and the objective values were obtained from the simulation of the exact system (VAN LAARHOVEN and AARTS, 1987).

The temperature reduction factor considered for each step was 0.985 for the stiffness estimation in both directions, 0.99 for the damping proportionality factor estimation and 0.975 for the unbalance estimation. The global stop criteria consider an error of 0.25 Hz for the estimates that use the critical speed as a reference and 0.01 mm for the estimates that use the maximum amplitude as a reference. The temperature variation along the four stages is shown in Figure 51.

Figure 51 – Simulated Annealing temperature variation

The initial temperature values for the horizontal and vertical stiffness estimations were, respectively, 0.870 and 0.888. For the proportional damping factor estimation, the initial temperature was 14.08 and for the unbalance estimation, 14.01. The results obtained with SA are presented in Table 26, including the error for each value when compared to the exact model solution.

Table 26 – Mathematical expectation and Error for SA results

Parameters	Values	Error
$m_{u,\varepsilon}$	0.000919 kg.m	5.0%
k_{xx}	1.45×10^7 N/m	61.1%
k_{yy}	1.55×10^7 N/m	55.0 %
β	2.59×10^{-5} s	35.3%
U_{max}	1.60 mm	0.6%
V_{max}	1.50 mm	4.2%
Ω_x	53.58 Hz	0.6%
Ω_y	54.03 Hz	0.2%

Source: Author

Figure 52 presents the system FRF estimated with the SA method compared with the same result obtained from the exact model simulation. It can be noticed that the FRF, in this case, is closer to the exact response than the response obtained just with MCM (presented in Figure 42, page 125).

Figure 52 – Comparison between the FRF exact solution and the SA solution

As observed, the two methods used in this application lead to more than satisfactory results. Considering the unbalance estimation and the bearings' damping factor, simply applying the application of MCM was more efficient than the combined method using MCM and SA.

Regarding the maximum displacement amplitude in the horizontal direction, there is no significant difference between the methods. However, for other parameters, the combined application of MCM and SA led to better results, as presented in Table 27. The same can be said comparing the system frequency response in each case (Figure 42 and Figure 52).

Table 27 – Mathematical expectation and Error for MCM and SA results

Parameters	MCM	Error	SA	Error
$m_{u,\varepsilon}$	0.000879 kg.m	0.5%	0.000919 kg.m	5.0%
k_{xx}	2.44×10^7 N/m	171.1%	1.45×10^7 N/m	61.1%
k_{yy}	2.44×10^7 N/m	144.0%	1.55×10^7 N/m	55.0 %
β	4.63×10^{-5} s	15.8%	2.59×10^{-5} s	35.3%
u_{max}	1.50 mm	5.7%	1.60 mm	0.6%
v_{max}	1.50 mm	4.2%	1.50 mm	4.2%
Ω_x	54.94 Hz	3.2%	53.58 Hz	0.6%
Ω_y	54.94 Hz	1.9%	54.03 Hz	0.2%

Source: Author

Despite the inverse crime committed in this application (KAPIO and SOMERSALO, 2005), it can be said that, for an initial approach, both methods have achieved their goal more than satisfactorily. The use of an extremely simple model compensates for the fact that several parameters are estimated simultaneously concerning the difficulties of the algorithm and the processing time.

The use of the MCM was fundamental for the *a priori* distributions estimation used in the Simulated Annealing method. Without the MCM, the Simulated Annealing convergence would be much more difficult and less accurate.

Although the unbalance estimation was more precise with just the use of the MCM, the combined method presents a more accurate overall estimate, considering all results. The errors, in general, become smaller with the combined method, especially for the bearing's parameters.

7.1.4. Steady-state simulation and PCA analysis

Following the proposed framework sequence, once the updated model is obtained, the next step is to consider this model to simulate several steady-state conditions and to map the different operational conditions obtained with the RMPCA application.

In this work, simulations in steady-state conditions are based on the amplitude of the system's response for each considered unbalanced condition at a given rotation speed (Ω). Once the system rotation speed is defined, simulations in steady-state will

consist of temporal responses of the rotor with the amplitude in each direction defined by the chosen rotation, that is, 90° lagged sinusoidal responses with the frequency and amplitudes previously defined for each fault condition.

Besides, to simulate a real operating condition of a rotating machine, a noise signal is added to the generated sinusoidal waves. In this first example, an Additive White Gaussian Noise (AWGN) was chosen, since in this case there is no experimental data to take as a basis and extract the real noise. Thus, with mean equals to zero, only the standard deviation of the random signal must be defined.

To obtain the predicted unbalance mapping, following the proposed framework presented in Figure 27 (page 104), the RMPCA must be applied to a continuous signal with variations related to different severities of the considered fault. A reference signal, related to the "healthy" condition of the analyzed equipment, is also necessary, with the same size as the RMPCA's analysis window.

For all simulated signals, both the reference and the continuous data that will be analyzed, being necessary to establish a sampling rate. Once the sampling rate and the time windows of the analyzed signals are defined, the number of samples in each case is consequently established.

The variables necessary for the data simulation in steady-state are the different operational conditions that will be mapped (related to the different levels of degradation of the considered fault), the considered rotation speed (usually established from the operational speed of the analyzed equipment), the time windows for the reference and the analysis signals (considering each operational condition), the sample rate of the simulations and the level of noise added to the signals (related to the AWGN variance).

In this example, ten different unbalance conditions are considered: 437.5 g.mm, 612.5 g.mm, 875 g.mm, 919 g.mm, 927.5 g.mm, 946 g.mm, 962.5 g.mm, 993 g.mm, 1050 g.mm, and 1137.5 g.mm.

Next, in Figure 53, the Jeffcott rotor FRF simulated for the chosen unbalance conditions is presented (horizontal response, "a", and vertical response, "b").

Figure 53 – Jeffcott rotor FRF for several unbalance conditions

For the steady-state data simulation, a chosen rotational speed of 52 Hz and a sampling rate of 2048 samples per second (S/s) is adopted. The considered reference time window is 0.125 seconds (256 samples) and for each operational condition, the time window is defined as presented in Table 28, totaling 8 seconds. The simulations of the analyzed data consider the different unbalance levels in ascending order, that is, from the lowest level of unbalance to the highest level of unbalance. The level of unbalance considered for the reference data is 437.5 g.mm, that is, the lowest value among the different conditions considered.

Table 28 – Unbalance conditions time windows and number of samples

Unbalance (g.mm)	Time window (s)	Samples
437.5	2.00	4096
612.5	1.00	2048
875.0	1.00	2048
919.0	1.00	2048
927.5	0.75	1536
946.0	0.75	1536
962.5	0.50	1024
993.0	0.50	1024
1050.0	0.25	512
1137.5	0.25	512

Source: Author

The value of the noise standard deviation, in this case, is 0.05 mm, which means a signal-to-noise ratio (SNR) of around 20 dB for the reference data and 25 dB for the analyzed data. SNR is obtained from Eq. 75, in which the RMS value of the reference and analysis signals are considered.

$$\text{SNR}_{\text{dB}} = 20 \log \left(\frac{\text{RMS}_{\text{signal}}}{\text{RMS}_{\text{noise}}} \right) \quad (75)$$

Figure 54 presents the reference signal and Figure 55 the analyzed data considered in this first example (example A).

Figure 54 – Jeffcott rotor steady-state analysis reference – example A

Figure 55 – Jeffcott rotor steady-state continuous signal – example A

The simulated sinusoidal signal is a continuous and smooth function; however, the maximum value of the function varies abruptly between two consecutive samples when the unbalance level changes.

This characteristic can be related to a non-continuous degradation of the considered fault. In the case of unbalance, a change in the position of the center of mass of the rotating system can occur when equipment items are detached. In turbines and compressors, for example, the detachment of blades or parts of them would be examples of the origin of this type of non-continuous degradation.

The variations in the operational condition that occur in the second- and third-seconds cause clear changes in the simulated signals, showing the dynamics of fault degradation. However, changes in the unbalance level between 4 and 7.25 seconds occur in much smaller steps, causing variations in the simulated signal amplitude proportionally smaller than the previous changes. During this time window, due to the noise added to the signal, the behavior of the system concerning changes in operational conditions appears to be continuous.

Following the dynamic example of the RMPCA application, presented in section 5.2.2 (page 95), the obtained result considering the data presented in Figure 54 and Figure 55 is presented in Figure 56, where PCw 1, PCw 2, and PCw 3 are, respectively, the weights of the first three principal components.

Figure 56 – Jeffcott rotor RMPCA results – example A

It is noted that the sum of the weights of the first three principal components is greater than 95% in the entire period analyzed, strengthening the idea that only the first three components would be necessary for the analysis. The variation in the components' weights is also clearly seen, following the variations in the amplitude of the analyzed signal.

To further clarify the RMPCA analysis, Figure 57 presents the graph over time showing the weight of the first three components individually normalized by their maximum value, with the results varying from 0 to 1.

Figure 57 – Jeffcott rotor RMPCA results with normalized weights – example A

Note that although the PCw 3 has the lowest values among the three considered components, it has the highest sensitivity to changes in the analyzed signal over time, which becomes more evident when analyzing the normalized data of the three components. This can be explained by the fact that PCw 1 and PCw 2 retain the largest share of variation of the original data. As the signals analyzed in the vertical and horizontal directions have a low correlation, the weight of the first two principal components ends up being equivalent, leaving the fluctuations of the original data for the third principal component. Such fluctuations end up being the main indicator of the system fault, making the sensitivity of PCw 3 greater than the others.

For comparison, the vibration amplitude signals over time have a peak-to-peak value (pk-pk) slightly less than 2 mm initially, reaching a value slightly greater than 4 mm peak to peak after the 8 seconds of analysis, which represents a variation slightly greater than 100% in the peak-to-peak value. On the other hand, the value of PCw 3 starts slightly above 0.7, reaching a value slightly below 0.3 after 8 seconds, indicating a variation of more than 50% in relation to the initial value. In other words, the value of PCw 3 is practically inversely proportional to the peak-to-peak value of the vibration signals of the analyzed rotor.

The noticed changes in the simulated signal in the second and third seconds are also noticed in the RMPCA result in the form of Dirac deltas in the third principal component. Similarly, the more subtle variations from the fourth second on are expressed through the continuous decay of the same component. On the other hand, PCw 1 and PCw 2 do not present significant variations that can be considered for detecting unbalance changes.

It is noted that, even in a condition in which the unbalance variation is relatively small (less than 10% between seconds 4.0 and 7.5), the RMPCA method can detect variations in the analyzed fault.

Figure 58 presents the unbalance mapping for this example, considering the first three principal components as a function of the unbalance level. Each principal component is represented, in this case, by a range of values. The upper limit of this range is the average value plus three times the standard deviation ($\text{Mean} + 3.\text{sd}$) calculated for each operating condition. The lower limit, in turn, is the mean value

minus three times the standard deviation (Mean - 3.sd) calculated for the same periods, as established in Table 28.

Also, trend curves are presented for each case. For the first two principal components, a linear function can approximate the trend, while for the third principal component the approximation is made from an exponential function.

Figure 58 – Jeffcott rotor unbalance mapping – example A

Table 29 presents the mean and standard deviation values for each condition considered in the previous mapping.

Table 29 – PC weights' means and standard deviations (sd) vs. unbalance level – example A

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	51.506	1.128	46.772	1.128	0.913	0.040
612.5	51.725	1.055	46.762	1.053	0.748	0.018
875.0	52.328	0.884	46.608	0.870	0.509	0.010
919.0	52.467	0.840	46.595	0.838	0.481	0.011
927.5	52.506	0.837	46.575	0.836	0.471	0.010
946.0	52.495	0.832	46.608	0.831	0.460	0.010
962.5	52.506	0.814	46.618	0.813	0.447	0.010
993.0	52.647	0.813	46.511	0.812	0.430	0.012
1050.0	52.482	0.787	46.725	0.789	0.405	0.014
1137.5	52.726	0.803	46.566	0.794	0.362	0.019

Source: Author

The main objective of this first example is to present the RMPCA and how it integrates with the model-based methods previously presented. However, to explore the sensitivity of this method about some of the variables inherent to the input data, such as reference time window and noise level, in the next section, some cases based on this first example will be analyzed.

7.1.5. Method's sensitivity regarding the analyzed data parameters

Regarding the variables presented, they can be classified into two distinct groups: those that in a real application are intrinsic to the analyzed system and those that can be adjusted regardless of the problem. Generally, the machine rotating speed, the fault degradation level when considered the reference data, the fault degradation speed, and the data noise level belongs to the former group, while the data signal sampling rate and the analysis window belongs to the latter group. However, among the mentioned variables, three stand out and their influence on the RMPCA result will be analyzed in detail: the fault degradation level when considered the reference data, the

data noise level, and the time window analysis. In Table 30, the Jeffcott simulated system test examples with each variable change are presented.

Table 30 – Jeffcott simulated system test examples

Jeffcott system example	Rotating speed	Sampling rate	Reference unbalance level	Noise level standard deviation	Reference time window
A	52 Hz	2048 S/s	437.5 g.mm	0.05 mm	0.125 s
B1	52 Hz	2048 S/s	919.0 g.mm	0.05 mm	0.125 s
B2	52 Hz	2048 S/s	1137.5 g.mm	0.05 mm	0.125 s
C1	52 Hz	2048 S/s	437.5 g.mm	zero	0.125 s
C2	52 Hz	2048 S/s	437.5 g.mm	1.00 mm	0.125 s
C3	52 Hz	2048 S/s	437.5 g.mm	2.00 mm	0.125 s
D1	52 Hz	2048 S/s	437.5 g.mm	0.05 mm	0.03125 s
D2	52 Hz	2048 S/s	437.5 g.mm	0.05 mm	0.500 s

Source: Author

Influence of the reference data unbalance level

To evaluate the influence of the reference operational condition considered in the RMPCA analyzes, two alternative scenarios to the previous example presented will be considered.

The first alternative scenario considers a change in the level of unbalance of the reference data. Initially, the level of unbalance considered for the reference data was 437.5 g.mm. In this second example (example B1), a level of unbalance of 919 g.mm will be considered, that is, the same value found for the unbalance of the estimated system considering the SA combined with the MCM.

The other variables remain the same concerning the first example previously presented, that is, rotation speed of 52 Hz, sampling rate of 2048 S/s, reference time window of 0.125 seconds, analysis data time window of 8 seconds (still considering the different unbalance levels in ascending order), and noise standard deviation of 0.05 mm. That is, SNR for the analysis data remains unchanged, but for the reference data suffers a slight increase to around 26 dB.

Figure 59 shows the reference signal and Figure 60 presents the RMPCA results with normalized weights for this second example.

Figure 59 – Jeffcott rotor steady-state analysis reference – example B1

Figure 60 – Jeffcott rotor RMPCA results with normalized weights – example B1

Figure 61 presents the unbalance mapping for this example, considering once more the first three principal components as a function of the unbalance level. The same limits previously considered in Figure 58 (page 141) are also applied here.

Figure 61 – Jeffcott rotor unbalance mapping – example B1

Regarding the trend lines shown in Figure 61, for the first two principal components, a linear function once more can approximate the trend, while for the third principal component the approximation is made with a second-order polynomial function.

In this case, a lower sensitivity of PCw 3 is observed regarding the different operating conditions. That is, the range of values between which the possible results of the PCw 3 vary is smaller in this second example (between 0.514 and 0.730,

considering the mean value), as shown in Table 31 than in example A (between 0.362 and 0.913, considering also the mean value), as presented in Table 29 (page 142).

Table 31 – PC weights' means and standard deviations (sd) vs. unbalance level – example B1

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	52.407	0.428	46.646	0.429	0.514	0.014
612.5	52.031	0.730	46.708	0.733	0.651	0.021
875.0	51.704	1.044	46.845	1.050	0.729	0.019
919.0	51.739	1.132	46.865	1.133	0.730	0.019
927.5	51.739	1.145	46.869	1.146	0.729	0.020
946.0	51.724	1.131	46.887	1.132	0.727	0.020
962.5	51.741	1.160	46.872	1.161	0.724	0.018
993.0	51.687	1.132	46.933	1.133	0.721	0.019
1050.0	51.675	1.138	46.953	1.140	0.713	0.025
1137.5	51.741	1.141	46.923	1.140	0.696	0.023

Source: Author

Also, it is noted in this second example that the difference in the PCw 3 value between the unbalance levels 875 g.mm and 1050 g.mm is practically undetectable, which does not occur in the first example, considering the same operational conditions.

Considering now a third example (example B2) in which all variables and operational conditions are kept identical to those of the two previously presented examples, except for the reference data unbalance level, which in this case is 1137.5 g.mm, that is, the maximum value of the imbalance found in Table 28. In this case, SNR for the analysis data did not change but, again, it increased to slightly above 28 dB in the case of the reference data.

Figure 62 shows the reference data for this example and Figure 63 presents the RMPCA results with normalized weights.

Figure 62 – Jeffcott rotor steady-state analysis reference – example B2

Figure 63 – Jeffcott rotor RMPCA results with normalized weights – example B2

Figure 64 is presented the unbalance mapping for example B2, considering once more the first three principal components as a function of the unbalance level and the same limits previously considered. The trend curves are shown in this figure follow a linear function for the first two principal components and, once more, a second-order polynomial function for the third principal component.

Figure 64 – Jeffcott rotor unbalance mapping – example B2

Regarding sensitivity, it is noted that the results of this third example are inside the limit levels of the other two examples previously presented (A and B1). According to Table 32, the mean values results for the PCw 3 range between 0.359 and 0.693 considering the several unbalance conditions simulated in this last example. This range is greater than that presented in example B1 (between 0.514 and 0.730, as shown in Table 31), when the reference data was related to an intermediate unbalance condition (919 g.mm), and slightly lesser than that of example A (between 0.362 and

0.913, as presented in Table 29), when the reference data was related to the less severe condition of unbalance (437.5 g.mm).

Table 32 – PC weights' means and standard deviations (sd) vs. unbalance level – example B2

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	52.927	0.322	46.395	0.322	0.359	0.009
612.5	52.549	0.537	46.462	0.540	0.516	0.019
875.0	52.087	0.862	46.621	0.869	0.657	0.018
919.0	52.027	0.901	46.694	0.902	0.669	0.020
927.5	52.000	0.890	46.713	0.891	0.673	0.017
946.0	52.028	0.984	46.686	0.985	0.673	0.015
962.5	51.983	0.961	46.715	0.962	0.680	0.016
993.0	51.950	0.981	46.743	0.982	0.680	0.018
1050.0	51.926	1.037	46.751	1.037	0.693	0.015
1137.5	51.893	1.124	46.781	1.125	0.691	0.022

Source: Author

Comparing the results obtained for the average weight of the three principal components considering the three examples presented, it is possible to analyze the influence of the chosen reference. On the next page, Figure 65 presents this comparison.

Examples B1 and B2 present a great similarity for the responses of PCw 1, PCw 2 and PCw 3 due to the unbalance variation. On the other hand, the expected behavior due to operational condition variation is completely different in example A. Also, as the standard deviations are greater in PCw 1 and PCw 2 than in PCw 3, as shown in Figure 58 (page 141), Figure 61 (page 144), and Figure 64 (page 148), the correlation between RMPCA results and the operational conditions becomes evident considering just PCw 3.

In a real operational context, if the considered reference is obtained after commissioning or returning of the analyzed machine from major maintenance or an overhaul, it will be more likely that the first analyzed example will occur. That is, the reference data considered would be related to the less severe operational condition. This can be considered the ideal scenario.

Figure 65 – Unbalance mapping comparison – Reference data influence

On the other hand, if the reference considered is obtained after some level of degradation of the analyzed machine, the second or third case will be more likely. In these cases, it will be more difficult to identify the continuous degradation of the equipment. However, after repairing the fault, the equipment would return to a less degraded condition and the reference data could be updated, falling in the first example presented. This is because, as the normalized values of the RMPCA eigenvalues are considered, there is a maximum limit for the method response (100%). In this way, the greater the residual unbalance of the analyzed machine when the reference data

sample is obtained, the smaller the variation range of the method to follow the failure degradation, which can result in a more difficult detection process.

Influence of the data noise level

To evaluate the influence of the noise level added to the simulated data on RMPCA results, an alternative scenario to example A will be considered. Thus, the same values for the steady-state data simulation considered in example A are applied in this example (example C1): 52 Hz for the rotational speed, 2048 S/s for the sampling rate, 437.5 g.mm for the reference unbalance level, 0.125 seconds (256 samples) for the considered reference time window, and 8 seconds for the analysis data, as presented in Table 28 (page 137).

The difference in this scenario is the level of noise added to the simulated data. In this case, the standard deviation considered for the AWGN is 1.00 mm, which represents an increase of 20 times the initial value. In this case, the SNR for the reference data became around -0.5 dB, and for the analyzed data -5.5 dB. A negative SNR (in dB) means that the power of the added noise has exceeded the power of the base signal.

Figure 66 presents the new reference signal and Figure 67 the analyzed data considered in this example.

Figure 66 – Jeffcott rotor steady-state analysis reference – example C1

Figure 67 – Jeffcott rotor steady-state continuous signal – example C1

It is noted that, due to the noise level added to the analysis data, presented in Figure 67, it is no longer possible to visually detect changes between different operating conditions.

Figure 68 presents the RMPCA results for this example. In this case, the results of PCw 1, PCw 2, and PCw 3 vary significantly according to the unbalance level, despite the greater fluctuation in the results obtained.

Figure 68 – Jeffcott rotor RMPCA results – example C1

Figure 69 presents the graph over time showing the weight of the first three components individually normalized by their maximum value, with the results varying from 0 to 1.

Figure 69 – Jeffcott rotor RMPCA results with normalized weights – example C1

Figure 70 presents the unbalance mapping for this fourth example, considering the first three principal components as a function of the unbalance level. As previously considered, each principal component ranges around a lower limit (Mean - 3.sd) and an upper limit (Mean + 3.sd), considering a sample of values in each operational condition, as defined in Table 28 (page 137).

The obtained results for PCw 1, PCw 2, and PCw 3 follow a pattern as a function of the level of unbalance. The trend line was obtained from a logarithmic function for PCw 1 and PCw 2, and from an exponential function for PCw 3. Also, it is noted that there is enough sensitivity, especially regarding PCw 3, capable of distinguishing different values for the weight of the principal components according to the different levels of unbalance.

Again, for comparison, the initial peak-to-peak value of the vibration signals was around 6 mm initially, coming close to 10 mm after 8 seconds, indicating in this case an increase of approximately 66% in the peak-to-peak value of the signal. On the other hand, the value of PCw 1 and PCw 2 has increased by approximately 16% and the value of PCw 3 has practically halved over the same time period.

Figure 70 – Jeffcott rotor unbalance mapping – example C1

As shown in the previous three examples (examples A, B1, and B2), Table 33 presents the results of the mean values and standard deviations for the weight of the principal components as a result of the unbalance in this example.

Table 33 – PC weights' means and standard deviations (sd) vs. unbalance level – example C1

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	32.871	1.433	28.269	1.447	21.062	1.222
612.5	34.639	1.497	29.736	1.492	18.982	1.137
875.0	37.763	1.481	32.376	1.363	15.783	0.825
919.0	38.245	1.395	33.099	1.519	15.293	0.844
927.5	37.763	1.475	33.414	1.335	15.389	0.904
946.0	38.744	1.529	33.288	1.240	14.934	0.862
962.5	39.206	1.519	33.004	1.467	14.838	0.751
993.0	38.665	1.263	33.881	1.119	14.642	0.685
1050.0	38.640	1.082	35.236	0.938	13.944	0.752
1137.5	39.980	1.075	35.446	1.115	13.129	0.700

Source: Author

Considering two more alternative situations, the first (example C2) in which there is no noise added to the data and the second (example C3) in which a noise with a standard deviation of 2 mm is added (resulting in an SNR of 60 dB for the reference data and 70 dB for the analyzed data), the mapping of the imbalance can be obtained, as shown in Figure 71 and Figure 72, respectively.

The trend curves shown in Figure 71 were obtained from linear functions, for PCw 1 and PCw 2, and by a third-order polynomial function for PCw 3, while the curves in Figure 72 were all obtained from linear functions.

Figure 71 – Jeffcott rotor unbalance mapping – example C2

Source: Author Figure 72 – Jeffcott rotor unbalance mapping – example C3

Following the pattern presented in the previous examples, Table 34 presents the results of the mean values and standard deviations for the PCw as a result of the unbalance for example C2, while Table 35 presents the same results considering example C3.

Table 34 – PC weights' means and standard deviations (sd) vs. unbalance level – example C2

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	51.795	1.115	46.933	1.116	0.658	0.006
612.5	51.973	1.105	46.827	1.099	0.583	0.008
875.0	52.460	0.915	46.664	0.902	0.416	0.005
919.0	52.573	0.862	46.661	0.861	0.395	0.007
927.5	52.585	0.856	46.661	0.856	0.387	0.005
946.0	52.618	0.846	46.646	0.846	0.378	0.005
962.5	52.634	0.839	46.646	0.839	0.370	0.004
993.0	52.670	0.826	46.637	0.826	0.357	0.007
1050.0	52.726	0.807	46.621	0.807	0.336	0.012
1137.5	52.820	0.777	46.591	0.777	0.302	0.017

Source: Author

Table 35 – PC weights' means and standard deviations (sd) vs. unbalance level – example C3

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	31.835	1.048	28.925	0.934	20.718	1.032
612.5	31.842	1.120	28.841	1.085	20.991	1.197
875.0	33.140	1.357	29.483	1.180	20.106	1.263
919.0	33.105	1.363	29.473	1.260	20.111	1.233
927.5	34.074	1.402	29.260	1.242	19.823	1.195
946.0	33.479	1.354	29.698	1.180	19.842	1.156
962.5	33.398	1.455	29.518	1.212	19.810	1.150
993.0	33.399	1.160	30.041	1.204	19.567	1.103
1050.0	33.664	1.137	30.294	1.085	19.557	1.078
1137.5	34.329	1.245	30.269	1.121	19.002	1.124

Source: Author

Figure 73 presents a comparison for the results obtained for the average weight of the three principal components considering example C1 (with noise standard deviation equals 1 mm), example C2 (without added noise), and example C3 (with noise standard deviation equals 2 mm).

Figure 73 – Unbalance mapping comparison – Noise level data influence

It can be seen from Figure 73 that variations in the noise level cause significant changes to the results of the RMPCA. The trend curves that map the PC weight as a function of the level of unbalance not only change the slope, but also the shape and scale.

However, regarding sensitivity, it is noted that the intermediate condition concerning the noise level added to the data is the most advantageous among the analyzed examples. Furthermore, if, on the one hand, even with the noise reduction to zero, it is possible to identify different responses of the RMPCA regarding variations in

the unbalance level, on the other hand, the increase in the noise level limits such analysis to the point that it is no longer possible to identify variations in the analyzed data for noise levels higher than the one in example C3.

Influence of the analysis time window

The third variable whose influence on RMPCA results will be considered is the analysis time window. Unlike the two variables previously analyzed, intrinsic to the system, the analysis time window can be changed regardless of the considered problem, thus serving as an adjustment mechanism to obtain better results.

The same assumptions considered in the first steady-state simulation example will be followed in this case, apart from the analysis time window. First, the variation of the RMPCA response will be verified for a window smaller than the one initially considered (256 samples or 0.125 seconds) and then for a window larger than the original.

Considering an analysis window with 64 points (or 0.03125 seconds), Figure 74 presents the new reference signal. The analyzed data considered in this case (example D1) is the same presented in Figure 55 (page 138) for example A.

Figure 74 – Jeffcott rotor steady-state analysis reference – example D1

Next, Figure 75, presents the RMPCA results for this example and, Figure 76 presents the graph over time showing the weight of the first three components individually normalized by their maximum value.

Figure 75 – Jeffcott rotor RMPCA results for– example D1

Figure 76 – Jeffcott rotor RMPCA results with normalized weights – example D1

Comparing these results with the ones presented in Figure 56 and Figure 57 (page 139) It is noted that there is a significant reduction in the sensitivity of the RMPCA results to variations in unbalance levels, as well as an increase in the fluctuation of the values obtained for each PC weight due to the noise of the data. Such changes can be confirmed by analyzing the unbalance mapping, as shown in Figure 77 and Table 36.

Figure 77 – Jeffcott rotor unbalance mapping – example D1

The trend curves shown in Figure 77 were obtained from linear functions, for PCw 1 and PCw 2, and by a second-order polynomial function for PCw 3.

Table 36 – PC weights' means and standard deviations (sd) vs. unbalance level – example D1

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	53.935	1.270	45.543	1.267	0.308	0.038
612.5	54.341	1.570	45.272	1.567	0.204	0.022
875.0	54.741	1.836	45.015	1.835	0.126	0.012
919.0	54.842	1.908	44.952	1.907	0.116	0.011
927.5	54.822	1.859	44.976	1.858	0.115	0.010
946.0	54.862	1.907	44.943	1.906	0.111	0.010
962.5	54.919	1.998	44.890	1.997	0.108	0.010
993.0	54.887	1.919	44.930	1.918	0.104	0.010
1050.0	54.935	2.021	44.895	2.019	0.096	0.009
1137.5	55.010	1.982	44.837	1.982	0.087	0.009

Source: Author

Continuing with the evaluation of the influence of the analysis window on the results of the RMPCA, a new example will be presented in which the premises of example A are considered, however in this case a 0.5-second analysis window (1024 samples) will be used.

Figure 78 presents the new reference signal for this example (example D2). Once again, the analyzed data considered in this case is the same presented in Figure 55 (page 138) for example A.

Figure 78 – Jeffcott rotor steady-state analysis reference – example D2

Figure 79 presents the RMPCA results for this example and, Figure 80 presents the graph over time showing the weight of the first three components individually normalized by their maximum value.

Figure 79 – Jeffcott rotor RMPCA results for– example D2

Figure 80 – Jeffcott rotor RMPCA results with normalized weights – example D2

Comparing the results of the RMPCA presented in Figure 79 and Figure 80, relating to example D2, with the results of example A, presented in Figure 56 and Figure 57 (page 139), some aspects are noticed: the increase in the sensitivity of the results to variations in the unbalance level, especially for PCw 1 and PCw 2; the reduction in fluctuations in the results, leading to more stable responses; and the increase in the delay for the RMPCA initial results. From this point of view, the increase in the number of samples considered for the analysis window means that the more

subtle changes in the original signals are perceived more clearly, at the same time as more significant changes, such as the step present in the vibration signals due to a sudden and considerable variation in the level of unbalance, are 'damped'. That is, small variations in the failure mode, whose effects are perceived in the system more slowly, are better detected with wider windows, while broad variations in the failure mode, whose effects in the system are practically instantaneous, are better detected with narrower windows. Such result changes can be confirmed by analyzing the unbalance mapping, as presented in Figure 81 and Table 37.

Figure 81 – Jeffcott rotor unbalance mapping – example D2

It should be noted that the trend curves in Figure 81 were obtained from third-order polynomials.

Table 37 – PC weights' means and standard deviations (sd) vs. unbalance level – example D2

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
437.5	42.871	0.917	38.919	0.950	9.451	0.139
612.5	44.188	0.640	39.909	0.662	8.245	0.101
875.0	47.426	0.332	41.816	0.342	5.633	0.043
919.0	47.794	0.304	42.124	0.310	5.284	0.033
927.5	47.755	0.297	42.293	0.303	5.215	0.021
946.0	47.962	0.285	42.346	0.292	5.082	0.031
962.5	47.974	0.276	42.561	0.285	4.964	0.033
993.0	48.131	0.287	42.606	0.279	4.859	0.054
1050.0	48.504	0.260	42.671	0.255	4.631	0.055
1137.5	48.967	0.243	42.968	0.254	4.237	0.106

Source: Author

Figure 82 presents a comparison for the results obtained for the average weight of the three principal components considering example A (with an analysis window of 256 samples, or 0.125 seconds), example D1 (with an analysis window of 64 samples, or 0.03125 seconds), and example D2 (with an analysis window of 1024 samples, or 0.5 seconds).

Note that the responses regarding the number of samples considered in the analysis window vary with the shape, the range, and, consequently, the sensitivity, in all three PCw. The increase in the number of samples in the analysis window brought benefits to the evaluated examples.

Figure 82 – Unbalance mapping comparison – Analysis window influence

Other notes regarding influence factors

As previously mentioned, six variables were considered to define the parameters of the simulated data. Three of them were considered more relevant and their influence on the results of the RMPCA was evaluated.

Regarding the rotation speed of the analyzed equipment, some tests were carried out in which no influence of this parameter was observed in the method response. Likewise, there were no significant changes in the method's response to variations in the signals sampling rate.

The fault degradation rate directly influences the response of the method. Although the influence of such a parameter has not been directly analyzed in this work, through the examples discussed it was observed that more subtle variations in the analyzed fault would be more difficult to be detected, while more abrupt variations would be easier to be detected.

In this case, the size of the analysis window could contribute to the detection of a certain failure mode as a function of the expected degradation speed. It is noted in examples D1 and D2 that smaller analysis windows highlight fast variations, while larger analysis windows would highlight more subtle variations and mitigate fast variations, as can be seen in Figure 76 (page 161) and Figure 80 (page 164).

In the next sections of this chapter, in which examples with real data will be analyzed, the premises discussed here will be applied.

7.2. Jeffcott Rotor Test Rig

The second application of the proposed framework in this thesis considers a real horizontal rotating machine. In this case, real and simulated data are used in the proposed method.

The analyzed rotating machinery is an experimental test rig with known behavior (MICHALSKI, 2004), the same one used as the basis for the theoretical rotor analyzed in section 7.1 (page 108). As presented before, the rotor consists of a disc (with an approximate mass of 1.0 kg), a continuous and flexible shaft (with an approximate mass of 470 g), and is supported by two hydrodynamic journal bearings. Again, the only fault considered in the system is the mechanical unbalance.

Except for the unbalance level, all parameters of the system are considered known *a priori*. In this case, the rotor will be considered a system with multiple degrees of freedom, and, regarding the method framework presented in Figure 28 (page 106), the discretization of the mathematical model is done using FEM. The unbalance estimation is based on the Kalman filtering estimation algorithm (MICHALSKI and SOUZA, 2018).

7.2.1. Rotor modeling

As previously presented, the analyzed rotor, in this case, is also a symmetrical Jeffcott rotor with a single central disc and supported by two hydrodynamic journal bearings.

According to the premise considered in this work, the fundamental elements of a rotor will be considered without the foundations' influence. Thus, for modeling purposes, the rotor will be subdivided into three fundamental components, as presented in Michalski (2004): the disk, modeled as a rigid body, being largely responsible for the system kinetic energy; the shaft, modeled as a flexible element, discretized and analyzed by the FEM, responsible for both the system kinetic and the potential energies; and the bearings, discrete support elements with their stiffness and damping properties, contributing with the system potential energy and energy dissipation.

Regarding the shaft, each of its discretized elements is represented by a Timoshenko beam element, having two nodes with four degrees of freedom each (two rotations and two translations; no displacement in the axial direction is considered and the rotation around this axis is constant – the rotation speed), totaling eight degrees of freedom per element. In each node, the disks and bearings elements are placed, contributing respectively to the nodal inertia, stiffness, and damping. Translational and rotational inertia can be also allocated in each node to improve the model.

The general equation of motion for rotors, in the matrix form, obtained from the Lagrange equations was presented in Eq. 19 (page 74). In this case, the inertial matrix, $\mathbf{M}$, the stiffness matrix, $\mathbf{K}$, and the gyroscopic and dissipation effect matrix, $\mathbf{C}$, are square matrices with dimension $4n \times 4n$. On the other hand, the length of the excitation forces vector, $\mathbf{F}_{exc}$, and the generalized coordinators' vector (or nodal displacements vector), $\mathbf{q}$, is $4n$, where n is the number of nodes resulting from the rotor discretization.

It is important to highlight the bearings contribution since some assumptions are considered about it in this case. First, it is assumed that, for each bearing, the stiffness and damping forces act in a single node independently and no moments are considered. From the principle of virtual works, as presented by Lalanne and Ferraris (1998), the expressions for the force due to the bearings' stiffness and damping is

given by Eq. 76, where $\mathbf{q}_b$ is the nodal displacement and $\mathbf{K}_b$ and $\mathbf{C}_b$ are, respectively, the bearing stiffness and damping matrices, given by Eq. 77 and Eq. 78.

$$\mathbf{f}_b = -\mathbf{K}_b \mathbf{q}_b - \mathbf{C}_b \dot{\mathbf{q}}_b \quad (76)$$

$$\mathbf{K}_b = \begin{bmatrix} k_{xx} & k_{xy} & 0 & 0 \\ k_{yx} & k_{yy} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (77)$$

$$\mathbf{C}_b = \begin{bmatrix} c_{xx} & c_{xy} & 0 & 0 \\ c_{yx} & c_{yy} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (78)$$

In both Eq. 77 and Eq. 78, the matrices' elements subscript with xx are related to the horizontal forces and the ones which are subscript with yy are related to vertical forces. Elements subscript with xy and yx are so-called coupling-terms, and will not be considered in this model, making $k_{xy} = k_{yx} = 0$ and $c_{xy} = c_{yx} = 0$. Also, the bearings will be considered isotropic, that is $k_{xx} = k_{yy}$ and $c_{xx} = c_{yy}$.

On the other hand, the excitation forces vector can be analyzed in detail. Since only unbalance will be considered in this case, the forces vector for each node can be defined as Eq. 79, where f_x and f_y are, respectively, the horizontal and vertical unbalance components are, given by Eq. 80, where m_u is the unbalance mass, ε is the unbalance eccentricity and ϕ is the unbalance phase. The index i refers to the node where the unbalance forces act.

$$\mathbf{f}_i(t) = \begin{Bmatrix} f_x \\ f_y \\ 0 \\ 0 \end{Bmatrix}_i \quad (79)$$

$$\begin{cases} f_x = m_u \varepsilon \Omega^2 \sin(\Omega t + \phi) \\ f_y = m_u \varepsilon \Omega^2 \cos(\Omega t + \phi) \end{cases} \quad (80)$$

Considering that the vector sum of all different sources of unbalance presented in rotating machinery can be combined into a single vector, this vector can represent an imaginary heavy spot on the rotor. Since this heavy spot location is previously defined and the rotational speed is known for every time instant (the experimental data were collected during a machine run-up), the pair of equations in Eq. 80 can be simplified to a time-independent single equation, presented in Eq. 81, where f_u is the force of unbalance.

$$f_u(\Omega) = m_u \varepsilon \Omega^2 \quad (81)$$

Figure 83 presents the discretized model of this rotor. The shaft is represented in blue, the disk in red, and the bearings in green (nodes 1 and 5). The blue dot in the disk (node 3) is the position of the imaginary heavy spot representing the unbalance. This is a very simple discretized model, with only 5 nodes.

Figure 83 – Test rig finite element model

Originally built in the Vibration and Acoustic Laboratory (LAVI) of COPPE/UFRJ (MICHALSKI, 2004), the test rig can be described as a Jeffcott rotor with the shaft and the disk made of steel SAE 1045, a total length of 420 mm and a shaft diameter of 12 mm. The disk is fixed in the shaft center, equally distanced from each bearing, with a diameter of 150 mm and thickness of 15 mm. The bearings were manufactured in bronze with an inside diameter of 8.1 mm and a length of 8.0 mm. The radial clearance is about 0.1 mm. The rotor mass is about 1.47 kg.

The bearings' stiffness coefficients nominal value is 5×10^4 N/m. On other hand, the damping coefficients nominal value is 1×10^3 N.s/m. As proposed by Lalanne and

Ferraris (1998), a single value for the entire speed range is considered for the bearing's stiffness and damping coefficients.

7.2.2. Test rig measurements experimental data

Once a real machine is being analyzed, experimental data will be used both in the unbalance estimation process using the Kalman filter and in the noise generation process for the simulations and mapping of the several operational conditions considered using the RMPCA.

The test rig's first critical speed is around 51.75 Hz (or 3105 RPM). In the considered operational range (2000-6000 RPM), the rotor just reaches one critical speed, thus only the vibration first mode will be considered hereafter.

Figure 84 presents the test rig experimental data in both directions (horizontal and vertical). Displacements are plotted according to the rotation speed, in rotations per minute (RPM). In this case, measurements are taken in the disk center (node 3, in the previously presented model) and inductive analog probes are used to collect the data.

Figure 84 – Test rig experimental data

7.2.3. Unbalance estimation

The unbalance estimate, in this case, is made as described in section 4.2 (page 70), starting from a state-space problem including the vector of external excitations in the state-vector.

No phase angle between the unbalance and the rotor displacement reference ($\phi = 0$) will be considered in this work. Also, the node where the unbalance is associated with is considered previously known, so the fault location is not addressed as well.

To simplify the unbalance estimation analysis, and following the same logic presented in the previous section for the unbalance force (Eq. 81, page 171), the orthogonal measurements are merged considering Eq. 82, in which z is the resulting amplitude and u and v are the displacements in the horizontal and vertical directions, respectively.

$$z^2 = u^2 + v^2 \quad (82)$$

Figure 85 presents the data obtained through Eq. 82.

Figure 85 – Test rig merged experimental data

In the test rig case, the process model noise covariance matrix is a diagonal matrix with the values of all elements equal to 50, the experimental data noise variance is

4.22×10^{-9} and the state estimation error covariance matrix, $\mathbf{P}_0$, is an identity matrix. The initial values for the error and the gain are, respectively, 0.05 and 0.5. All the initial state-vector values were zero, except for the unbalance force, with a level of unbalance of 1725 g.mm.

Figure 86 presents the displacement estimation, compared with the experimental data (previously presented in Figure 85), Figure 87 the unbalance level estimation, and Figure 88 the displacement estimation relative error (E_R , given by the Eq. 83).

$$E_R = \frac{z_{\text{experimental}} - z_{\text{estimated}}}{z_{\text{experimental}}} \quad (83)$$

Figure 86 – Test rig displacement estimation

Figure 87 – Test rig unbalance estimation

Figure 88 –Test rig displacement estimation error

Note that the unbalance estimate is made considering the monitored data up to approximately the critical rotation speed of the analyzed machine. This choice is made for two reasons: firstly, because the critical speeds of a rotating machine are the rotations at which the unbalance becomes more evident; secondly, after passing through the critical speed, the unbalance phase inversion occurs (MICHALSKI, 2004; LALANNE and FERRARIS, 1998). As the modeling assumptions considered in this

work does not take into account the phase measurement over time, such variation would not be noticed, which would generate an error in the unbalance estimation results.

The estimated unbalance level is 572.3 g.mm. On the other hand, it is previously known that the real unbalance value of the test rig is 562.5 g.mm. Considering that, the estimated value error is 1.74%, that is, virtually neglectable. Also, it is interesting to note that the state estimate values the model, rather than the signal, generating a smoother result.

To verify the method robustness considering data from a real machine, several estimates had been evaluated considering different initial values for the unbalance (the guess value). In this case, in addition to the Kalman filter, the Monte Carlo method had been applied to verify convergency.

Fifty iterations were carried out with the level of unbalance varying between 12.5 g.mm and 3725 g.mm. The other parameters (process model noise covariance matrix, experimental data noise variance, and the state estimation error covariance matrix, $\mathbf{P}_0$) remain the same as the ones used in the single unbalance estimation, presented before.

Figure 89 presents unbalance estimation and convergence. It is noticeable how robust the method can be, regarding the initial guess value. Even with significative differences in the filter initial value, convergence occurs and the state estimation is done without problems. The mean estimated value for the unbalance level was 562.08 g.mm. Considering the real value, 562.5 g.mm, the error was only 0.075%, and still fully neglectable.

Figure 89 – Test rig unbalance estimation with unbalance initial value variation

7.2.4. Steady-state simulation and PCA analysis

From the unbalance estimate made in the previous section of this work, and with the parameters related to the bearings' stiffness and damping being known *a priori*, an updated model has been obtained. Following the framework proposed in this work, the next step is to perform simulations of new operating conditions, considering the level of unbalance previously estimated as the reference condition for the fault mapping.

Simulations follow the same principles considered in section 7.1.4 (page 134): they are based on the amplitude of the system's response for each considered unbalance condition at a given rotation speed (Ω) and will consist of steady-state temporal 90° lagged sinusoidal responses with the frequency and amplitudes previously defined for each fault condition.

Next, in Figure 90, the test rig rotor FRF simulated for the chosen unbalance conditions is presented (horizontal response, “a”, and vertical response, “b”).

Figure 90 – Test rig rotor FRF for several unbalance conditions

In this example, also ten different unbalance conditions are considered: 562 g.mm, 562.5 g.mm, 567 g.mm, 572.5 g.mm, 598.5 g.mm, 641 g.mm, 683.5 g.mm, 726 g.mm, 768.5 g.mm, and 811 g.mm.

Since real data is available in this case, it is possible to extract the necessary noise for data simulations. Considering the signals collected during the machine start-up (Figure 84, page 172), the noise data is obtained by following the procedure below:

- Calculate the trend line of the monitored data from a B-spline function applied to each probe signal, as presented in Figure 91;
- Subtract the original signals from the trend lines obtained in step “a”, resulting in the noise signal, as presented in Figure 92.

Figure 91 – Test rig trend line experimental data

Figure 92 – Test rig noise data

The data obtained from step “b” represent the noise of each probe. As the signals from each sensor are subject to the same noise sources (electromagnetic noise due to fields acting on the data acquisition system or mechanical imperfections on the disk surface – mechanical runout), it is assumed that the signals can be merged, creating a single noise data vector. This vector, therefore, has twice the number of samples collected for each probe during the analyzed start-up.

Figure 93 presents the noise distribution histogram considering this single noise vector and Figure 94 shows the normalized Probability Density Function (PDF) for this noise data compared to a normalized PDF from an equivalent normal distribution (same mean and standard deviation), that would be obtained in the case of a gaussian noise.

Figure 93 – Noise level histogram

Figure 94 – Noise level probability density function

The real data noise in this case is not an AWGN. Thus, so that the noise added to the simulated data can be as reliable as possible, the direct application of the single noise data vector previously obtained was adopted in this work.

For this purpose, in each data simulation, k samples of the noise data vector are randomly drawn, with k being the number of samples simulated. The procedure must be repeated for each simulation and, despite using a previously defined and limited data sample, the randomness of the noise is guaranteed since the draws match the index of each noise sample in the vector and not its value. In other words, the position of the sample in the noise vector is drawn and not its value directly, so a finite number of results is considered for each draw with an equal chance of happening. Then, the value associated with each index of the vector is added to a sample of the simulated data.

For the steady-state data simulation, a chosen rotational speed of 52 Hz and a sampling rate of 2048 samples per second (S/s) is adopted. The considered reference time window is 0.5 seconds (1024 samples) and for each operational condition, the time window is defined as presented in Table 38, totaling 11.25 seconds of simulation.

Table 38 – Unbalance conditions time windows and number of samples

Unbalance (g.mm)	Time window (s)	Samples
562.0	3.00	6144
562.5	2.00	4096
567.0	1.00	2048
572.5	1.00	2048
598.5	1.00	2048
641.0	1.00	2048
683.5	1.00	2048
726.0	0.50	1024
768.5	0.50	1024
811.0	0.25	512

Source: Author

Again, the simulations of the analyzed data consider the different unbalance levels in ascending order, that is, from the lowest level of unbalance to the highest level of

unbalance. The level of unbalance considered for the reference data is the value estimated with the Kalman filter, that is, 562 g.mm, the lowest value among the different conditions considered.

Next, Figure 95 presents the reference signal, and Figure 96 presents the analyzed data considered in this example. The SNR is around 19 dB for the reference data and 20 dB for the analyzed data.

Figure 95 – Test rig rotor steady-state analysis reference

Figure 96 – Test rig rotor steady-state continuous signal

Following the RMPCA dynamic application and considering both the analysis and reference data, Figure 97 presents the RMPCA results, where PCw 1, PCw 2, and PCw 3 are, respectively, the weights of the first three principal components.

Figure 97 – Test rig rotor RMPCA results

Figure 98 presents the graph over time showing the weight of the first three components individually normalized by their maximum value, with the results varying from 0 to 1.

Figure 98 – Test rig rotor RMPCA results with normalized weights

Figure 99 presents the unbalance mapping for this example, considering the first three principal components as a function of the unbalance level. As in the mappings presented before, in addition to the average value (Mean), the graphs have an upper limit (Mean + 3.sd) and a lower limit (Mean - 3.sd), calculated as a function of the average and standard deviation of the weights of the principal components.

Figure 99 – Test rig rotor unbalance mapping

For the first two principal components, a linear function can approximate the trend, while for the third principal component the approximation is made from a second-order polynomial function.

Table 39 presents the mean and standard deviation values for each condition considered in the previous mapping. Analyzing the RMPCA results presented in this table, particularly the obtained unbalance mapping, it is noted that for unbalance levels between 562.5 g.mm and 572.5 g.mm, which respectively correspond to levels between 0.09% and 1.9% above the reference value, the method shows no variation

in the results, demonstrating that the sensitivity of the RMPCA in these cases is not sufficient for such detection. However, once the unbalance reaches a level of 598.5 g.mm (from the eighth second of the analysis data), that is, 6.5% above the level of the reference signal, the method can detect the variations of the analyzed fault especially considering de PCw 3 variation.

Table 39 – PC weights' means and standard deviations (sd) vs. unbalance level – Test rig example

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
562.0	49.893	0.084	49.574	0.083	0.275	0.008
562.5	49.925	0.053	49.539	0.053	0.277	0.008
567.0	49.877	0.042	49.594	0.043	0.276	0.009
572.5	49.877	0.048	49.596	0.048	0.273	0.007
598.5	49.847	0.048	49.655	0.050	0.257	0.007
641.0	49.965	0.055	49.572	0.053	0.241	0.008
683.5	50.059	0.045	49.511	0.044	0.223	0.006
726.0	49.874	0.031	49.711	0.031	0.214	0.008
768.5	50.021	0.054	49.591	0.048	0.200	0.006
811.0	50.025	0.041	49.597	0.042	0.194	0.005

Source: Author

7.3.FPSO Centrifugal Compressor

The third case example presented in this work concerns an FPSO centrifugal compressor with previously known behavior (MELO, 2019; MICHALSKI, MELO and SOUZA, 2019; SOUZA, MELO and MICHALSKI, 2018). This is the second real equipment analyzed and the first subjected to industrial operating conditions, unlike the test rig in the previous case, whose operating conditions are much better controlled since it is laboratory equipment.

Centrifugal compressors used in FPSO generally have a smaller footprint when compared to onshore units, imposing manufacturers to build up machines capable to operate at higher speeds to achieve the required process performance. Hence, these centrifugal compressors are often designed as flexible rotors and operate above the first critical speed. Furthermore, under these operating and design conditions, a special

balance procedure called high-speed balancing (BOYCE, 2012; EHRICH, 1990) can be necessary.

This procedure is generally done in a special workbench, found in specialized companies, and to execute a field balance in these machines is an unlikely alternative. In this way, develop techniques to identify unbalance malfunction prior it reaches the machine vibration trip limit is essential to minimize the unit downtime (MICHALSKI, MELO and SOUZA, 2019).

The same steps are taken in the previous example, section 7.2 (page 168), will be considered in this example. The mathematical model discretization in this example is also done using FEM and the unbalance estimation is based on the Kalman filtering estimation algorithm (MICHALSKI and SOUZA, 2018). All compressor parameters are considered previously known, except for the unbalance level.

7.3.1. Rotor modeling

As mentioned before, the industrial centrifugal compressor considered in this work is used in the petrochemical industry. Due to industrial secrecy issues, there is not much information about the machine. However, it is known that the total length is about 1590.75 mm and the rotor mass is about 246.5 kg. The first bearing is set up about 173 mm from the left end and the second bearing is set up about 227.75 mm from the right end. The rotor Maximum Continuous Speed (MCOS) is 10400 RPM, or 173.33 Hz (MELO, 2019).

In this model the effects of the rotor foundation will also be neglected and, for modeling purposes, the rotor will be subdivided into the three fundamental components presented in Michalski (2004): the disk, the shaft, and the bearings.

As in the test rig example, the shaft is discretized from Timoshenko beam elements, having two nodes with four degrees of freedom each. The bearings and disks contribution for the model follows the same principles presented before, as well as translational and rotational additional inertia that can be also allocated in each node considered for a better model fit.

The bearings, in this case, are also considered isotropic (or symmetric) and the coupling-terms are null. In this way, the bearings' stiffness and damping matrices are the same as presented in Eq. 77 and Eq. 78 (page 170). The bearings' stiffness coefficients nominal value is 1.75×10^8 N/m, and the damping coefficients nominal value is 1.86×10^5 N.s/m. Likewise in this case a single value for the entire speed range is considered for the bearing's stiffness and damping coefficients, as proposed by Lalanne and Ferraris (1998).

Also, the unbalance phase will not be considered and the unbalance forces equation simplification to a single time-independent equation, as presented in Eq. 81 (page 171) is also performed.

Figure 100 presents the discretized model of this rotor. As mentioned before, the shaft is represented in blue, the disks elements in red, and the bearings in green. The blue dot in the left end (node 1) is the position of the imaginary heavy spot representing unbalance. The red dots along the shaft centerline are concentrated elements of inertia (nodes 2, 31, 36, 46, 51, and 56). This is a much more complex discretized model if compared to the test rig, with 87 nodes.

Figure 100 – Centrifugal compressor finite element model

7.3.2. Compressor measurements and experimental data

As in the previous case, a real machine is being analyzed and real data will be used in the unbalance estimation process using the Kalman filter and in the noise generation process for the simulations and mapping of the various operating conditions using the RMPCA.

In this case, the displacement measurements are taken in the Drive End (DE) and Non-Drive End (NDE) bearings (nodes 5 and 79 of the model presented in Figure 100). Also, inductive analog probes are used to collect the data displacements, measured at 45° and 315° with respect to the horizontal plane, as presented in Figure 101 (MELO, 2019).

Figure 101 – Drive end (left) and non-drive end (right) radial vibration probes

Source: Melo (2019)

The compressor's first critical speed is around 105 Hz (or 6300 RPM) and the considered operational speed range is between 3000 RPM and 11000 RPM. In this range the rotor just reaches one critical speed, thus only the vibration first mode will be considered.

Figure 102 presents the test rig experimental data in both directions (horizontal and vertical) for each monitored bearing (DE and NDE), collected during the manufacturer's commissioning.

Figure 102 – FPSO compressor experimental data

7.3.3. Unbalance estimation

The unbalance estimate, in this case, is also performed as described in section 4.2 (page 70), starting from a state-space problem including the vector of external excitations in the state-vector.

No phase angle between the unbalance and the rotor displacement reference will be considered in this case ($\phi = 0$), as well as the fault location since the node with which the unbalance is associated has been previously determined.

The data simplification mentioned before (Eq. 82, page 173) is considered once more and the sensor data are merged considering the square root of the sum of squares for each bearing. Figure 103 presents the DE and NDE merged experimental data.

Figure 103 – Centrifugal compressor merged experimental data

Regarding the centrifugal compressor balance estimation, the process model noise covariance matrix is the same used in the test rig case, the experimental data noise variance is 5.5×10^{-14} and the state estimation error covariance matrix, $\mathbf{P}_0$, is a diagonal matrix with the values of all elements equal 10. The initial values of error and gain are, respectively, 0.05 and 0.5. Once again, all the initial state-vector values were zero, except for the unbalance force, with an unbalance level equals to 1440 g.mm. Besides, only the NDE bearing data will be considered in the unbalance estimation process.

Figure 104 presents the NDE displacement estimation, compared with the experimental data (previously presented in Figure 103), Figure 105 the unbalance level estimation, and the displacement estimation relative error, ER, given by the Eq.83 (page 174).

Figure 104 – Centrifugal compressor displacement estimation

Figure 105 – Centrifugal compressor unbalance estimation

Figure 106 – Centrifugal compressor displacement estimation error

In relation to Figure 104, it is noted that the values initially estimated for the NDE displacement are very far from the trend value, but end up converging to this value before the maximum amplitude value. This is probably because the order of magnitude of the value of the experimental data is initially very small, making the results of the model have a greater preponderance in the initial estimate. However, as the displacement amplitude increases, convergence occurs and the estimated value starts to follow the experimental value, demonstrating that it has become predominant in relation to the model value.

This relationship between the preponderance of the model and the experimental data is also noted in Figure 106, since initially the estimated displacement error, in addition to being high, fluctuates significantly. However, after the estimated value converges to the experimental value, the fluctuation of the error is no longer perceived.

In this case, the unbalance level estimated value is 1365.9 g.mm. On the other hand, it was previously known that the real value of the centrifugal compressor unbalance was 1097 g.mm when the real data were acquired. Considering that, the estimated value error is 24.5%. Although it is a considerable deviation in the result, it is justifiable: unlike the test rig, the signal noise magnitude, in this case, is too small, and the state estimate values the measurements, generating a less filtered result. It is noticeable, especially considering the displacement, that as the estimate is perfectly

filtered initially, and as the filter begins to adjust to the measurements, the response behavior changes, to the point that the model response begins to be disregarded by the filter.

7.3.4. Steady-state simulation and PCA analysis

Considering the unbalance value estimated in the previous section, and with the parameters related to the bearings' stiffness and damping being known *a priori*, an updated model for the FPSO centrifugal compressor has been obtained. Following the framework proposed in this work, the next step is to perform simulations of new operating conditions, considering the level of unbalance previously estimated as the reference condition for the fault mapping.

Simulations follow the same principles considered in sections 7.1.4 (page 134) and 7.2.4 (page 177): are based on the amplitude of the system's response for each considered unbalance condition at a given rotation speed (Ω) and will consist of steady-state temporal 90° lagged sinusoidal signals with the frequency and amplitudes previously defined for each fault condition.

Next, in Figure 107 (DE bearing) and Figure 108 (NDE bearing), the test rig rotor FRF simulated for the chosen unbalance conditions is presented (horizontal response, on the top, and vertical response, below).

Figure 107 – Centrifugal compressor FRF for several unbalance conditions – DE

Figure 108 – Centrifugal compressor FRF for several unbalance conditions – NDE

In this example, also ten different unbalance conditions are considered: 1365.9 g.mm, 1426.1 g.mm, 1440 g.mm, 1535.8 g.mm, 1645.5 g.mm, 1700 g.mm, 1755.2 g.mm, 1774.5 g.mm, 1785 g.mm, and 1828 g.mm.

Since real experimental data is also available and considered in this case, the additive noise used in the steady-state simulations can be extracted from the experimental data. Considering the signals collected during the machine start-up (Figure 102, page 189), the noise data is obtained by following the same procedure presented in section 7.2.4 (page 177). In this case, the trend line of the monitored data obtained considering a B-spline function applied to each probe signal is presented in Figure 109 and the resulting noise signal is presented in Figure 110.

Figure 109 – Centrifugal compressor trend line experimental data

Figure 110 – Centrifugal compressor noise data

In this case, it is considered that each pair of sensors (correlated with the bearings of the DE and NDE) are subject to the same noise sources and can be merged, creating two noise data vectors. This vector, therefore, has twice the number of samples collected for each probe during the analyzed start-up.

Figure 111 and Figure 112 present the noise distribution histograms considering these noise vectors and Figure 113 and Figure 114 show the normalized Probability Density Function (PDF) for these noise data compared to a normalized PDF from an equivalent normal distribution (same mean and standard deviation, for each case), that would be obtained in the case of a gaussian noise.

Figure 111 – Noise level histogram – DE

Figure 112 – Noise level histogram – NDE

Figure 113 – Noise level probability density function – DE

Figure 114 – Noise level probability density function – NDE

In this case, it is noted that the noise data distribution for both bearings is very close to an AWGN distribution. Even so, the same procedure previously considered in section 7.1.4 will be adopted for the generation of simulated noise data from the actual data collected in the two bearings.

For the steady-state data simulation, a chosen rotational speed of 173.33 Hz and a sampling rate of 2048 samples per second (S/s) is adopted. The considered reference time window is 0.25 seconds (512 samples) and for each operational

condition, the time window is defined as presented in Table 40, totalizing 10 seconds of simulation.

Table 40 – Unbalance conditions time windows and number of samples

Unbalance (g.mm)	Time window (s)	Samples
1365.9	4.00	8192
1426.1	1.00	2048
1440.0	1.00	2048
1535.8	1.00	2048
1645.5	1.00	2048
1700.0	0.50	1024
1755.2	0.50	1024
1774.5	0.50	1024
1785.0	0.25	512
1828.0	0.25	512

Source: Author

Also, in this example, the data simulations consider the different unbalance levels in ascending order, that is, from the lowest level of unbalance to the highest level of unbalance. The level of unbalance considered for the reference data is the value estimated with the Kalman filter, that is, 1365.9 g.mm, the lowest value among the different conditions considered.

Figure 115 presents the reference signal and Figure 116 shows the analyzed data considered in this example. The SNR is around 30 dB (DE) and 14.5 dB (NDE) for the reference data and 31 dB (DE) and 15 dB (NDE) for the analyzed data.

Figure 115 – Centrifugal compressor steady-state analysis reference

Figure 116 – Centrifugal compressor steady-state continuous signal

Following the RMPCA dynamic application and considering both the analysis and reference data, Figure 117 presents the RMPCA results, where PCw 1, PCw 2, and PCw 3 are, respectively, the weights of the first three principal components.

Figure 117 – Centrifugal compressor RMPCA results

Figure 118 presents the graph over time showing the weight of the first three components individually normalized by their maximum value, with the results varying from 0 to 1.

Figure 118 – Centrifugal compressor RMPCA results with normalized weights

It is interesting to note from the previous figure that, due to a lower noise level in the analyzed data, the steps caused by the most drastic variations in the unbalance level in the analyzed signal are noted in the result of the RMPCA.

Figure 119 presents the unbalance mapping for this case, considering the first three principal components as a function of the unbalance level. As in the mappings presented before, in addition to the average value (Mean), the graphs have an upper

limit ($\text{Mean} + 3\text{.sd}$) and a lower limit ($\text{Mean} - 3\text{.sd}$), calculated as a function of the average and standard deviation of the weights of the principal components.

Figure 119 – Centrifugal compressor unbalance mapping

For the first two principal components, a linear function can approximate the plotted trend line, while for the third principal component the approximation is made from an exponential function.

Table 41 presents the mean and standard deviation values for each condition considered in the previous mapping. Analyzing the RMPCA results, particularly the obtained unbalance mapping, for the third principal component weight, it is noted that the RMPCA sensitivity for the unbalance level range considered in this example is suitable for detecting the variations considered.

Table 41 – PC weights' means and standard deviations (sd) vs. unbalance level – Test rig example

Unbalance (g.mm)	PCw 1 (mean)	PCw 1 (sd)	PCw 2 (mean)	PCw 2 (sd)	PCw 3 (mean)	PCw 3 (sd)
1365.9	50.140	0.052	49.729	0.050	0.02690	0.00114
1426.1	50.129	0.046	49.728	0.045	0.02521	0.00093
1440.0	50.151	0.053	49.738	0.053	0.02490	0.00100
1535.8	50.144	0.050	49.745	0.050	0.02385	0.00082
1645.5	50.150	0.062	49.742	0.062	0.02144	0.00073
1700.0	50.151	0.052	49.748	0.051	0.02132	0.00086
1755.2	50.149	0.054	49.754	0.054	0.01970	0.00069
1774.5	50.151	0.055	49.754	0.055	0.01982	0.00071
1785.0	50.144	0.050	49.761	0.049	0.01934	0.00065
1828.0	50.138	0.049	49.767	0.048	0.01950	0.00091

Source: Author

7.4. Validating the Method with Real Data

One of the great motivations for the proposal presented in this work is the great difficulty in obtaining real data that represent the degradation of a rotating machine due to a fault.

Despite the presented method enable the fault mapping (as demonstrated in the three examples previously presented in sections 7.1 – page 108, 7.2 – page 168, and 7.3 – page 185) with the combination of model-based and data-based techniques, real data is still needed to fully validate the proposal.

Thus, the objective of this section is to present an example of the application of the method in which it is possible to compare the obtained mapping with real data from equipment in different operational conditions.

However, in this case, the RPCA (section 5.2.1, page 87) will be used instead of the RMPCA since the data analyzed does not continuously represent the operational condition variation over time. In this case, samples of different operating conditions will be considered, which will be analyzed together with a reference sample.

The chosen equipment to be analyzed is the test rig Jeffcott rotor presented in section 7.2 (page 168). However, in this case, instead of being considered a single rotation speed and the operational condition varying as a function of the unbalance level, a single level of unbalance is considered and the variation of the operational condition will be a function of the rotation speed. The rotor modeling and the unbalance estimation, previously presented in sections 7.1.1 (page 109) and 7.1.3 (page 115), are considered again and the model unbalance level, in this case, is 562 g.mm. The reference rotation speed is 52 Hz (or 3120 RPM). Figure 120 and Figure 121 present some operational conditions examples considering collected experimental data and simulated data, respectively.

Figure 120 – Steady-state experimental data samples

Figure 121 – Steady-state simulated data samples

For the simulated data, a rotation speed variation from 35 Hz to 100 Hz was considered, with a step of 0.08 Hz for each operational condition. On the other hand, the experimental data were collected considering 25 conditions with the rotation speed varying between 5 Hz and 120 Hz with a step of 5 Hz. However, only the rotating speeds between 35 Hz and 100 Hz are considered (to allow a direct comparison with simulated data), totalizing 15 operational conditions.

For the reference data simulation and each simulated sample analyzed, it was selected a sampling rate of 2048 samples per second (S/s) and a time window of 10 seconds (20480 samples). These values are, respectively, the acquisition rate and the acquisition period of the experimental data collected under different steady-state operating conditions.

Two situations will be considered in this analysis: both simulated data and experimental data are analyzed, however in the first situation the reference considered will be simulated and in the second, experimental data will be used as a reference.

Figure 122 and Figure 123 present, respectively, the experimental reference data and the simulated reference data. In both cases, as previously mentioned, the rotation speed is 52 Hz.

Figure 122 – Steady-state experimental reference data

Figure 123 – Steady-state simulated reference data

The results for the RPCA are presented below considering the simulated data as a reference. In Figure 124 the results for the simulated analyzed data of the several operational conditions considered and in Figure 125 the results for the experimental analyzed data.

Figure 124 – RPCA results – Simulated analyzed data and simulated reference

Figure 125 – RPCA results – Experimental analyzed data and simulated reference

Analyzing the results, it can be said that the behavior of the weights of the principal components is quite similar in the two graphs presented. Also, in these cases the result of the three components is sensitive to the equipment operational condition variation, that is, the variation of the rotation speed.

The greatest difference between the results is noticed in Figure 124 at 52 Hz, in the form of a Dirac delta, as a result of the self-referenced data condition (section 5.2.1), that is, when the simulated data analyzed is identical to the simulated reference data. Due to the inaccuracies of the model, the simulated data are not identical to the experimental data, causing the self-referenced data condition not to occur in the second case, Figure 125.

In Figure 126 and Table 42, the comparison of the results obtained is presented, also considering the absolute error (difference) between the weights of the principal components (PCw 1, PCw 2, and PCw 3) in both analyzed cases.

Figure 126 – RPCA results comparison with simulated reference data

Table 42 – RPCA results comparison with simulated reference data

Experimental results				Simulation results			Error		
Ω (Hz)	PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3
35.00	46.80	46.70	3.64	48.00	48.00	2.01	1.20	1.30	1.63
40.00	45.00	45.00	5.86	45.20	45.10	4.87	0.20	0.10	0.99
45.00	39.60	39.50	13.10	37.70	37.70	12.30	1.90	1.80	0.80
50.00	30.40	30.30	29.90	26.60	26.60	23.40	3.80	3.70	6.50
52.00	29.90	28.30	27.10	49.90	49.90	0.08	20.00	21.60	27.02
55.00	31.50	31.50	23.70	27.20	27.20	22.80	4.30	4.30	0.90
60.00	42.60	42.60	8.76	34.10	34.10	15.90	8.50	8.50	7.14
65.00	47.30	47.30	3.15	38.80	38.80	11.30	8.50	8.50	8.15
70.00	48.70	48.70	1.47	41.40	41.40	8.61	7.30	7.30	7.14
75.00	49.30	49.20	0.82	43.00	43.00	6.99	6.30	6.20	6.17
80.00	49.50	49.50	0.54	44.10	44.00	5.97	5.40	5.50	5.43
85.00	49.70	49.60	0.41	44.80	44.70	5.25	4.90	4.90	4.84
90.00	49.70	49.70	0.34	45.30	45.20	4.74	4.40	4.50	4.40
95.00	49.80	49.70	0.30	45.70	45.60	4.38	4.10	4.10	4.08
100.00	49.80	49.80	0.24	46.00	45.90	4.07	3.80	3.90	3.83

Source: Author

The results for the RPCA are presented considering the experimental data as reference: in Figure 127 the results for the simulated analyzed data of the several operational conditions considered and in Figure 128 the results for the experimental analyzed data.

Figure 127 – RPCA results – Simulated analyzed data and experimental reference

Figure 128 – RPCA results – Experimental analyzed data and experimental reference

Analyzing the previous results, it is noted that the behavior of the weights of the principal components is quite similar in the two graphs presented. In addition, in these cases the results of the three components are still sensitive to the equipment operational condition variation, that is, the variation of the rotation speed. In this case, however, the self-referenced data condition effect can be noted in both graphs.

In Figure 129 and in Table 43, the comparison of the results obtained in this second condition is presented, considering again the absolute error (difference) between the weights of the principal components (PCw 1, PCw 2, and PCw 3) in both analyzed cases.

Figure 129 – RPCA results comparison with experimental reference data

Table 43 – RPCA results comparison with experimental reference data

Ω (Hz)	Experimental results			Simulation results			Error (Difference)		
	PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3	PCw 1	PCw 2	PCw 3
35.00	60.70	31.00	4.64	62.80	32.10	2.58	2.10	1.10	2.06
40.00	57.80	29.50	7.40	58.00	29.70	6.15	0.20	0.20	1.25
45.00	49.30	25.20	16.10	46.50	23.80	14.90	2.80	1.40	1.20
50.00	36.10	34.70	18.40	31.00	26.70	26.60	5.10	8.00	8.20
52.00	66.20	33.80	0.00	29.90	28.30	27.10	36.30	5.50	27.10
55.00	37.60	27.70	19.20	31.70	26.00	26.00	5.90	1.70	6.80
60.00	54.00	27.60	10.90	41.30	21.10	18.80	12.70	6.50	7.90
65.00	61.60	31.50	4.03	48.10	24.60	13.70	13.50	6.90	9.67
70.00	64.00	32.70	1.89	52.10	26.60	10.60	11.90	6.10	8.71
75.00	64.90	33.20	1.07	54.70	27.90	8.71	10.20	5.30	7.64
80.00	65.30	33.40	0.70	56.30	28.80	7.48	9.00	4.60	6.79
85.00	65.60	33.50	0.53	57.40	29.30	6.62	8.20	4.20	6.09
90.00	65.70	33.60	0.44	58.30	29.80	5.99	7.40	3.80	5.55
95.00	65.70	33.60	0.39	58.90	30.10	5.55	6.80	3.50	5.16
100.00	65.80	33.60	0.32	59.40	30.30	5.17	6.40	3.30	4.85

Source: Author

In Figure 130, the results for the four possible data combinations are presented (Sim. Analyz. Data + Sim. Ref. = simulated analyzed data with simulated data reference; Exp. Analyz. Data + Sim. Ref. = experimental analyzed data with simulated data reference; Sim. Analyz. Data + Exp. Ref. = simulated analyzed data with experimental data reference; and Exp. Analyz. Data + Exp. Ref. = experimental analyzed data with experimental data reference).

Analyzing the four results presented, it is noted that the method is quite consistent, especially in relation to the rotation speeds below the critical speed, which in this case was used as the reference speed.

Figure 130 – RPCA results comparison with both reference data

For the first two PCs, both in the case of simulated data being used as a reference, as in the case of real data being used in this function, the results obtained with simulated data in the several operational conditions are very close to the results obtained with real data. This statement is clarified by the proximity between the blue and yellow lines, as well as between the green and red lines, presented in Figure 130.

For the case of the third PC, however, it is noted that the greatest similarity occurs between results when considering the same type of analyzed data, which is highlighted by the proximity between the blue and red lines (both related to simulated data analysis) and the proximity between the green and yellow lines (related to the analysis of experimental data). Still, all four results are quite close, except for the self-referenced data region.

It is noted in this region, close to the critical speed of the rotor, also used as reference speed for the analyzes, that the error between the results of the simulated and experimental data increases considerably. This is due, first, to the abrupt variation in the value of the PCw as a function of the self-referencing of the RPCA input matrix that occurs at the critical speed. And, mostly, it must be considered that the discretization of the experimental data is much poorer than in the case of simulated data. That is, if a greater number of intermediate operational conditions are observed experimentally, the results would tend to be even closer.

7.5. Results Discussion

As mentioned earlier, the main objective of this chapter is to present examples that prove the viability of the method proposed in this work. Three case studies were considered: a theoretical Jeffcott rotor, a Jeffcott rotor test rig, and a FPSO centrifugal compressor. The first case took into account only simulated data, while the other cases used real data. Likewise, the modeling as well as the technique used to estimate the unknown parameters in the first case differs in relation to the others. Table 44 presents a summary regarding applied methods and data sources of these case studies.

Table 44 – Case studies summary

Case Study	Data Source	Modeling Method	Estimated Parameters	Model Updating Method
Theoretical Jeffcott Rotor	Simulated data	Rayleigh-Ritz	Unbalance + Bearings' stiffnesses and damping factors	Monte Carlo + Simulated Annealing
Jeffcott Test Rig	Real data	Finite Element Method	Unbalance	Kalman Filter
FPSO Centrifugal Compressor	Real data	Finite Element Method	Unbalance	Kalman Filter

Source: Author

The presented studies' purpose also differs slightly from one another. The first case study, when considering a hypothetical system with simulated data, provides a more controlled analysis environment. Thus, the proposed hybrid method could be presented as well as having its sensitivity evaluated regarding several parameters. The result of the model update can be considered very good and the application of the RMPCA demonstrated that it is possible to create a mapping that relates the RMPCA response to the rotor unbalance level.

Regarding the sensitivity of the results in relation to the method's parameters, six variables were highlighted:

- The fault degradation level when considered the reference data;
- The data noise level;
- The method analysis window;
- The data signal sampling rate;
- The machine rotating speed;
- The fault degradation speed.

For the first three variables listed, a detailed analysis was made. Briefly, in relation to the fault level of the reference data, it is noted that the lower the level of unbalance in the reference data, that is, the healthier the equipment is when the reference data is acquired, the more likely it will be to detect the fault degradation. On the other hand, in relation to the data noise level, it is noted that a hypothetical total noise absence is not beneficial for the method, as well as high levels that invert the SNR (negative values in dB). Regarding the size of the analysis window, the limitation observed is related to

the delay in the responses of the method, or in other words, how long the machine is considered healthy.

The second case study, in turn, presents a real machine that, even though it is an experimental laboratory bench, already takes a step forward that brings the method closer to an industrial application. In this case, the unbalance estimate showed a good convergence and the application of the RMPCA presented a sensitive response sufficient to distinguish different operational conditions. The same can be said for the third example, which in this case presents the analysis of an FPSO centrifugal compressor, subjecting the proposed method to a de facto industrial application.

The purpose of these two case studies was to present the feasibility of the method, demonstrating that from an initially unknown condition it is possible to estimate the residual unbalance of a rotating machine and to forecast its dynamic behavior considering the degradation of the machine due to the analyzed failure mode. However, due to the difficulty of seeding faults in real equipment or even obtaining data that are related to the degradation of such machines, the method validation is impaired.

In order to overcome this issue, a variation of the second case study was proposed, considering the same model and initial condition, however, in this case, the operational condition varies due to changes in the rotation speed and not the unbalance degradation. The results obtained demonstrate that the method allows a good approximation between the simulated projections and the real behavior of the equipment under the same operational conditions. Furthermore, because PCA is defined as an orthogonal linear transformation, the error (difference between the responses of the real system and the simulated model) found in this analysis can be attributed to the modeling uncertainties. That is, with a more accurate model, the better results would be found.

8 CONCLUSIONS AND PROPOSAL OF FUTURE STUDIES

The present work introduced a hybrid method for unbalance detection and diagnosis of rotating machines based on independent but complementary strategies, belonging to the two major families of FDD techniques: data-based and model-based methods.

The choice of a hybrid method for rotating machinery FDD, built from the integration of model-based and data-based methods, rather than using a single technique, attempt to balance the best of both worlds: the ability to quantify faults, as in model-based methods, and the rapid response to variations in systems operating conditions, characteristic of data-based methods.

Model-based methods can quantify faults without prior machine behavior knowledge. Another great advantage of model-based methods is the fact that physics-based modeling has provided significant advances where techniques like FEM can provide easier, faster, and cheaper data trials when compared to seeding faults into real machinery. In this way, to build a model that represents a machine dynamic behavior can be the key to virtual process prototyping in rotating machinery fault diagnosis and prognosis.

However, an issue regarding model-based techniques is the fact that these approaches are generally based on a specific, and sometimes, hard to build a model. And naturally, the complexity of more detailed models tends to have a high computational cost, in addition to requiring significant time to deliver a response, when compared to traditional techniques based on data analysis (signal-based methods), for example. Besides, the model is generally tuned to a single fault set, and conditions not previously established cannot be detected.

To overcome such weakness, integrating data-based methods, especially data-driven statistical methods, with model-based techniques becomes extremely promising, since the former is sensitive to changes not necessarily predicted in the machine behavior by modeling. Indeed, data-based techniques allow multiple variables analysis of a large amount of data, responding quickly to variations in the monitored

system, without needing any prior knowledge about the system or related faults, being, therefore, ideal for real-time analysis.

The disadvantage of data-based techniques is mainly the inability to quantify or locate faults. However, when considering the result of applying such techniques to previously performed simulations in which the system operating conditions are known, it is possible to compare such results to those obtained from the same analyzes applied to real data. That is, a map of the considered faults can be pre-established allowing the evolution of the problem to be monitored and quantified directly from experimental data.

Regarding the chosen data-based techniques in this work, for modeling purposes, when few degrees of freedom could represent the dynamics of the analyzed system, the Rayleigh-Ritz method was proposed as a solution (as presented in section 7.1 – page 108, considering the theoretical Jeffcott model). In the case of multiple degrees of freedom being necessary, the FEM was considered to be more appropriate (as presented in sections 7.2 – page 168 – and 7.3 – page 185, for the test rig model and the FPSO compressor model).

On the other hand, for the model update and parameter estimation, when only the unbalance level was considered as an unknown variable, the Kalman filter was the chosen method (as in the test rig and centrifugal compressor cases). However, when in addition to the unbalance level, the bearings' stiffness and damping parameters were estimated, a combination of SA and MCM was applied (as in the case of the theoretical Jeffcott rotor).

Regarding the data-based technique, the chosen tool for detecting distinct operation conditions was the PCA. Being a robust tool, well established, very popular, and with a simple computational implementation, PCA seemed to be the ideal method for this work. And, to get around some drawbacks regarding the technique, a novel variation of the method was proposed (the RMPCA), being one of the main aspects of innovation of this work.

It is important to emphasize that, since one of the main motivations for this work is the possibility of developing an ISHM tool for rotating machinery in the future, the

techniques to integrate such methods must allow some degree of automation, which can be easily developed regarding PCA.

The proposed method was structured based on a conceptual framework, with the main objective of solving a recurring problem generically, allowing the efforts necessary for this to be focused on the problem-solution itself and not on developing the necessary tools for the task. That is, despite the innovations and developments carried out in the single methods, it is their integration that should be considered as the focus of this work.

From the establishment of a work domain and some premises, the key aspects of the proposed framework were modularity and reusability. That is, although all the work in this thesis has been developed for a specific fault considering only two model-based techniques and a single data-based technique, it is expected that the proposed method could be reused in the analysis of other faults in rotating machines (or even for other types of equipment) with the application of different methods since common points are previously established and the application data flow is maintained.

Considering a general perspective, the proposed method's framework can be divided into four major steps: data acquisition, modeling, simulation, and detection. On the other hand, the common aspect among the applied techniques is the use of the system's measurements for FDD.

One major aspect that should be highlighted considering the proposed method is the order between the fault detection and diagnosis. Generally, FDD methods identify an anomaly in an operating condition of the analyzed equipment and then associate that anomaly as a symptom of a pre-existing fault, diagnosing it. In this case, however, it is assumed a pre-existing fault in the analyzed equipment could be quantified and identified, after the establishment of a fault map (working like an abacus), with simulations.

Thus, the first premise considered in this work was the evaluated fault choice. In this case, based on the review of rotating machine faults presented in section 2.4, the chosen analyzed fault was the mechanical unbalance. This decision was motivated by two fundamental reasons: unbalance can be considered as practically an omnipresent fault in all rotating machines and, although it is not a fault that directly generates

damages, it can be considered the origin of other more severe faults with catastrophic consequences.

Considering the method application, the second premise was the existence of enough information for building a model that minimally represents the dynamics of the considered equipment when subjected to the selected fault. That is, the commitment between the machine model and the fault model is satisfied. In this case, depending on the available information, as proposed, two possibilities for modeling and two for parameters estimation could be followed.

Regardless of the chosen methods, just three basic elements were considered for rotor modeling: shaft, discs, and bearings. The foundations' effects were disregarded in all analyzed cases.

It was also considered that the necessary conditions for the system excitability and observability were satisfied in all analyzed cases. This argument is primarily since the load generated by the unbalance is synchronous, that is, proportional to the equipment's rotation speed. Also, only the first mode of vibration of the analyzed equipment is considered. In this way, a transient operational condition (a machine startup in this case) that goes through a single critical speed would guarantee the system excitability, the same way that the data analysis from this transient condition would guarantee the fault observability.

Once the models for each analyzed case were established, including the initial level of the considered fault, the simulation of different operational conditions could be performed. In this case, due to unbalance being the only analyzed fault, it was established that simulations would depend on only two parameters: the amplitude of the simulated signals according to the simulated operational condition and the additive noise level.

The simulated signals amplitudes were obtained directly from the previously established models, being defined by the levels of unbalance for each analyzed case. On the other hand, the noise level was considered a property of the signals previously collected in a transient regime (for the cases in which experimental data were used, that is, the test rig Jeffcott rotor and the FPSO centrifugal compressor). In the case of the theoretical Jeffcott rotor, an AWGN was simulated.

The theoretical Jeffcott rotor was the first case study analyzed. The combination of SA and MCM brought good results for the modeling and parameters estimation. Thus, with a reliable model, it was possible to evaluate the RMPCA's sensitivity regarding some of its input parameters, demonstrating the method's robustness and applicability.

Next, the experimental test rig Jeffcott rotor and the FPSO centrifugal compressor were analyzed and, in both cases, modeling considering FEM and estimation of the parameters with the Kalman filter were performed successfully. Applying a non-linear variation of the filter allowed the unbalance level estimation without major problems. However, the algorithm behavior was completely different in the two models since the difference between scale factors from what is desired to be estimated (the unbalance level) and what is measured (the displacement amplitude) makes the filter behavior more sensitive in the compressor case.

Moreover, with a measurement error so small in the compressor case, the filter disregards the model from the moment it approaches convergence with the response. As a result, while the unbalance could be estimated with a very small error in the test rig case, the error in the centrifugal compressor case was significantly higher, although still satisfactory. Regarding the filter robustness, the obtained response can be considered excellent. Since the system parameters are known, significant variations in the kick-off (initial value) do not bring variations to the final response, considering the used data, both for the test rig and the centrifugal compressor.

The application of RMPCA in the simulated data was also very positive. Both in the case of the test rig and the compressor, the unbalance mapping considering the RMPCA results was carried out without major problems. Theoretically, from the obtained mapping, it would be possible to detect the level of unbalance in real-time for the analyzed machines considering the application of the RMPCA in experimental data.

To validate such a statement, a fourth case study was proposed in which the RPCA was applied (a simplified version of the RMPCA in which there is no use of the dynamic window previously presented).

The test rig Jeffcott rotor was considered again and from the same model previously updated, different operating conditions were simulated in which the variable became the rotation speed and no longer the unbalance level. From several data samples previously collected at different rotation speeds from the test rig, it was possible to compare the results of the RPCA applied to the simulated data and the experimental data.

The conclusion was very promising, with great adherence between the results, found especially in the regions where the rotor model is more accurate. In other words, the application of the RMPCA has great potential for fault detection, even allowing its quantification in real-time, once an accurate model has been previously established. It is noticed, therefore, that the proposed method is valid, generating good results.

As all the mapping work is done in advance, the difficulty of running a model for different operational conditions and different fault degradation levels in real-time is overcome. On the other hand, the PCA ability to quickly detect variations in the signals analyzed is maintained, allowing the comparison between real and simulated data, identifying, and quantifying a fault in real-time.

As a proposal for future works, studies of different approaches for rotating machinery modeling, allowing multiple faults to be simulated and evaluated simultaneously, seems a promising path.

Another aspect that can be improved is the accuracy of the models. As they are used entirely offline considering the proposed method, more complex models that could represent the analyzed equipment more accurately should be used. This idea is reinforced by the fact that errors observed in the results are much more associated with the model than the data-based method.

Consider a robust variation of the RMPCA to overcome the presence of outliers in the collected signals can be another future improvement of the proposed methods. Although some Supervisory Control and Data Acquisition (SCADA) and Condition Monitoring and Diagnosis commercial systems, in theory, make use of parametric filters that eliminate corrupted data, in practice this cannot always be guaranteed. In this way, it is not difficult to find data with false values in such systems' databases. A

failure in the measurement chain or even in a system thread can lead to such a situation.

9 BIBLIOGRAPHIC REFERENCES

AARTS, E. H. L.; VAN LAARHOVEN, P. J. M. Simulated Annealing: A pedestrian review of the theory and some application. In: **Pattern Recognition Theory and Applications**, NATO ASI Series (Series F: Computer and Systems Sciences), 1987, Vol. 30, p. 179–192. Springer, Berlin, Heidelberg. Devijver P.A., Kittler J. (ed.).

ABDI, H.; WILLIAMS, L. J. Principal component analysis. **Wiley Interdisciplinary Reviews: Computational Statistics**. Vol. 2, no. 4, p. 433-459, 2010.

ADAMS, M. L., **Rotating Machinery Vibration: From Analysis to Troubleshooting**. Marcel Dekker, 2001.

AJAMI, A.; DANESHVAR, M. Data driven approach for fault detection and diagnosis of turbine in thermal power plant using Independent Component Analysis (ICA). **International Journal of Electrical Power and Energy Systems**. Vol. 43, no. 1, p. 728–735, 2012.

ALAUDDIN, M. et al. A Bibliometric Review and Analysis of Data-Driven Fault Detection and Diagnosis Methods for Process Systems. **Industrial and Engineering Chemistry Research**. Vol. 57, no. 32, p. 10719-10735, 2018.

ALMEIDA, F. C. L. **Diagnóstico automático de falhas em turbinas hidráulicas de pequenas centrais hidroelétricas utilizando técnicas preditivas de manutenção e redes neurais artificiais**. 309 p. Dissertation (Master Degree) – Programa de Pós-graduação em Engenharia Mecânica da Universidade Estadual Paulista Júlia de Mesquita Filho (UNESP), Campus Ilha Solteira, Ilha Solteira, SP, Brazil. 2008.

ALZGHOUL, A. et al. Comparing a knowledge-based and a data-driven method in querying data streams for system fault detection: A hydraulic drive system application. **Computers in Industry**. Vol. 65, no. 8, p. 1126-1135, 2014.

AMIN, M. T.; IMTIAZ, S.; KHAN, F. Process system fault detection and diagnosis using a hybrid technique. **Chemical Engineering Science**. Vol. 189, p. 191-211, 2018.

ANDRUȘCĂ, M. et al. Electrical Equipment Maintenance Component of the Asset Management. **Buletinul AGIR**. An XVII, no. 3, p. 513-520, Jun.-Aug. 2012.

ARAÚJO, C. W.; CULLEN, J.; TSAMENYI, M. Privatisation and electricity sector reforms in Brazil: accounting perspective. **Journal of Accounting in Emerging Economies**. Vol. 1, no. 1, p. 53-75, 2011.

ASSIS, E. G.; STEFFEN, V. Inverse problem techniques for the identification of rotor-bearing systems. **Inverse Problems in Engineering**. Vol. 11, no. 1, p. 39-53, 2003.

AYECH, N.; CHAKOUR, C.; HARKAT, M.-F. New Adaptive Moving Window PCA for Process Monitoring. **IFAC Proceedings Volumes**. Vol. 45, no. 20, p. 606–611, Jan. 2012.

BACHSCHMID, N.; PENNACCHI, P. Faults identification and corrective actions in rotating machinery at rated speed. **Shock and Vibration**. Vol. 13, no. 4-5, p. 485-503, 2006.

_____. Accuracy of Fault Detection in Real Rotating Machinery Using Model Based Diagnostic Techniques. **JSME International Journal – Series C: Mechanical Systems, Machine Elements and Manufacturing**. Vol. 46, p. 1026-1034, 2003.

BACHSCHMID, N.; PENNACCHI, P.; TANZI, E. Cracked rotating shafts: typical behaviors, modeling and diagnosis. **Proceedings**. IUTAM Symposium on Emerging Trends in Rotordynamics. Vol. 1011, p. 441-454, 2011.

_____. **Cracked Rotors – A Survey on Static and Dynamic Behaviour Including Modeling and Diagnosis**. Springer, 2010.

BACHSCHMID, N.; PENNACCHI, P.; VANIA, A. Identification of multiple faults in rotor systems. **Journal of Sound and Vibration**. Vol. 254, no. 2, p. 441-454, 2002.

BEN-AMEUR, W. Computing the Initial Temperature of Simulated Annealing. **Computational Optimization and Applications**, Vol. 29, no. 3, p. 369–385, 2004.

BENEDETTINI, O. et al. State of-the-art in integrated vehicle health management (Review Paper). **Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering**. Vol. 223, p. 157-170, 2009.

BENTLY, D. E.; HATCH, C. T. **Fundamentals of Rotating Machinery Diagnostics**, 1st Edition. ASME Press (American Society of Mechanical Engineers), 2003. 725 p. Grissom, B. (Ed.).

BORGHESANI, P. et al. Application of cepstrum pre-whitening for the diagnosis of bearing faults under variable speed conditions. **Mechanical Systems and Signal Processing**. Vol. 36, no. 2, p. 370-384, April 2013.

BOTTURA, F. B. **Arranjo otimizado de monitores para sistemas de distribuição frente às variações de tensão de curta duração e potenciais condições de ressonância harmônica**. 180 p. Thesis (Doctoral Degree) – São Carlos School of Engineering, University of São Paulo, São Paulo, Brazil. 2019.

BOSISIO, A. et al. Improving DTR assessment by means of PCA applied to wind data. **Electric Power Systems Research**. Vol. 172, p. 193-200, January 2019.

BOYCE, P. B. **Gas Turbine Engineering Handbook**, 4th Edition, Butterworth-Heinemann, Elsevier Inc., MA, USA, 2012.

BUCHER, I., EWINS, D. J. Modal analysis and testing of rotating structures. **Philosophical Transactions of the Royal Society of London – Series A: Mathematical Physical and Engineering Sciences**. Vol. 359, issue 1778, p. 61-96, 2001.

CACHADA, A. et al., **Maintenance 4.0: Intelligent and Predictive Maintenance System Architecture**. International Conference on Emerging Technologies and Factory Automation (ETFA). Vol. 2018-Sep., p. 139–146, 2018.

CALVETTI, D.; SOMERSALO, E. **Inverse problems: From regularization to Bayesian inference**. Wiley Interdisciplinary Reviews: Computational Statistics. Vol. 10, no. 3, p. 1-19, 2018.

ČERNÝ, V. Thermodynamical approach to the traveling salesman problem: an efficient simulation algorithm. **Journal of Optimization Theory and Applications**. Vol. 45, no.1, p. 41-51, 1985.

CHEN, W. J. **Rotordynamic Modeling and Analysis**. In: Practical Rotordynamics and Fluid Film Bearing Design. Trafford Pub., 2015, cap. 6, p. 341–430.

CHEN, X. et al. Basic research on machinery fault diagnostics: Past, present, and future trends. **Frontiers of Mechanical Engineering**. Vol. 13, no. 2, p. 264–291, 2018.

CHRÉTIEN, S.; CLARKSON, P.; GARCIA, M. S. Application of Robust PCA with a structured outlier matrix to topology estimation in power grids. **International Journal of Electrical Power and Energy Systems**. Vol. 100, p. 559–564, Feb. 2018.

CHIBANTE, R. (ed.) **Simulated Annealing: Theory with Applications**. Sciyo, Rijeka, Croatia, 2010.

CHILDS, D. **Turbomachinery Rotordynamics – Phenomena, Modeling and Analysis**. John Wiley & Sons, Inc., 1993.

DAI, X.; GAO, Z. From Model, Signal to Knowledge: A Data-Driven Perspective of Fault Detection and Diagnosis. **IEEE Transactions on Industrial Informatics**. Vol. 9, no. 4, p. 2226–2238, Nov. 2013.

DE CASTRO, H. F.; CAVALCA, K. L.; NORDMANN, R. Whirl and whip instabilities in rotor-bearing system considering a nonlinear force model. **Journal of Sound and Vibration**. Vol. 317, no. 1–2, p. 273–293, 2008.

DEEPAK PRABHAKAR, P.; and JAGATHY RAJ V. P. CBM, TPM, RCM and A-RCM - A Qualitative Comparison of Maintenance Management Strategies. **International Journal of Management & Business Studies – IJMBS**. Vol. 4, issue 3, Jul. –Sep. 2014.

DEWELL, D. L.; MITCHELL, L. D. Detection of a misaligned disk coupling using spectrum analysis. **Transactions of the American Society of Mechanical Engineers, Journal of Vibration, Acoustics, Stress and Reliability in Design**. Vol. 106, p. 9–16, 1984.

DOMES, B. Vibration phenomena in aero-engines. **Proceedings**. 9th International Conference on Vibrations in Rotating Machinery (IMEchE '08). Vol. 1, p. 15–32. Exeter, UK, September 2008.

DONG, S. et al. A Fault Diagnosis Method for Rotating Machinery Based on PCA and Morlet Kernel SVM. **Mathematical Problems in Engineering**, Hindawi Publishing Corporation, v. 2014, article ID 293878, 2014.

DOWSLAND, K. A.; DÍAZ, B. A. Diseño de Heurísticas y Fundamentos del Recocido Simulado. **Revista Iberoamericana de Inteligencia Artificial**. Vol. 20, p. 34–52, 2003.

ECHEVERRÍA, L. C. et al. **Fault Diagnosis Inverse Problems: Solution with Metaheuristics**. Springer International Publishing, 2019.

EDWARDS, S.; LEES, A. W.; FRISWELL, M. I. Experimental identification of excitation and support parameters of a flexible rotor-bearing-foundation system from a single run-down. **Journal of Sound and Vibration**. Vol. 232, no. 5, p. 963–992, 2000.

EHRICH, F. F. (Ed.). **Handbook of Rotordynamics**. McGraw-Hill, New York, 1992.

_____. Pseudo-High-Speed Balancing. **Journal of Vibration and Acoustic**. Vol. 112, no. 4, p. 418-426, 1990.

EISENMANN, R. C.; EISENMANN, R. C. **Machinery Malfunction Diagnosis and Correction**, Vibration Analysis and Troubleshooting for the Process Industries. Prentice Hall PTR, Hewlett-Packard Professional Books. New Jersey, USA, 1998.

EL-SHAFEI, A., TAWFICK, S. H., MOKHTAR, M. O. A. Experimental investigation of the effect of angular misalignment on the instability of plain journal bearings. **Proceedings**. ASME/STLE International Joint Tribology Conference (IJTC'09), p. 171-173, Memphis, Tennessee, USA, October 2009a.

_____. Misalignment modeling in rotating systems. **Proceedings**. ASME Turbo Expo. Vol. 1711, p. 973-979. Bahaloo, H.; Ebrahimi, A. and Samadi, M. (Ed.). Orlando, Florida, USA, June 2009b.

FALCETTA, F. A. M. **Evolução da capacidade de regularização do sistema hidrelétrico brasileiro**. 66 p. Dissertation (Master Degree) – Departamento de Engenharia de Hidráulica e Ambiental, Escola Politécnica, Universidade de São Paulo, São Paulo, SP, Brazil. 2015.

FAN, C. C. Study of Start-Up Vibration Response for Oil Whirl and Dry Whip. **Mechanical Systems and Signal Processing**. Vol. 25, p. 3102-3115, 2011.

FANG, H. et al. Nonlinear Bayesian estimation: From Kalman filtering to a broader horizon. **IEEE/CAA Journal of Automatica Sinica**. Vol. 5, no. 2, p. 401–417, 2018.

FARIAS, R. C. G. B. **Atuação Estatal e a Privatização do Setor Elétrico Brasileiro**. 115p. Dissertation (Master Degree) – Instituto de Ciência Política (IPOL), Universidade de Brasília (UNB), Brasília, DF, Brazil. 2006.

FERRARO, P. et al. Comparison and clustering analysis of the daily electrical load in eight European countries. **Electric Power Systems Research**. Vol. 141, p. 114-123, 2016.

FRISWELL, M. I., MOTTERSHEAD, J. E. **Finite element model updating in structural dynamics**. The Netherlands: Kluwer Academic Publishers, Vol. 286, Dordrecht, 1995.

FREIRE, E. Vibração em Hidrogeradores. III ENAM – Encontro Nacional de Máquinas Rotativas. **Proceedings**. Foz do Iguaçu. PR. Brazil. 19-22 Nov., 2006.

GAKA, T., TABASZEWSKI, M. An application of statistical symptoms in machine condition diagnostics. **Mechanical Systems and Signal Processing**. Vol. 25, no. 1, p. 253-265, 2011.

GANERIWALA, S. N.; SCHWARZ, B.; RICHARDSON, M. H. Operating detection shapes detect unbalance in rotating equipment. **Sound and Vibration**. Vol. 43, no. 5, p. 11-13, 2009.

GAO, Z.; CECATI, C.; DING, S. X. A survey of fault diagnosis and fault-tolerant techniques-part I: Fault diagnosis with model-based and signal-based approaches. **IEEE Transactions on Industrial Electronics**. Vol. 62, no. 6, p. 3757-3767, 2015a.

_____. A survey of fault diagnosis and fault-tolerant techniques-part II: Fault diagnosis with knowledge-based and hybrid/active approaches. **IEEE Transactions on Industrial Electronics**, Vol. 62, n. 6, p. 3768-3774, 2015b.

GENDREAU, M.; POTVIN, J.-Y. (ed.). **Handbook of Metaheuristics**, 3rd edition. International Series in Operations Research & Management Science, Vol. 272. Springer International Publishing, 2019.

GENTA, G. **Dynamics of Rotating Systems**, 1st edition. 658 p. New York, USA. Springer-Verlag, Mechanical Engineering Series, 2005.

GIBBONS, C. B. Coupling misalignment forces. **Proceedings**. 15th Turbomachinery Symposium, p. 111-116, Gas Turbine Laboratory, College Station, Texas, USA, 1976.

GIBBS, B. P. **Advanced Kalman Filtering, Least -Squares and Modeling – A Practical Handbook**. John Wiley & Sons, Inc., 2011.

GOLFIERI, C. I. **Estudo Investigativo da Análise Modal aplicada a Sistemas de Distribuição frente às Distorções Harmônicas**. 285 p. Dissertation (Master Degree) – São Carlos School of Engineering, University of São Paulo, São Paulo, SP, Brazil. 2018.

GREEN, I.; CASEY, C. Crack detection in a rotor dynamic system by vibration monitoring - part I: analysis. **Journal of Engineering for Gas Turbines and Power**. Vol. 127, no. 2, p. 425-436, 2005.

GUPTA, T. C.; GUPTA, K.; SEHGAL, D. K. Instability and chaos of a flexible rotor ball bearing system: an investigation on the influence of rotating imbalance and bearing clearance. **Journal of Engineering for Gas Turbines and Power**. Vol. 133, no. 8, Article ID 082501, 11 p., 2011.

HABIBI, H.; HOWARD, I.; SIMANI, S. Reliability improvement of wind turbine power generation using model-based fault detection and fault tolerant control: A review. **Renewable Energy**. Vol. 135, p. 877–896, 2019.

HALIPCHUK, P.; PENNER, K.; SMITH, S. Machining Solutions: Repairing Cracked Turbine Shafts at Jenpeg. **Hydro Review**. Hydro World. Vol. 30, Issue 7, Jan. 10, 2011.

HAMROCK, B. J.; SCHMID, S. R.; JACOBSON, B. O. **Fundamentals of fluid film lubrication**. Marcel Dekker Inc., 2004.

HAN, Q.; ZHANG, Z.; WEN, B. Periodic motions of a dual disc rotor system with rub impact at fixed limiter. **Proceedings of the Institution of Mechanical Engineers**. Vol. 222, no. 10, p. 1935-1946, 2008.

HARKAT, M. F. et al. Uncertain Dynamic Process Monitoring Using Moving Window PCA for Interval-Valued Data. **Proceedings**. 29th International Workshop on Principles of Diagnosis (DX 2018), Warsaw, Poland. Aug. 27-30, 2018.

HASTINGS, W. K. Monte Carlo sampling methods using Markov chains and their applications. **Biometrika**. Vol. 57, no. 1, p. 97-109, 1970.

HAUG, A. J. **Bayesian Estimation and Tracking: A Practical Guide**, 1st edition. John Wiley & Sons, Inc., 2012.

HE, M.; CLOUD, C. H.; BYRNE, J. M. Fundamentals of Fluid Film Journal Bearing Operation and Modeling. **Proceedings**. Thirty-Fourth Turbomachinery Symposium, p. 155-175, Houston, Texas. Sep. 12-15, 2005.

HONG, J. et al. Prognostics model for predicting aero-engine bearing grade-life. **Proceedings**. ASME Turbo Expo. Vol. 1, p. 639-647, Orlando, Florida, USA, June 2009.

INGBER, L. Simulated annealing: Practice versus theory. **Mathematical and Computer Modeling**. Vol. 18, no. 11, p. 29–57, 1993.

INOUE, T.; NAGATA, N.; ISHIDA, Y. FEM modeling and experimental verification of a rotor system with an open crack. **Proceedings**. ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (DETC '09), p. 1113-1122, San Diego, California, USA, September 2009.

ISERMANN, R. **Fault-Diagnosis Applications**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011.

_____. Model-Based Fault Detection and Diagnosis - Status and Applications. **IFAC Proceedings Volumes**. Vol. 37, no. 6, p. 49–60, 2004.

_____. Model Based Fault Detection and Diagnosis Methods. **Proceedings**. American Control Conference, Seattle, Washington, US, June 1995.

_____. Integration of Fault Detection and Diagnosis Methods. **IFAC Proceedings Volumes**. Vol. 27, no. 5, p. 575–590, 1994.

ISO STANDARDS. **ISO 13379-1**: Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques — Part 1: General guidelines. BSI Standards Publication, 2012.

JAYNES, E. T. Information Theory and Statistical Mechanics. **Physical Review**. Vol. 106, no. 4, p. 620-630, 1957.

_____. Information Theory and Statistical Mechanics II. **Physical Review**. Vol. 108, no. 2, p. 171-190, 1957.

JIANG, Q.; YAN, X.; HUANG, B. Performance-Driven Distributed PCA Process Monitoring Based on Fault-Relevant Variable Selection and Bayesian Inference. **IEEE Transactions on Industrial Electronics**. Vol. 63, no. 1, p. 377-386, 2016.

JOLLIFFE, I. T. **Principal Component Analysis**. 2nd edition, Springer, 2002.

JORDAN, M. A. What are orbit plots, anyway? **Orbit**. December 1993, p. 8-15, 1993.

KADLEC, P.; GABRYS, B.; STRANDT, S. Data-driven Soft Sensors in the process industry. **Computers and Chemical Engineering**. Vol. 33, no. 4, p. 795–814, 2009.

KAPIO, J. P.; SOMERSALO, E. **Statistical and Computational Inverse Problems**. Applied Mathematical Sciences, vol. 160, Springer, 2005. Antman, S. S.; Marsden, J. E.; Sirovich, L. (Ed.).

KAPIO, J. P. et al. **Statistical inversion and Monte Carlo sampling methods in electrical impedance tomography**. 2000. Report No. 9/2000, Report Series ISSN 0788-4672, University of Kuopio, Department of Applied Physics, Kuopio, Finland.

KAPPAGANTHU, K.; NATARAJ, C. Nonlinear modeling and analysis of a rolling element bearing with a clearance. **Communications in Nonlinear Science and Numerical Simulation**. Vol. 16, no. 10, p. 4134-4145, 2011.

KARDEC, A.; NASCIF, J. **Manutenção – Função Estratégica**, 4th edition, Qualitymark, 2012.

KHORASGANI, H. et al. A Framework for Unifying Model-based and Data-driven Fault Diagnosis. **PHM Society Conference**. Vol. 10, no. 1, p. 1–10, 2018.

KIM, B.; LEE, J. H. Improved Parameter Estimation of Ill-Conditioned Problems. **Proceedings**. 2018 IEEE Conference on Decision and Control (CDC), p. 3044-3049. Miami Beach, FL, USA, Dec. 17-19, 2018.

KIRKPATRICK, S.; GELATT, C. D.; VECCHI, M.P. Optimization by simulated annealing. **Science**. Vol. 220, no. 4598, p. 671-680, 1983.

KRICHEN, M. et al. Fault Detection and Diagnosis Methods in Permanent Magnet Synchronous Machines: A Review. **Proceedings**. International Conference on Recent Advances in Electrical Systems (ICRAES'17). Hammamet, Tunisia. December 2017.

LIZARRAGA, M. del C. G.; SINHA, J. K. Development of a Quantitative Maintenance Model. **Proceedings**. 1st International Conference on Maintenance Engineering, IncoME-I 2016, The University of Manchester, UK, 2016.

LALANNE, M.; FERRARIS, G. **Rotordynamics Prediction in Engineering**, 2nd edition, John Wiley & Sons Ltd., 1998.

LEES, A. W. **Vibration Problems in Machines - Diagnosis and Resolution**, 1st edition, Taylor & Francis Group, CRC Press, 2016.

LEES, A. W.; FRISWELL, M. I.; JENNIONS, I. K. Where Next for Condition Monitoring of Rotating Machinery? **Advances in Vibration Engineering**. Vol. 5, no. 4, p. 263-277, 2006.

LEES, A. W., SINHA, J. K., FRISWELL, M. I. Model-based identification of rotating machines. **Mechanical Systems and Signal Processing**. Vol. 23, no. 6, p. 1884-1893, 2009.

_____. The identification of unbalance of a flexible rotating machine from a single run-down. **Transactions of the ASME, Journal of Engineering for Gas Turbines and Power**. Vol. 126, no. 2, p. 416-421, 2004.

LIZARRAGA, M. del C. G.; SINHA, J. K. Development of a Quantitative Maintenance Model. **Proceedings**. 1st International Conference on Maintenance Engineering, IncoME-I 2016, The University of Manchester, UK, 2016.

LOBATO, F. S.; STEFFEN, V.; NETO, A. J. S. A comparative study of the application of differential evolution and simulated annealing in radiative transfer problems. **Journal of the Brazilian Society of Mechanical Sciences and Engineering**. Vol. 32, no. 5 SPEC. ISSUE, p. 518-526, 2010.

LU, Y. et al. Study on looseness and impact-rub coupling faults of a vertical dual-disk cantilever rotor-bearing system. **Key Engineering Materials**. Vol. 353-358, no. 4, p. 2479-2482, 2007.

LUWEI, K. C.; YUNUSA-KALTUNGO, A.; SHA'ABAN, Y. A. Integrated Fault Detection Framework for Classifying Rotating Machine Faults Using Frequency Domain Data Fusion and Artificial Neural Networks. **Machines**. Vol. 6, no. 59, p. 1-16, 2018.

MA, J.; JIANG, J. Detection and Identification of Faults in NPP Instruments Using Kernel Principal Component Analysis. **Journal of Engineering for Gas Turbines and Power**. Vol. 134, no. 3, 6 p., 2012.

MAALOUF, M. G. Slow speed vibration signal analysis: if you can't do it slow, you can't do it fast. **Proceedings**. ASME Turbo Expo, p. 559-567. Montreal, Canada, May 2007.

MACGREGOR, J. F.; CINAR, A. Monitoring, fault diagnosis, fault-tolerant control and optimization: Data driven methods. **Computers and Chemical Engineering**. Vol. 47, p. 111-120, 2012.

MACGREGOR, J. F.; YOON, S. Fault diagnosis with multivariate statistical models part I: using steady-state fault signatures. **Journal of Process Control**. Vol. 11, p. 387-400, 2001.

MALINVERNO, A. A Bayesian criterion for simplicity in inverse problem parametrization. **Geophysical Journal International**. Vol. 140, no. 2, p. 267–285, 2000.

MATSUO, T. K. et al. Metodologia para o Diagnóstico de Defeitos em Hidrogeradores através da Análise de Vibrações em Sistemas de Monitoramento Permanente Utilizando Técnicas no Domínio do Tempo e Frequência. **Proceedings**. XXIV SNPTEE Seminário Nacional de Produção e Transmissão de Energia Elétrica. Curitiba, Paraná, Brazil. Oct. 22-25, 2017.

MEAGHHER, J., WU, X., LENCIONI, C. Response of a warped flexible rotor with a fluid bearing. **International Journal of Rotating Machinery**. Vol. 2008, Article ID 147653, 9 p., 2008.

MECHEFSKE, C. K. **Vibration and Shock Handbook**. Florida, USA. Taylor & Francis Group, Ed. CRC Press, 2005. 1771 p. Mechanical Engineering Series. SILVA, C. W, ed. Kreith, F., Series Ed.

MELO, I. S. **Proposta de sistemática de manutenção baseada na condição aplicada a compressores centrífugos de gás de plataformas de produção de petróleo do pré-sal**. 124 p. Dissertation (Master Degree) – Departamento de Engenharia Mecânica, Escola Politécnica, Universidade de São Paulo, São Paulo, SP, Brazil. 2019.

METROPOLIS, N. et al. Equation of State Calculations by Fast Computing Machines. **The Journal of Chemical Physics**. Vol. 21, no. 6, p. 1087-1092, 1953.

MICHALSKI, M. A. C. **Análise Teórico Experimental do Comportamento Dinâmico de um Rotor Horizontal Suportado por Mancais Hidrodinâmicos**. 192 p. Dissertation (Master Degree) – Programa de Pós-graduação em Engenharia Mecânica da Universidade Federal do Rio de Janeiro – COPPE/UFRJ, Rio de Janeiro, RJ, Brazil.

MICHALSKI, M. A. C. et al. Identifying oil instability phenomena in rotors using nonlinear techniques analysis. **Proceedings**. XII International Symposium on Dynamic

Problems of Mechanics – DINAME 2007. Varoto, P. S. and Trindade, M. A. (Editors), ABCM, Ilhabela, SP, Brazil, February 26 - March 2, 2007.

MICHALSKI, M. A. C.; MELO, I. S.; SOUZA, G. Comparing Principal Component Analysis and Mahalanobis-Taguchi System to Detect Unbalance in a Centrifugal Compressor in a Floating Production Storage and Offloading. **ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering**, v. 5, 14 p., 2019.

MICHALSKI, M. A. C.; SOUZA, G. F. M. Applying Kalman filtering to unbalance estimation in rotating machinery. **Proceedings**. 2018 ICVRAM ISUMA UNCERTAINTIES conference, Florianopolis, SC, Brazil, April 8-11, 2018.

MICHALSKI, M. A. C.; ZINDELUK, M.; ROCHA, R. O. Influence of journal bearing axial grooves on the dynamic behavior of horizontal rotors. **Shock and Vibration**. Vol. 13, no. 4-5, p. 285-300, 2006

MOMČILOVIĆ, D. et al. Failure analysis of hydraulic turbine shaft. **Engineering Failure Analysis**. Vol. 20, p. 54-66, 2012.

MORAIS, T. S. et al. Rotating machinery health evaluation by modal force identification. **Inverse Problems in Science and Engineering**. Vol. 5977, p. 1–21, 2019.

MORGAN, E. Technical Topic: Unit unbalance problems. **Orbit Magazine**. Article Archives. Hydro Corner: Third Quarter 2015. Aug. 25, 2015.

MOUBRAY, J. **Reliability Centered Maintenance**, 2nd edition. 448 p. Oxford: Butterworth-Heinemann. Industrial Press, 1997.

MUSZYNSKA, A. **Rotordynamics**, 1st edition. 1085 p. Faulkner, L. L. (Ed.). Florida, USA. Taylor & Francis Group, Mechanical Engineering Series, 2005.

_____. Whirl and Whip – Rotor/Bearing Stability Problems. **Journal of Sound and Vibration**. Vol. 110, no. 3, p. 443-462, 1986.

NELSON, H. D. **A Finite Rotating Shaft Element Using Timoshenko Beam Theory**. 1979. Report ERC-R-77023, Engineering Research Center, College of Engineering & Applied Sciences, Arizona State University, Arizona, USA.

NEMBARD, A. D. et al. Fault Diagnosis of Rotating Machines Using Vibration and Bearing Temperature Measurements. **Diagnostyka**. Vol. 14, no. 3, p. 45-51, 2013.

NEVES, M. M. **Difficulties in Expanding Hydropower Generation in Brazil**. 2009. 56 p. School of Business and Public Management, Institute of Brazilian Issues – IBI, Minerva Program, The George Washington University, Washington, D.C., USA. 2009.

NGOLAH, C. F. et al. Intelligent fault recognition and diagnosis for rotating machines using neural networks. **Software Science and Computational Intelligence**. Vol. 3, no. 4, 17 p., 2011.

NIU, G.; YANG, B. S.; PECHT, M. Development of an optimized condition-based maintenance system by data fusion and reliability-centered maintenance. **Reliability Engineering and System Safety**, Vol. 95, no. 7, p. 786-796, 2010.

OAK RIDGE NATIONAL LABORATORY. **HAP – Best Practice Catalog – Machine Condition Monitoring**. Revision 2.0, 08/20/2012. 19 p. Oak Ridge, Tennessee, USA. 2012.

PALUSZEK, M.; THOMAS, S. **MATLAB machine learning recipes: A problem-solution approach**, 2nd edition. Apress, 2019.

PENNACCHI, P.; BACHSCHMID, N.; VANIA, A. A model-based identification method of transverse cracks in rotating shafts suitable for industrial machines. **Mechanical Systems and Signal Processing**. Vol. 20, p. 2112-2147, 2006.

PENNACCHI, P.; VANIA, A. Shaft crack detection in a steam turbine: experimental evidences and model-based simulations. **Proceedings**. ISMA 2010: International Conference on Noise and Vibration Engineering including USD 2010, p. 1055-1070. Leuven, Belgium, Sep. 20-22, 2010.

_____. Diagnostics of a crack in a load coupling of a gas turbine using the machine model and the analysis of the shaft vibrations. **Mechanical Systems and Signal Processing**. Vol. 22, p. 1157-1178, 2008.

_____. Diagnosis and model-based identification of a coupling misalignment. **Shock and Vibration**. Vol. 12, p. 293-308, 2005.

_____. Identification of a generator fault by model-based diagnostic techniques. **International Journal of Rotating Machinery**. Vol. 10, no. 4, p. 293-300, 2004a.

_____. Accuracy in the identification of a generator thermal bow. **Journal of Sound and Vibration**. Vol. 274, p. 273-295, 2004b.

PENNACCHI, P.; VANIA, A.; CHARTTERTON, S. Identification of mechanical faults in rotating machinery for power generation. **Proceedings**. 2010 IEEE International Symposium on Industrial Electronics, p. 2109-2114. Bari, Italy, Jul. 4-7, 2010.

PINZÓN, H. et al. A Comparative Assessment on Static and Dynamic PCA for Fault Detection in Natural Gas Transmission Systems. **Proceedings**. ASME 2017 – 11th International Conference on Energy Sustainability – ES2017, p. 1-8. Charlotte, North Carolina, USA, Jun. 26-30, 2017.

PLANTE, T. et al. Rotating machine fault detection using principal component analysis of vibration signal. In: 2016 IEEE AUTOTESTCON. **Proceedings**. Anaheim, CA, USA.

PLESIUTSCHNIG, E. et al. Fracture analysis of a low-pressure steam turbine blade. **Case Studies in Engineering Failure Analysis**. Vol. 5-6, p. 39-50, 2016.

PŮST, L. Determining the Resonance Frequencies of Forced Vibrations of Turbogenerators with Foundations. **Experimental Mechanics**. Vol. 7, no. 6, p. 265-271, Jun. 1967.

QUEIROZ, A. R. et al. Climate change impacts in the energy supply of the Brazilian hydro-dominant power system. **Renewable Energy**. Vol. 99, p. 379–389, 2016.

RANI, S.; AGRAWAL, A. K.; RASTOGI, V. Failure analysis of a first stage IN738 gas turbine blade tip cracking in a thermal power plant. **Case Studies in Engineering Failure Analysis**. Vol. 8, p. 1-10, 2017.

RAO, J. S. **History of Rotating Machinery**. History of Mechanism and Machine Science, Volume 20. Springer, 2011. Ceccarelli, M. (Ed.).

RAUSAND, M. **Reliability of Safety-Critical Systems: Theory and Applications**. 2014. 1st edition, John Wiley & Sons, Inc.

_____. Reliability Centered Maintenance. **Reliability Engineering and System Safety**. Vol. 60, p. 121-132, 1998.

RUBINSTEIN, R. Y.; KROESE, D. P. **Simulation and the Monte Carlo Method**. 2018. 3rd edition, Wiley-Interscience, John Wiley & Sons, Inc., Hoboken, New Jersey.

RUSSELL, E. L.; CHIANG, L. H.; BRAATZ, R. D. Fault detection in industrial processes using canonical variate analysis and dynamic principal component analysis. **Chemometrics and Intelligent Laboratory Systems**. Vol. 51, p. 81-93, 2000.

RYU, S. R.; NODA, I.; JUNG, Y. M. Moving window principal component analysis for detecting positional fluctuation of spectral changes. **Bulletin of the Korean Chemical Society**. Vol. 32, no. 7, p. 2332–2338, 2011.

SANCHES, F. D. **Identificação simultânea de desbalanceamento e empeno de eixo em rotores através de análise de correlações**. 263 p. Thesis (Doctoral Degree) – Programa de Pós-graduação em Engenharia Mecânica da Universidade Estadual de Campinas (UNICAMP), Campinas, SP, Brazil. 2015.

SANCHES, F. D.; PEDERIVA, R. Simultaneous identification of unbalance and shaft bow in a two-disk rotor based on correlation analysis and the SEREP model order reduction method. **Journal of Sound and Vibration**. Vol. 433, p. 230-247, 2018.

_____. Theoretical and experimental identification of the simultaneous occurrence of unbalance and shaft bow in a Laval rotor. **Mechanism and Machine Theory**. Vol. 101, p. 209-221, 2016.

SARKAR, J.; SAHA, S.; AGRAWAL, S. An Efficient Use of Principal Component Analysis in Workload Characterization - A Study. **AASRI Procedia**. Vol. 8, p. 68-74, 2014.

SÄRKKÄ, S. **Bayesian Filtering and Smoothing**. 2013. Cambridge University Press.

SARTORI, I. et al. Detecção, diagnóstico e correção de falhas: Uma proposição consistente de definições e terminologias. **Ciência e Engenharia**. Vol. 21, no. 2, p. 41–53, 2012.

SAWICKI, J. T. et al. Condition monitoring of rotor using active magnetic actuator. **Proceedings**. ASME Turbo Expo, p. 1257-1265, Berlin, Germany, June 2008.

SCHWAB, K. **The Fourth Industrial Revolution**, 1st ed. Cologny/Genova, Switzerland: World Economic Forum, 2016.

SCHWARZ, B.; RICHARDSON, M. Proportional Damping from Experimental Data. **Sound and Vibration Magazine**. Computer-Aided Engineering issue, June 2013.

SHEN, X., JIA, J., ZHAO, M., Nonlinear analysis of a rub-impact rotor-bearing system with initial permanent rotor bow. **Archive of Applied Mechanics**. Vol. 78, no. 3, p. 225-240, 2008.

SILVA, D. H. J. **Processamento de Sinais para Monitoramento de Vibrações em Unidades Geradoras Hidrelétricas**. 136 p. Dissertation (Master Degree) – Programa de Pós-graduação em Engenharia Elétrica, Universidade Federal de Minas Gerais, Belo Horizonte, Minas Gerais, Brazil. Dec. 2013.

SILVA JÚNIOR, A. F.; DE CAMPOS, M. F.; MARTINS, A. S. Domain wall structure in metals: A new approach to an old problem. **Journal of Magnetism and Magnetic Materials**. Vol. 442, p. 236–241, 2017.

SINHA, J. K. Recent trends in fault quantification in rotating machines. **Advances in Vibration Engineering**. Vol. 8, no. 1, p. 79-85, 2009.

SINHA, J. K.; FRISWELL, M. I.; LEES, A. W. The identification of the unbalance and the foundation model of a flexible rotating machine from a single run-down. **Mechanical Systems and Signal Processing**. Vol. 16, no. 2-3, p. 255-271, 2002.

SINHA, J. K.; LEES, A. W.; FRISWELL, M. I. Estimating unbalance and misalignment of a flexible rotating machine from a single run-down. **Journal of Sound and Vibration**. Vol. 272, no. 2-3, p. 967-989, 2004a.

_____. Estimating the static load on the fluid bearings of a flexible machine from run-down data. **Mechanical Systems and Signal Processing**. Vol. 18, p. 1349-1368, 2004b.

SINOUE, J.-J. A review of damage detection and health monitoring of mechanical systems from changes in the measurement of linear and non-linear vibrations. **Mechanical Vibrations: Measurement, Effects and Control**. Chapter 13, Nova Science Publishers, Editor: Robert R. Sapri, p. 643-702, 2009.

SIOGHANSI, F.; PFAFFENBERGER, W. **Electricity Market Reform an International Perspective**. 2006. 1st ed. Oxford. Henri van Dorssen (ed.).

SMITH, L. I. **A Tutorial on Principal Components Analysis**. 2002. Technical Report, Cornell University, USA.

SMITH, E. O.; NEEL, A. J.; PALFREY-SNEDDON, H. The impact of gas turbine compressor rotor bow on aircraft operations. **The Aeronautical Journal**. Vol. 121, no. 1246, p. 1808-1832, Dec. 2017.

SONNICHSEN, H. E. Real-time detection of developing cracks in jet engine rotors. **Proceedings**. IEEE Aerospace Conference, p. 173-184. Big Sky, MT, USA, March, 25 2000.

SOUZA, G. F. M.; MELO, I. S.; MICHALSKI, M. A. C. Applying Mahalanobis-Taguchi method to detect faults in rotating machinery. **Proceedings**. 28th International European Safety and Reliability Conference – ESREL 2018, p. 1115–1123. Trondheim, Norway, Jun. 17-21, 2018.

SOUZA, V. V. **Gestão da Manutenção: Estudo de Caso de uma Empresa de Pavimentação**. 69 p. Final Project (Undergraduate Degree) – Departamento de Engenharia de Materiais, Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, SP, Brazil. 2018.

SRIVASTAVA, A. N.; MAH, R. W.; MEYER, C. **Integrated Vehicle Health Management – Technical Plan**, Version 2.03. National Aeronautics and Space Administration Aeronautics, Research Mission Directorate, Aviation Safety Program, Nov. 2009.

SUDHAKAR, G. N. D. S.; SEKHAR, A. S. Identification of unbalance in a rotor bearing system. **Journal of Sound and Vibration**. Vol. 330, no. 10, p. 2299-2313, 2011.

_____. Coupling Misalignment in Rotating Machines: Modeling, Effects and Monitoring. **Noise & Vibration Worldwide**. Vol. 40, no. 1, p. 17-39, Jan. 2009.

TIDRIRI, K. et al. Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: A review of researches and future challenges. **Annual Reviews in Control**. Vol. 42, p. 63–81, 2016.

TIWARI, R.; LEES, A. W.; FRISWELL, M. I. Identification of speed-dependent bearing parameters. **Journal of Sound and Vibration**. Vol. 254, no. 5, p. 967-986, 2002.
TREBUÑA, P. et al. The analysis of failure causes of the rotor shaft of steam turbines. **Metalurgija**. Vol. 56, no. 1-2, p. 233-236, 2017.

VAN LAARHOVEN, P. J. M.; AARTS, E. H. L. **Simulated Annealing: Theory and Applications**. First Edition, Kluwer Academic Publishers, 1987. Norwell, MA, USA.

VANIA, A. Model-based identification of a shaft bow caused by rubs in the generator of a power unit. **Proceedings**. ESDA 2006 – 8th Biennial ASME Conference on Engineering Systems Design and Analysis, p. 1-10. Torino, Italy. Jul. 4-7, 2006.

VANIA, A.; PENNACCHI, P.; CHATTERTON, S. Identification of a shaft thermal bow by means of model-based diagnostic techniques. **Proceedings**. Surveillance 7

International Conference, p. 1-11. Institute of Technology of Chartres, France. Oct. 29-30, 2013a.

_____. Fault diagnosis and prognosis in rotating machines carried out by means of model-based methods: a case study. **Proceedings**. ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2013), p. 1-8. Portland, Oregon, USA. Aug. 4-7, 2013b.

VANCE, J.; ZEIDAN, F.; MURPHY, B. **Machinery Vibration and Rotordynamics**. John Wiley & Sons, Inc., Hoboken, New Jersey, 2010.

VENKATASUBRAMANIAN, V. et al. A review of process fault detection and diagnosis Part I: Quantitative model-based methods. **Computers & Chemical Engineering**. Vol. 27, no. 3, p. 293–311, 2003a.

_____. A review of fault detection and diagnosis. Part III: Process history based methods. **Computers and Chemical Engineering**. Vol. 27, p. 327–346, 2003b.

VENKATASUBRAMANIAN, V.; RENGASWAMY, R.; KAVURI, S. N. A review of process fault detection and diagnosis part II: Qualitative models and search strategies. **Computers and Chemical Engineering**. Vol. 27, no. 3, p. 313–326, 2003.

VILLA, L. F., et al., Statistical diagnosis based on vibration analysis for gear test-bench under non-stationary conditions of speed and load. **Mechanical Systems and Signal Processing**. Vol. 29, p. 436-446, 2012.

WALKER, R. **Localising Imbalance Faults in Rotating Machinery**. 280 p. Thesis (Doctoral Degree) – School of Applied Science, IVHM Centre, Cranfield University, Cranfield, UK. 2013.

WALKER, R.; PERINPANAYAGAM, S.; JENNIONS, I. K. Rotordynamic Faults: Recent Advances in Diagnosis and Prognosis (Review Article). **International Journal of Rotating Machinery**. Hindawi Publishing Corporation. Vol. 2013, Article ID 856865, 12 p., 2013.

WANG, M.; ZHOU, H.; CHEN, J. A Moving Window Principal Components Analysis Based Anomaly Detection and Mitigation Approach in SDN Network. **KSII Transactions on Internet and Information Systems**. Vol. 12, no. 8, p. 3946–3965, 2018.

WITEK, L. Simulation of crack growth in the compressor blade subjected to resonant vibration using hybrid method. **Engineering Failure Analysis**. Vol. 49, p. 57-66, 2015.

XIANG, J. et al. Identification of crack in a rotor system based on wavelet finite element method. **Finite Elements in Analysis and Design**. Vol. 43, no. 14, p. 1068-1081, 2007.

XU, H.; CARAMANIS, C.; SANGHAVI, S. Robust PCA via outlier pursuit. **IEEE Transactions on Information Theory**. Vol. 58, no. 5, p. 3047-3064, 2012.

XU, W. et al. Harmonic resonance mode analysis. **2005 IEEE Power Engineering Society General Meeting**. Vol. 3, no. 2, p. 1182-1190, 2005.

YANG, Q. **Model-based and data driven fault diagnosis methods with applications to process monitoring**. 203 p. Thesis (Doctoral Degree) – Electrical Engineering and Computer Sciences, School of Graduate Studies, Case Western Reserve University, 2004.

YANG, T.M., HSU, W., An efficient diagnosis technique for variations of shaft-bow and unbalance. **Proceedings**. ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (DETC'09), p. 57-66. San Diego, California, USA, September 2009.

YIN, S. et al. Data-Based Techniques Focused on Modern Industry: An Overview. **IEEE Transactions on Industrial Electronics**. Vol. 62, no. 1, p. 657-667, Jan. 2015.

_____. A review on basic data-driven approaches for industrial process monitoring. **IEEE Transactions on Industrial Electronics**. Vol. 61, no. 11, p. 6414–6428, 2014.

_____. A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark Tennessee Eastman process. **Journal of Process Control**. Vol. 22, p. 1557-1581, 2012.

ZHAO, Y. et al. A novel two-step parameter identification method for GyroWheel system. **Measurement: Journal of the International Measurement Confederation**. Vol. 136, p. 367–381, 2019.

ZHANG, Y.; JIANG, J. Bibliographical review on reconfigurable fault-tolerant control systems. **Annual Reviews in Control**. Vol. 32, p. 229-252, 2008.

ZHOU, J. H. et al. Comparative study of data driven and model-based approaches of rotary machines fault detection and diagnosis. **SIMTech Technical Reports**. Vol. 11, no. 4, p. 195-201, Oct.-Dec. 2010.

ZHOU, E.; CHEN, X. Sequential Monte Carlo simulated annealing. **Journal of Global Optimization**. Vol. 55, no. 1, p. 101–124, 2013.