Fellipe Garcia Marques

**Modeling and Automatic Friction Compensation of Pneumatic Diaphragm
Valves with Digital Positioners**

São Paulo
2020

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Versão Corrigida

(Versão original encontra-se na unidade que aloja o Programa de Pós-Graduação)

Ph.D. Thesis presented to the Escola Politécnica of the Universidade de São Paulo, to obtain the degree of Doctor of Science.

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Advisor: Prof. Dr. Claudio Garcia

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The Brazilian Navy, for all these years of constant improvement as a professional.

Science is the captain, and practice the
soldiers.

(Leonardo da Vinci)

Abstract

Pneumatic diaphragm valves with high friction index have the potential to decrease the control loop performance and induce limit cycles. Usually, the friction models used to model diaphragm valves are the simplest ones, mainly because there are not precise sensors available to benefit from friction models with higher complexity, as the dynamics that are modeled by more complex friction models can not be observed experimentally. In this thesis, algorithms and guidelines are designed to estimate, in open and closed loop, the valve model with simpler friction models, such as the Kano and Karnopp, as well as more complex friction models, such as the LuGre and GMS. The experimental tests, performed with two industrial valves with stem position and diaphragm pressure sensors, one with higher and the other with lower friction index, show that the GMS model has the most consistent prediction precision, with slightly better accuracy than the Karnopp model. The automatic friction compensation is developed using the Adaptive Inverse Control framework, where an offline process tunes a given controller using the previously estimated valve model. Experimental tests were performed, with several different control structures, using the Kano, Karnopp and GMS friction models to tune the controller. The results indicates that when the GMS friction model is used in the Adaptive Inverse Control framework, it is more likely to obtain optimal controller tunings, even though the Kano and Karnopp models provide pretty good tunings, as well.

Keywords: diaphragm valves, friction compensation, friction modeling, friction parameters estimation, adaptive inverse control.

Resumo

Válvulas pneumáticas de controle com alto índice de atrito podem interferir negativamente no desempenho de malhas de controle, podendo induzir ciclos limite. Em geral, os modelos de atrito utilizados para modelar válvulas de controle são bastante simples, principalmente devido a uma indisponibilidade de sensores de alta precisão, pois não é possível observar experimentalmente os comportamentos que os modelos mais complexos são capazes de reproduzir. Neste trabalho, são desenvolvidos algoritmos e métodos para estimar, em malha aberta e fechada, o modelo da válvula utilizando tanto modelos de atrito mais simples, como o de Kano e o de Karnopp, quanto modelos de atrito mais complexos, como o de LuGre e o de GMS. Os testes experimentais, realizados utilizando duas válvulas pneumáticas industriais com sensores de posição da haste e pressão do diafragma, uma com alto e outra com baixo índice de atrito, indicam que o modelo GMS é o mais preciso, possuindo um desempenho levemente superior ao modelo de Karnopp. A compensação automática de atrito é realizada usando o método de Controle Adaptativo por Inversão, em que uma estrutura de controle é sintonizada em paralelo, utilizando o modelo estimado da válvula de controle. Inúmeros testes experimentais foram realizados, utilizando diversas estruturas de controle diferentes e empregando os modelos de atrito de Kano, Karnopp e GMS para sintonizar os controladores. Os resultados obtidos indicam que quando o modelo GMS é utilizado no método de Controle Adaptativo por Inversão, maior é a chance de se obter uma sintonia ótima do controlador, muito embora os modelos de Kano e Karnopp também sejam capazes de prover boas sintonias.

Palavras-chave: válvulas pneumáticas, compensação de atrito, modelagem de atrito, estimação de parâmetros de atrito, controle adaptativo.

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Symbology and Abbreviations

Abbreviations and Acronyms

AIC	Adaptive Inverse Control;
CF	Control Freezing Algorithm;
CR	Constant Reinforcement Compensator;
DC	Direct Current;
DCS	Digital Control System;
DE	Differential Evolution Optimization;
DS	Direct Synthesis;
EPUSP	Escola Politécnica of the University of São Paulo;
FFPID	Feed Forward PID with Integral Deadband;
FPGA	Field Programmable Gate Array;
FPP	Flow Pilot Plant;
GA	Genetic Algorithm Optimization;
GDES	Grid Search with Differential Evolution and Simplex Optimization;
GMS	Generalized Maxwell-Slip;
I/P	Current to Pressure;
IAE	Integral Absolute Error;
IFAC	International Federation of Automatic Control;
IPCL	Industrial Process Control Laboratory;
IRAE	Integral Root Absolute Error;
ISMC	Integrative Sliding Mode Control;
LSE	Least Squares Estimator;
LVDT	Linear Variable Differential Transformer;
LuGre	Leuven–Grenoble;
MS	Monte Carlo with Simplex Optimization;
MSE	Mean Squared Error;
OP	Controller Output;
PID	Proportional Integral Derivative Controller;
P&ID	Piping & Instrumentation Diagram;
SNL	Successive Nonlinear Linear Regression;
SNR	Signal to Noise Ratio;
SP	Set Point.

Operators and Mathematical Notation

$\dot{x}$	Time derivative of x ;
$\ddot{x}$	Second order time derivative of x ;
$\hat{x}$	Estimated value of x ;
$\text{sgn}(\cdot)$	Signal function;
$\min(\cdot)$	Minimum function;
$\max(\cdot)$	Maximum function;
$\text{sat}(\cdot)$	Saturation function;
$\mu(\cdot)$	Mean value function;
$\text{std}(\cdot)$	Standard deviation function;
$\mu_3(\cdot)$	Third order moment function;
$E(\cdot)$	Expectation function;
q	Time shift operator;
n	Discrete time;
t	Continuous time;
fit	Goodness of fit index;
$\mathbb{R}^N$	Set of real numbers of dimension N ;
$\mathbb{N}$	Set of natural numbers;
$\arg \min V$	Function that returns the argument that minimizes the function V .

Valve and Friction Model Symbols

x	Valve stem position;
P	Diaphragm air pressure;
OP	I/P converter input signal;
T_s	Discrete model sampling time;
S_a	Diaphragm cross sectional area;
m	Pneumatic diaphragm valve moving parts mass;
k	Valve spring constant;
F_{init}	Valve initial force;
F_f	Friction force;
P_{min}	Minimum diaphragm pressure;
P_{max}	Maximum diaphragm pressure;
x_{min}	Valve stem minimum position;
x_{max}	Valve stem maximum position;
K_{P_g}	I/P converter pressure gain;
$\tau_{\text{I/P}}$	I/P converter model time constant;
a_0	I/P converter discrete model parameter;

b_0	I/P converter discrete model parameter;
b_1	I/P converter discrete model parameter;
F_s	Static friction force;
F_c	Coulomb friction force;
F_v	Viscous friction parameter;
v_s	Stribeck velocity;
DV	Stem velocity that defines when the Karnopp model is in the presliding state;
z	LuGre model internal state;
σ_0	LuGre model elastic coefficient;
σ_1	Lugre model friction damping coefficient;
i	i th Maxwell element of the GMS model;
ψ_i	i th internal state of the GMS model;
N_{Me}	Number of Maxwell elements of the GMS model;
κ_i	GMS model elastic coefficient of the i th Maxwell element;
ν_i	GMS model friction damping coefficient of the i th Maxwell element;
α_i	GMS model contribution coefficient of the i th Maxwell element;
C	GMS model attraction constant;
S	Kano model deadband parameter;
J	Kano model slip band parameter;
D	Kano model initial force parameter;
$x_{\max_P}$	Kano model maximum stem position when the diaphragm pressure is $P_{\max}$;
$x_{\min_P}$	Kano model minimum stem position when the diaphragm pressure is $P_{\min}$;
$\theta_{I/P}$	Vector that groups the I/P converter model parameters;
θ_f	Vector that groups the friction model parameters;
$\hat{\tau}_{I/P_r}$	I/P model estimated time constant using ramps as excitation signal;
$\hat{\tau}_{I/P_s}$	I/P model estimated time constant using steps as excitation signal;
V_{n_f}	Stem position prediction residual function.

Valve Stem Position Controller Symbols

x_d	Desired stem position signal;
g_x	Stem position deviation gain;
g_u	Control effort gain;
θ_p	Stem position controller parameter vector;
θ_p^*	Optimal tuning of the stem position controller parameter vector;
$J_C(\theta_p)$	AIC cost function for a given θ_p ;
C_H	Hydraulic system controller;
SP_H	Hydraulic system controller set point;
K_H	Hydraulic system controller proportional gain;

K_{iH}	Hydraulic system controller integral gain;
C_p	Valve stem position controller;
SP	Stem position controller set point;
K_p	Position controller proportional gain;
K_i	Position controller integral gain;
K_d	Position controller derivative gain;
τ_{df}	Position controller derivative filter time constant;
T_{sCp}	Position controller sampling time;
e_l	CF algorithm low error threshold;
e_h	CF algorithm high error threshold;
t_{e_l}	CF algorithm time with low error threshold;
t_{e_h}	CF algorithm time with high error threshold;
t_{kp}	Knocker compensator pulse signal period;
d_{kp}	Knocker compensator signal duty cycle;
a_{kn}	Knocker compensator signal amplitude;
a_{CR}	CR compensator signal amplitude;
$sd_{\hat{e}}$	Fuzzy PID controller standard deviation parameter of the control error;
$sd_{\dot{\hat{e}}}$	Fuzzy PID controller standard deviation parameter of the time derivative of the control error;
K_{i1}	Fuzzy PID controller integral gain when the control error and its time derivative are nonzero;
K_{i2}	Fuzzy PID controller integral gain when the control error is zero and its time derivative is nonzero;
K_{i3}	Fuzzy PID controller integral gain when the control error is nonzero and its time derivative is zero;
K_{i4}	Fuzzy PID controller integral gain when the control error and its time derivative are zero;
λ_{ismc}	ISMC sliding surface time constant;
k_{ismc}	ISMC gain;
Θ_{ismc}	ISMC sliding surface dead zone;
τ_{ismc}	ISMC control error filter time constant;
$e_{I_{th}}$	FFPID error threshold to activate the integral action;
k_{ff}	FFPID feed forward gain.

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1 Introduction

Pneumatic diaphragm valves are extensively used in the process industries to regulate flow (GARCIA, 2008). The valve performance is important to guarantee control loops stability, compensate process perturbations and maintain production quality. Evidently, the valves are designed to reach a high reliability, as most industries tend to work uninterruptedly for several months. However, defects may appear due to wear or an external event, reducing considerably the production quality.

The pneumatic diaphragm valve is essentially a servomechanism. It transforms the air pressure into a stem movement using a diaphragm and a mechanical system. For each stem position there is a corresponding pressure drop across the valve, which is used to modify the process flow rate. A very frequent defect in pneumatic diaphragm valves is a friction increase in the stem packing, which can severely affect the system precision, as is the case for any other servomechanism (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994). Regarding diaphragm valves, this friction increase results in oscillatory control loops, which can potentially affect many coupled control loops. In fact, defective valves accounts for a fair proportion of suboptimal performing control loops in industry (CHOUDHURY et al., 2006; THORNHILL; HORCH, 2007).

If the control loop oscillations are tolerable, the plant manager may decide to endure the consequences of this defective valve (e.g. production drop) rather than stop the system to perform maintenance. This scenario motivated the design of friction compensation algorithms, implemented in the control system, that are able to improve the performance of such defective valves. Inevitably, these algorithms rely on estimating parameters of a given friction model for then tuning the friction compensation algorithm (SILVA; GARCIA, 2014; HIDALGO; GARCIA, 2017).

Modeling friction, however, is often a difficult task, as the models are usually nonlinear and discontinuous. Yet, friction modeling is a research area that evolves with higher precision instruments and experiment design. Therefore, many friction models were suggested by researchers, as older models were not able to predict novel experimental data. With respect to pneumatic diaphragm valves, the vast majority of researchers focused on working with the most frequently encountered valves in industries, which are the simplest ones, with open loop stem position control and no embedded sensors. Naturally, the friction models selected to simulate such simple valves were also the simplest ones. However, valve suppliers are starting to use embedded digital systems and sensors in new pneumatic diaphragm valves, in order to increase their performance and reliability. Therefore, in such valves, it is possible to apply state of the art friction models and compensation algorithms.

This thesis aims to provide an algorithm, to be embedded in a digital positioner, that is able to detect, estimate and compensate friction in pneumatic diaphragm valves with dedicated sensors. Necessarily, to estimate friction, it is imperative to select a model. In this work, two friction models, which were vastly explored in the diaphragm valves modeling area are compared to two relatively new friction models, which rarely or were never used at all for modeling diaphragm valves.

The automatic friction compensation is developed by using the Adaptive Inverse Control (AIC) technique, which is a branch of adaptive indirect control method, that relies on estimating the plant parameters for then tuning the controller parameters (ÅSTRÖM; WITTENMARK, 1995; WIDROW; WALACH, 2008).

1.1 Motivation

The friction compensation techniques are usually difficult to be applied in practice, since they demand knowledge in estimating friction and in implementing the compensation in the control system. The development of an algorithm that is able to maintain the valve performance, regardless of friction deviations and with minimal external influence brings the research developments closer to the industrial applications.

The diaphragm valves modeling and friction compensation techniques are strongly based on friction models that are outdated with the state of the art related to friction models proposed by tribology science. This has attracted criticism from the scientific community and therefore demands analysis and testings of these models.

The AIC framework is able to deliver optimal controllers for nonlinear and discontinuous plants, regardless of the controller structure. Consequently, some empirical or practical rules used to tune friction compensators can be improved.

1.2 Objectives

The objective of this thesis is to deliver a framework to detect and estimate friction deviations of a pneumatic diaphragm valve and automatically tune the stem position controller to compensate such friction fluctuation. To achieve this overall objective, the following intermediate objectives are necessary:

- i. Study the friction characteristics, its models and select the most reasonable model;
- ii. Design a method to estimate the valve and friction parameters in open and closed loop systems;
- iii. Design the stem position controller and friction compensation, based on the AIC framework;

- iv. Perform proof of concept tests of the proposed methods using the Flow Pilot Plant (FPP) of the Industrial Process Control Laboratory (IPCL).

1.3 Literature Review

This section presents some of the most relevant works for this thesis development.

With regard to pneumatic diaphragm valves modeling, there are two model structure choices: the first principle and the data driven models. The latter are the simpler models, simplifying many valve and friction characteristics to obtain a fair simulation of a valve with given friction index. The first principle modeling uses well known physical laws to create the valve model. One unknown variable in these models is the friction force, which has to be calculated using one of the available friction models.

The most relevant pneumatic diaphragm valves data driven models, that are broadly used for modeling and compensation of diaphragm valves are the Kano and Choudhury models (KANO et al., 2004; CHOUDHURY; THORNHILL; SHAH, 2005). The Kano model is capable of predicting the expected behavior of valve signature curves, which are used for valve diagnostics (GARCIA, 2008). These models are frequently used to model valves with no embedded sensors and position controllers, as it would be difficult to estimate the parameters of a more complex valve model without proper sensors.

Modeling pneumatic control valves using a first principle modeling technique is straightforward, as shown by Kayihan and Doyle III (2000), Garcia (2008). The friction model, though, is the most complex part of the first principle valve model.

Many friction models were proposed by researchers and the greater reason for that is because older models failed to predict new experimental data, as the sensor precision and experiment design improved. Other friction models were proposed to ease the simulation complexity and mathematical analysis, as the most complex models are discontinuous and nonlinear. Sometimes, simpler friction models are selected to permit mathematical analysis, at the expense of a poorer friction prediction. Karnopp (1985) proposed a method to simulate the transition from static to dynamic friction using the Stribeck curve. This model is frequently used for modeling pneumatic diaphragm valves. Armstrong-Hélouvry, Dupont and Canudas de Wit (1994) reviewed the tribology literature, exposing relevant friction aspects and models and eventually suggesting a new model named Seven Parameter Friction Model, which is able to predict many friction characteristics that can be observed experimentally. Canudas de Wit et al. (1995) proposed the Leuven–Grenoble (LuGre) model, aiming to deliver a fair prediction of the most important friction dynamics in presliding and sliding states while maintaining a rather simple mathematical structure in order to favor control system design and analysis. This model was only tested for simulation of pneumatic diaphragm valves Garcia (2008), but was never used for friction compensation.

The LuGre model, although efficient and useful for friction compensation, was proven imprecise for presliding state friction prediction. To correct this inaccuracy, Swevers et al. (2000) proposed the Leuven friction model but, as it was considered complex for simulation and analysis, Al-Bender, Lampaert and Swevers (2005) suggested a generalization of the Maxwell-Slip (GMS) model that was able to fix the LuGre model flaw while using simple mathematical functions. In this thesis, the Karnopp, LuGre and GMS models are used for simulating pneumatic diaphragm valves.

The estimation of the friction parameters of data driven pneumatic diaphragm valve models is studied by many authors. Some propose analysis of the valve signature curve, using the stem position and controller output, which is pretty straightforward (KANO et al., 2004; CHOUDHURY; JAIN; SHAH, 2008). Other methods are more complex, as they assume that the stem position is not available and deliver the friction parameters by analyzing the oscillatory behavior of the controller output and process variable (KANO et al., 2004; CHOUDHURY et al., 2006). Jelali (2008) proposed an algorithm to estimate the friction parameters, in closed loop systems, using a Hammerstein model, where the Kano model was considered as the nonlinear input function, using only the controller output and process variable. The Hammerstein model parameters, and consequently the Kano model parameters, were estimated using a genetic algorithm for the nonlinear model and a linear estimator for the dynamic model. Romano and Garcia (2011) expanded the work of Jelali (2008), by estimating the parameters of a Hammerstein–Wiener model, composed by the Kano model as the nonlinear model input function, followed by a dynamic linear system and then a static cubic splines function. The parameters were estimated using grid search, simplex and quadratic programming. Additionally, Romano and Garcia (2011) used a specific residual function to avoid parameter bias due to the correlation between input and process noise when estimating Wiener models.

The estimation of valve and friction parameters using first principle valve modeling and Karnopp friction model was discussed by Garcia (2007), Romano and Garcia (2007), Romano and Garcia (2008), who proposed force balance equation analysis and linear regression methods.

Other than pneumatic diaphragm valves, friction parameters estimation is a widely explored research area. For the simpler models, authors usually suggest linear estimator techniques, as the least squares estimator (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994). As the friction model gets more complex, the use of derivative free optimization methods, either alone or combined with a linear estimator, is commonplace (CANUDAS de WIT; LISCHINSKY, 1997; SWEVERs et al., 2000; TJAHOJOWIDODO; BRUSSEL, 2005; AL-BENDER; LAMPAERT; SWEVERs, 2005; WORDEN et al., 2007; RIZOS; FASSOIS, 2009). Usually, researchers suggest that the excitation signal design need to evidence all friction phenomena for a correct parameter estimation. The methods they propose, however, are based on indirect but precise friction force measurement, which

is unavailable when dealing with pneumatic diaphragm valves.

As for friction compensation, many researchers have proposed techniques for a wide range of systems. Regardless of the knowledge area, researchers often suggest using high frequency signals, added to the system controller, to overcome the static friction (CANUDAS de WIT et al., 1991; HÄGGLUND, 2002; SRINIVASAN; RENGASWAMY, 2008; CUADROS; MUNARO; MUNARETO, 2012; SILVA; GARCIA, 2014). Feedback linearization and sliding mode control are also common methods for servomechanisms and pneumatic diaphragm valves (CANUDAS de WIT; LISCHINSKY, 1997; KAYIHAN; DOYLE III, 2000; FREIDOVICH et al., 2010; BAEZA; GARCIA, 2018). Hidalgo and Garcia (2017) designed a sliding mode control with feedback linearization and friction observer using the Karnopp friction model, for valves with digital positioners.

With respect to diaphragm valves friction compensation, some authors suggest that the backlash compensation method can be used to overcome static friction as well, resulting in the constant reinforcement compensator (IVAN; LAKSHMINARAYANAN, 2009). Retuning the controller or using an adaptive integral term is often proposed by authors, since the controller integral term plays a major role in inducing limit-cycles in control loops (MOHAMMAD; HUANG, 2012; MISHRA; KUMAR; RANA, 2014).

Regarding motor operated servomechanisms, many authors suggest adaptive friction compensation due to its easier implementation: it eliminates the need to know any parameters beforehand and may be able to compensate for time-varying characteristics (FEEMSTER et al., 1999; MÁRTON; LANTOS, 2007; SOBCZYK et al., 2016; VERBERT; TÓTH; BABUSKA, 2016). Adaptive friction compensation, however, result in complex nonlinear equations and to prove the closed loop system stability, in some cases it is necessary to simplify the friction model. Yet, some authors suggest using feedforward compensation, by calculating the friction force given the system set point (SWEVERIS et al., 2000; TJAHJOWIDODO; BRUSSEL, 2005).

1.4 Contributions

Some of the new friction models proposed by the tribology science researchers have never been tested for diaphragm valves modeling. The main reason for that is because the friction compensation area focused on delivering solutions for the already installed valves, which frequently lack sensors and therefore would hardly benefit from new models. However, this assumption was never tested and analyzed properly.

Estimating friction parameters is usually a difficult task, due to its nonlinear and discontinuous nature. It is an even more complex task with regard to diaphragm valves as the friction force is not measured, its parameters have to be estimated indirectly from stem position and diaphragm pressure measurements. No other work has focused on

estimating friction parameters of novel models, for diaphragm valves. In this work the GMS model is used to describe the effect of friction in diaphragm control valves, as seen in Subsection 3.2.4, something that was never made before, therefore constituting an important contribution of this thesis. An enhancement in the Karnopp friction model, that is frequently used for modeling pneumatic control valves, is also proposed in this work, as can be seen in Subsection 3.2.2.

Diaphragm valves friction compensation using the AIC framework has never been developed. This method is rarely used for control systems, but has the potential to improve the tuning of already developed friction compensation techniques and to be used to solve many other control problems.

1.5 Publications

The question that arises when dealing with nonlinear and discontinuous systems parameter estimation is whether a linear objective function optimization technique would be enough for parameters estimation. This problem was addressed and published in the annals of the 12th international IFAC Symposium on Dynamics and Control of Process Systems, Including Biosystems, whose title is *Stribeck Parameters Estimation of a Diaphragm Valve Using Quasi Newton Method*. In this paper, analytical derivatives of the valve with Karnopp friction model were derived and the Quasi Newton method was used to estimate the friction parameters. The results, however, were not promising, due to the high mathematical complexity of the method and numerical problems, but it is enough to support the use of derivative free optimization methods for friction parameters estimation.

The diaphragm valve modeling and parameters estimation was transformed into a paper and was sent to a control systems journal.

The software and experimental data of this work are stored in Zenodo (MARQUES, 2019).

1.6 Thesis Outline

The objective of Chapter 2 is to introduce the laboratory used to obtain the proof of concept tests. The instruments, equipment and materials used to obtain the experimental data are presented.

Modeling diaphragm valves with continuous and discrete equations is presented in Chapter 3.

The valve model parameters estimation in open loop systems is developed in Chapter 4, whereas the closed loop systems estimation method is designed in Chapter 5.

The automatic compensation of the valve friction is developed in Chapter 6, using the Adaptive Inverse Control framework.

The conclusions and final remarks of this work are presented in Chapter 7.

Appendix A presents the optimization algorithms used in this thesis.

2 The Flow Pilot Plant

2.1 Functional Description

The FPP is a closed loop hydraulic circuit that uses a pump to increase the fluid pressure and thus forces a flow through its pipes. The tank TK-001 stores filtered water, accommodates density variations and guarantees the minimum suction pressure of the pump P-001, in order to avoid cavitation. If TK-01 water level is low (LSL-18), the interlock I-1 turns off P-001. The pump has a velocity regulator (SC-17), which is able to control the pump discharge pressure.

The hydraulic circuit flow rate is measured using an orifice plate (FE-10) and differential pressure measurements (FIT-10A/10D) or using a Coriolis sensor (FIT-10B). The flow can be controlled using a teflon (FV-10T) or graphite (FV-10G) gasket pneumatic diaphragm valve. The teflon gasket usually presents lower friction index than the graphite, but the latter is preferable when controlling high temperature fluids. Therefore, it is possible to test real valves with different friction characteristics. The valve FV-13 is used to cause control loop perturbations.

The control system can be implemented in an ABB® model 800xA Digital Control System (DCS), or using the PCI-6229 module from National Instruments® and a real-time computer software.

2.2 The Pneumatic Diaphragm Valves

The pneumatic diaphragm valves (FV-10T/10G) are manufactured by Fisher and are air-to-close, with globe plug. The diaphragm pressure (PT-10T/10G) and the stem position (ZT-10T/10G) are measured variables. A Linear Variable Differential Transformer (LVDT) is used for measuring the stem position.

In this thesis, the diaphragm pressure is controlled by using a current to pressure converter (I/P converter FY-10T/10G), which converts a 4 – 20 mA DC current to a 6 – 30 psi pressure. Even though it is not used in this thesis, there is the possibility to use an electro-pneumatic or a digital positioner. The former has a mechanical feedback of the valve stem position to adjust the diaphragm pressure and the latter uses an embedded digital system to adjust the diaphragm pressure given a deviation from desired and measured stem position.

Both valves have the same diaphragm actuator (Fisher 657) which has a cross sectional area of $S_a = 445 \cdot 10^{-4} \text{ m}^2$ and works from 6 to 30 psi (EMERSON, 2000). Therefore, from the valve manual, the minimum pressure is $P_{\min} = 41368.5 \text{ Pa}$ and considering that the controller output is normalized from 0 – 100%, the I/P converter pressure gain is $K_{P_g} = 1654.75 \text{ Pa}/\%$. The valve moving parts mass is $m = 1.6 \text{ kg}$, as informed by the vendor. The minimum and maximum stem position physical constraints

are $x_{\min} = 0$ m and $x_{\max} = 28.58 \cdot 10^{-3}$ m, respectively.

The experimental data presented in this thesis are obtained using the MATLAB[®] Real-Time toolbox and the PCI-6229 hardware interface.

In this thesis, the diaphragm pressure and stem position are assumed to be available to the digital positioner, in which the algorithms developed in this work are to be embedded. It is not common to measure the diaphragm pressure in digital positioners, but as the sensors are constantly getting cheaper with the internet of things development, the added sensor is worth the cost, as the valve performance can be improved even when there are deviations from its design parameters and yet, it allows the development of better defect detection algorithms.

3 Diaphragm Valve Modeling

The diaphragm valve modeling is addressed in this chapter. It starts by presenting how pneumatic diaphragm valves are modeled using the first principles method. As this modeling requires a friction model, the observed experimental friction characteristics and the Karnopp, LuGre and GMS friction models are presented. Yet, the Kano data driven diaphragm friction valve model is also presented. The models are discretized to be used in further developments.

3.1 First Principle Diaphragm Valves Modeling

The diaphragm control valves operate by the interaction of electro-pneumatic, mechanical and hydraulic systems. Figure 3.1 presents a simplified schematic air to open diaphragm valve.

Figure 3.1 – Simplified schematic representation of a pneumatic diaphragm valve.
Source: Based on Emerson (2005).

As the pressure varies, the diaphragm converts the pressure into a force, which accelerates the mechanical system, moving the stem until a new stable point is reached due to spring compression or extension. As the stem position changes, the pressure drop across the valve is modified, which in turn modifies the hydraulic system flow rate.

The first principles modeling is straightforward, by applying force balance in the simplified pneumatic and mechanical systems shown in Figure 3.1, one obtains (KAYIHAN; DOYLE III, 2000; GARCIA, 2008):

$$m\ddot{x}(t) = F_{\text{diaphragm}}(t) - F_{\text{spring}}(t) - F_f(t) - F_{\text{flow}}(t) - F_{\text{init}}, \quad (3.1)$$

where x is the stem position, m is the moving parts mass, $F_{\text{diaphragm}}$ is the diaphragm force, F_{spring} is the spring force, F_f is the friction force, F_{flow} is the force the fluid exerts on the valve plug due the flow and F_{init} is the spring initial force, when the system is at rest. The diaphragm force is:

$$F_{\text{diaphragm}}(t) = S_a P(t), \quad (3.2)$$

where S_a is the diaphragm section area and $P(t)$ is the air pressure in the valve diaphragm chamber. The spring force can be modeled as:

$$F_{\text{spring}}(t) = k x(t), \quad (3.3)$$

where k is the spring constant. F_{flow} can be neglected, since it is much lower than the other forces (KAYIHAN; DOYLE III, 2000).

The I/P converter has nonlinear dynamics, presenting different characteristics given the controller output (OP) magnitude, direction and signal characteristics (MARQUES; GARCIA, 2019). As for filtering and estimating the valve bandwidth, since the diaphragm pressure is considered a measured variable in this thesis, a first order filter suffices to model the diaphragm pressure:

$$\dot{P}(t) = \frac{(K_{P_g} \text{OP}(t) + P_{\min}) - P(t)}{\tau_{\text{I/P}}}, \quad (3.4)$$

where OP is the controller output, normalized to 0 – 100%, K_{P_g} is a pressure gain, $P_{\min}$ is the pressure when OP is zero and $\tau_{\text{I/P}}$ is the I/P model time constant. The pressure gain is defined as:

$$K_{P_g} = \frac{P_{\max} - P_{\min}}{100}, \quad (3.5)$$

where $P_{\max}$ is the maximum diaphragm pressure.

With all terms defined but the friction force, F_f , the friction characteristics are discussed and the Karnopp, LuGre and GMS friction models are presented in the following sections.

3.1.1 Friction Phenomenon

Friction is a phenomenon that has been studied since Leonardo da Vinci, however, due to its complexity, there is not a universal friction model that would be suitable for all applications. In practice, every friction model has a foundation in experimental data (is a data driven model) and is created to encompass some objectives, such as ease of mathematical analysis, ease of implementation, prediction precision and physical consonance. Understanding friction is imperative for selecting a proper model.

The friction force, F_f , arises from the microscopic interactions between two surfaces, as presented in Figure 3.2, which makes it practically impossible to create an extensive model, which considers every microscopic interaction between the material surfaces. In practice, the friction models intend to capture one or more macroscopic behaviors observed experimentally. Often, friction is classified into two states with different characteristics: presliding and sliding.

Figure 3.2 – Friction origin.
Source: Based on Olsson (1996).

3.1.1.1 Presliding State

In the presliding state, the surfaces remain sticking until the external force (F) is higher than the static friction force or stiction (F_s). Some models assume that there is no motion between the surfaces until $F > F_s$. However, experimental data has proven that there is a relative motion between the surfaces, proportional to the external force, which is often explained as the elastic deformation between the surfaces irregularities as shows the Figure 3.3 depiction.

Figure 3.3 – Depiction of presliding state.
Source: Based on Olsson (1996).

This motion is of the order of a few micrometers, but can be amplified by the mechanical system to an order of a few millimeters (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994). Additionally, the experimental findings suggest that the presliding regime can be described by a hysteresis function with nonlocal memory (SWEVERS et al., 2000). Figure 3.4 summarizes the previous statement, which is known as presliding displacement. Note that there is a remnant displacement when the external force is removed, but, this does not imply that it is possible to reach any displacement by applying and removing a force lower than F_s .

Another presliding characteristic that is common to observe experimentally is the inverse relationship between the external force rate of change and the breakaway force (F_s). This behavior is shown qualitatively in Figure 3.5.

Figure 3.4 – Presliding displacement.

Source: Based on Olsson et al. (1998), Swevers et al. (2000).

Figure 3.5 – Decrease of F_s with an increase in the rate of change of the external force F .

Source: Based on Olsson et al. (1998).

Yet, F_s increases with the amount of time the system has spent sticking. The increased magnitude and the times involved depend on the materials and lubricant used in the mechanical system. This relationship is shown in Figure 3.6.

Figure 3.6 – The relationship between F_s and the dwell time.

Source: Based on Armstrong-Hélouvry, Dupont and Canudas de Wit (1994).

3.1.1.2 Sliding state

The most known characteristic of the sliding state is a friction–velocity steady state relationship, which can be modeled by a combination of three effects that are function of the materials, lubricant and normal force. The first is the Coulomb friction force (F_c) that is modeled as a constant force, opposed to the movement direction, as long as the relative velocity is different from zero. The second is a directly proportional relationship between velocity and the friction force, which is modeled by the viscous friction parameter (F_v). The last behavior corresponds to the transition from presliding to sliding. Many functions can be used to model this transition, but in any case it is characterized by a constant, the Stribeck Velocity (v_s), which dictates the velocity range in which F_s converges to F_c . Figure 3.7 aggregates all the three behaviors. Note that, in general, $F_s \geq F_c$.

Figure 3.7 – The friction–velocity relationship in steady state condition.
Source: Based on Armstrong-Hélouvry, Dupont and Canudas de Wit (1994).

Although Figure 3.7 suggests an apparent instantaneous change in the friction force due a velocity variation, this is not what occurs in experimental observations. There is a lag between the velocity variation and its respective change in the friction force, which can be observed by varying the velocity sinusoidally, without reversing the movement direction. The friction force lag creates a hysteretic behavior, as shown in Figure 3.8.

Figure 3.8 – Depiction of friction lag, perceived due to different oscillation frequencies.

Source: Based on Armstrong-Hélouvry, Dupont and Canudas de Wit (1994).

3.1.2 Friction Models

Each friction model tends to capture one or more friction characteristics. Naturally, a very precise model tends to be more complex and has more parameters than a model which is able to predict only a few characteristics. The Karnopp, LuGre and GMS models are presented in the following sections.

3.1.2.1 The Karnopp Model

The Karnopp model is useful when it is necessary to predict the friction–velocity in steady state (KARNOPP, 1985). This model disregards all presliding characteristics and the dynamic behaviors of the sliding regime. The friction force (F_f) is calculated as:

$$F_f = \begin{cases} F, & \text{if } |v| < DV \text{ and } |F| \leq F_s \\ F_s \operatorname{sgn}(F), & \text{if } |v| < DV \text{ and } |F| > F_s \\ F_d(v), & \text{if } |v| \geq DV \end{cases} \quad (3.6)$$

where F is the external force, DV is a velocity that determines when the system is considered sticking, v is the relative velocity of the system, $\operatorname{sgn}(x)$ is the signal function, defined as:

$$\operatorname{sgn}(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \\ -1, & \text{if } x < 0 \end{cases} \quad (3.7)$$

and $F_d(v)$ is the steady state friction–velocity relation, also known as the Stribeck curve, which is commonly defined as:

$$F_d(v) = \left[F_c + (F_s - F_c) e^{-(v/v_s)^2} \right] \operatorname{sgn}(v) + F_v v. \quad (3.8)$$

Generally, to achieve better simulation results, when the valve is sticking – first case of Eq. (3.6) –, the system velocity is set to zero.

3.1.2.2 The LuGre Model

The LuGre model is designed to predict the presliding displacement, the decrease of F_s with an F rate of change increase, the friction–velocity relationship in steady state and the friction lag (CANUDAS de WIT et al., 1995). The model is described by the following equation:

$$F_f(z, v) = \sigma_0 z + \sigma_1 \frac{dz}{dt} + F_v v, \quad (3.9)$$

where z is a virtual state regarded as the average deflection of the material surface bristles, σ_0 represents the elastic constant of the bristles and σ_1 is a damping coefficient. The variable z is calculated as:

$$\frac{dz}{dt} = v - \frac{|v|}{g(v)} z, \quad (3.10)$$

where $g(v)$ is the friction–velocity function in steady state divided by σ_0 , that can be defined similarly as Eq. (3.8):

$$g(v) = \frac{F_c + (F_s - F_c) e^{-(v/v_s)^2}}{\sigma_0}. \quad (3.11)$$

In steady state, $z \rightarrow g(v) \operatorname{sgn}(v)$ and the average bristle deflection can be seen as a velocity filter with $g(v)/|v|$ time constant and variable gain.

3.1.2.3 The GMS Model

The LuGre model was proven to be imprecise in the predictions regarding the presliding displacement, as it can drift when in presliding state and excited with an external force lower than breakaway force (SWEVERS et al., 2000). The Generalized Maxwell Slip Model (GMS) was developed to encompass a precise simulation of the presliding displacement and ease of implementation (AL-BENDER; LAMPAERT; SWEVERS, 2005), besides incorporating all friction characteristics that the LuGre model was already able to predict. The GMS model consists of N_{Me} virtual massless elements connected in parallel that, when the individual effects are added, results in the macroscopic friction effect, as shown in Figure 3.9.

The friction force is calculated as (PIATKOWSKI, 2014):

$$F_f = \sum_{i=1}^{N_{Me}} F_i + F_v v, \quad (3.12)$$

where $F_i = \kappa_i \psi_i + \nu_i \dot{\psi}_i$ is the friction force of element i , $\psi \in \mathbb{R}^{N_{Me}}$ represents the displacement of the virtual elements, κ_i is the elastic constant of the element i and ν_i is

Figure 3.9 – The virtual massless elements of the GMS model.

Source: Based on Piatkowski (2014).

the damping coefficient of element i . When the element i is in the presliding regime, ψ_i is equal to:

$$\dot{\psi}_i = v, \quad (3.13)$$

and the element remains in this state until $F_i > \alpha_i s(v)$, where $s(v)$ is the friction-velocity function:

$$s(v) = F_c + (F_s - F_c) e^{-(v/v_s)^2} \quad (3.14)$$

and α_i is a constant, such that $\{\alpha_i \mid \sum_{i=1}^{N_{Me}} \alpha_i = 1\}$. If the element i is in the sliding regime, ψ_i is calculated as:

$$\dot{\psi}_i = \frac{C\alpha_i}{\kappa_i} \left(\text{sgn}(v) - \frac{F_i}{\alpha_i s(v)} \right), \quad (3.15)$$

where C is an attraction constant, that defines how fast $|F_i|$ converges to $\alpha_i s(v)$. The element remains in the sliding regime until the velocity is reversed or is equal to zero. In this thesis, 3 Maxwell massless elements are used in the GMS model, which is enough to model mechanical systems with a fair precision, as seen in the work of Piatkowski (2014). It is important to emphasize that the application of this model in diaphragm control valves was never carried out before, being a relevant contribution of this work, since the dynamical models tend to be more precise for predicting systems that present low velocities (PIATKOWSKI, 2014).

In steady state, the Maxwell element displacement tends to $\psi_i \rightarrow \alpha_i s(v) \text{sgn}(v) / \kappa_i$.

3.1.2.4 The Dwell Time

The models described previously do not include a prediction for a F_s increase due to higher dwell times, however, this can be modeled by allowing F_s to vary with time, as

suggested by (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994):

$$F_s(t_{dt}, \lambda) = F_{s_0} + (F_{s_\infty} - F_{s_0}) \frac{t_{dt}}{t_{dt} + \lambda}, \quad (3.16)$$

where t_{dt} is the dwell time, F_{s_0} is the static friction force when the system has just reached the sticking state, F_{s_∞} is the static friction force when the system remained sticking for a long period and λ is a constant that is inversely proportional to how fast the static friction force increases from F_{s_0} to F_{s_∞} . This behavior is neglected in this work, since the measurement noise and control loop perturbations usually results in frequent controlled variable corrections and thus stem movements.

3.2 Diaphragm Valve Model Discretization

The discretization of the valve and friction models discussed previously is fundamental for simulation and parameters estimation. In this section the models are discretized and the generic friction models presented in previous sections are modified to comply with the valve model. This is another contribution of this thesis.

3.2.1 Valve Discrete Model

From Eq. (3.1), the resultant force can be defined as:

$$F_{\text{res}}(t) = S_a P(t) - k x(t) - F_f(\dot{x}, t) - F_{\text{init}}. \quad (3.17)$$

The valve stem acceleration is:

$$a(t) = \ddot{x}(t) = \frac{F_{\text{res}}(t)}{m}. \quad (3.18)$$

The valve stem velocity ($\dot{x}$) and position (x) can be calculated easily, by integrating the valve stem acceleration. The numerical integration can be done using the bilinear transformation (FADALI; VISIOLI, 2013):

$$\begin{aligned} v[n+1] = \dot{x}[n+1] &\approx \frac{T_s}{2} \frac{1 + q^{-1}}{1 - q^{-1}} \ddot{x}[n] \\ x[n] &\approx \frac{T_s}{2} \frac{1 + q^{-1}}{1 - q^{-1}} \dot{x}[n], \end{aligned} \quad (3.19)$$

here $n \in \mathbb{N}$, $x[n] = x(n T_s)$ is the discrete signal, q is the time shift operator and T_s is the sampling time. The valve discrete model may include the physical stem constraints, $x_{\min}$ and $x_{\max}$, to prevent valve movements outside these limits. If these limits are reached, the resultant force, stem acceleration, velocity and position must be clipped accordingly.

The I/P converter is assumed to be a generic first order discrete equation:

$$P[n+1] = a_0 P[n] + b_0 + b_1 \text{OP}[n], \quad (3.20)$$

where a_0 , b_0 and b_1 are constants related to Eq. (3.4) parameters:

$$\begin{aligned}\tau_{I/P} &= -\frac{T_s}{\ln a_0} \\ P_{\min} &= (b_0 \cdot \tau_{I/P}) / T_s \\ K_{P_g} &= (b_1 \cdot \tau_{I/P}) / T_s.\end{aligned}\tag{3.21}$$

3.2.2 Karnopp Discrete Model

The Karnopp model has no dynamics, therefore its use is straightforward. However, inspired by the GMS model, there are some improvements that can be made to achieve more efficient simulations, which is also a small contribution of this work. The discrete Karnopp model is defined as:

$$F_f[n] = \begin{cases} \text{sgn}(F_r[n]) \cdot \min(F_s, |F_r[n]|) & , \text{ when in presliding state} \\ F_d(\dot{x}[n]) & , \text{ when in sliding state,} \end{cases}\tag{3.22}$$

here $F_r[n] = S_a P[n] - k x[n] - F_{\text{init}}$ and $F_d(\dot{x}[n])$ is directly obtained from Eq. (3.8). The sliding regime is active when $|F_f[n]|$ is higher than F_s and the stem accelerates. The presliding regime is active when it is detected a movement reversal or the system stops, which can be determined when the following equation is true:

$$\dot{x}[n] \cdot \dot{x}[n-1] \leq 0.\tag{3.23}$$

To increase the simulation precision, it is necessary to set $\dot{x}[n] = 0$, when the presliding state is detected.

Note that the Karnopp model used in this work is different from the original Karnopp model. As the differences do not significantly modify the model dynamics, the model is still referred to as the Karnopp model.

3.2.3 LuGre Discrete Model

The discrete derivative of the average bristle deflection is obtained directly from Eq. (3.10):

$$\dot{z}[n+1] = \dot{x}[n] - \frac{|\dot{x}[n]|}{g(\dot{x}[n])} z[n],\tag{3.24}$$

with $g(\dot{x}[n])$ derived directly from Eq. (3.11). Correspondingly, the average bristle deflection is obtained by the numerical integration of its derivative:

$$z[n] \approx \frac{T_s}{2} \frac{1 + q^{-1}}{1 - q^{-1}} \dot{z}[n].\tag{3.25}$$

The friction force is calculated as presented in Eq. (3.9).

3.2.4 GMS Discrete Model

The GMS discrete model development is a combination of the Karnopp and LuGre discrete model implementations. The Maxwell massless element is governed by two differential equations, whether in the sliding or presliding states. In the discrete form, these equations are written as:

$$\begin{cases} \dot{\psi}_i[n] = \dot{x}[n] & , \text{ when in presliding state} \\ \dot{\psi}_i[n+1] = \frac{C\alpha_i}{\kappa_i} \left(\text{sgn}(\dot{x}[n]) - \frac{F_i[n]}{\alpha_i s(\dot{x}[n])} \right) & , \text{ when in sliding state,} \end{cases} \quad (3.26)$$

The position of the Maxwell elements can be determined by the numerical integration of ψ_i , similarly as shown in Eq. (3.25). The friction force is calculated directly from Eq. (3.12).

The Maxwell elements are considered in the presliding state when there is a movement reversal, which is detected as presented in Eq. (3.23). The sliding state is active when $F_i[n] \geq \alpha_i s(\dot{x}[n])$.

3.2.5 Sampling Time Selection

When simulating discrete systems, the sampling time design is important, since it can lead to simulation failures. The LuGre and GMS models consider that friction force when in presliding state is a consequence of relative movements, with typical magnitudes of tens of micrometers (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994). This phenomenon usually imposes the most restrictive requirements for specifying the sampling time. By using the rectangular integration, it is possible to guarantee that the maximum stem position change in a time step is smaller than a constant:

$$T_s |v_{max}| < x_{\text{mchange}}, \quad (3.27)$$

where v_{max} is the maximum stem velocity and x_{mchange} is the desired maximum position change in a time step. Usually, the valve bandwidth is limited by the I/P converter dynamics, therefore a good estimate for the maximum stem velocity, considering sinusoidal excitation signals, is:

$$v_{max} \approx (x_{max} - x_{min}) \frac{2\pi}{\tau_{\text{I/P}}}, \quad (3.28)$$

with x_{max} and x_{min} the maximum and minimum stem position, respectively. To determine the value of x_{mchange} , it suffices to note that for the vast majority of applications, 5 μm is at least a third of the maximum displacement during presliding.

As the Karnopp model has no dynamics during presliding regime, Eq. (3.27) can be rewritten by considering that a conservative criterion is to set the maximum stem movement in a time step equal to a thousandth of the valve stroke:

$$T_s v_{max} < \frac{x_{max} - x_{min}}{1000}. \quad (3.29)$$

With the same estimation for the maximum stem velocity as in Eq. (3.28), the sampling time criteria for the Karnopp model reduces to:

$$T_s < \frac{\tau_{I/P}}{2000\pi}. \quad (3.30)$$

3.3 Data Driven Model of Pneumatic Control Valves

Amidst the empirical models, the Kano model can be considered the most suitable to predict the behavior of pneumatic control valves (GARCIA, 2008). As other data driven models, its design was inspired by the valve signature, which is obtained by varying the OP in a trapezoidal manner and plotting the stem position or valve flow rate in the y-axis and the diaphragm pressure or OP in the x-axis. Figure 3.10 presents a typical idealized valve signature. The Kano model considers that the valve behavior can be defined by a deadband (S) and a slip band (J). When the direction of the movement is reversed, the deadband has to be surpassed, as shown in position d . If the valve stops and the movement is to be initiated in the same direction as before, only the slip band has to be overcome, as shown in position c . This model neglects the effect of the viscous friction and considers that the transition from presliding to sliding occurs instantaneously, with a jump from the static friction force to Coulomb friction force, as shown in the path from a to b . Note that the Kano model simplifies the valve dynamics model, by considering instantaneous stem movements when OP varies and simplifies the friction model, neglecting many friction characteristics. The main advantage of the Kano model is that it operates at the same sampling time of the controller output, resulting in effective simulations.

Figure 3.10 – A typical valve signature curve.

Source: Based on Kano et al. (2004), Choudhury, Thornhill and Shah (2005).

The Kano model implementation is presented in Algorithm 3.1. In this thesis, the Kano model differs from the original algorithm, since it uses another parameter, D , which

simulates the effect of the initial force and uses a proper output function to match the valve stem position. This is another small contribution of this work. Yet, the model input is considered the normalized diaphragm pressure, since it is not physically feasible to have instantaneous stem movements with changes in OP. Note that for increase the simulation performance, the input has to be normalized. Observe that the stem limits shown in Kano algorithm are not the physical limits, but the maximum ($x_{\max P}$) and minimum ($x_{\min P}$) stem positions when the diaphragm pressure is maximum and minimum, respectively.

Algorithm 3.1 – A pseudo-code for the Kano model, extended with the initial force and output stem position matching function.

Input: The normalized diaphragm pressure $I[n]$ at each time step n , the deadband S , the stick band J , the initial force D , the minimum and maximum stem position, $x_{\min P}$ and $x_{\max P}$, respectively, the initial stem position, $x[0]$ and the initial input, $I[0]$.

```

1:  $d \leftarrow -1$ 
2:  $stp \leftarrow \text{True}$ 
3:  $xi[0] \leftarrow x[0]/(x_{\max P} - x_{\min P}) \cdot 100$ 
4: for  $n = 1$  : end of data do
5:    $I[n] \leftarrow I[n] - D$ 
6:    $\Delta I[n] \leftarrow I[n] - I[n-1]$ 
7:   if  $\Delta I[n] \cdot \Delta I[n-1] \leq 0$  and  $stp == \text{False}$  then
8:      $Is \leftarrow I[n]$ 
9:      $stp \leftarrow \text{True}$ 
10:  end if
11:  if  $stp == \text{False}$  then
12:     $xi[n] \leftarrow I[n] - d/2 \cdot (S - J)$ 
13:     $stp \leftarrow \text{False}$ 
14:  else if  $-d \cdot (I[n] - Is) > S$  then
15:     $d \leftarrow -d$ 
16:     $xi[n] \leftarrow I[n] - d/2 \cdot (S - J)$ 
17:     $stp \leftarrow \text{False}$ 
18:  else if  $d \cdot (I[n] - Is) > J$  then
19:     $xi[n] \leftarrow I[n] - d/2 \cdot (S - J)$ 
20:     $stp \leftarrow \text{False}$ 
21:  else
22:     $xi[n] \leftarrow xi[n-1]$ 
23:  end if
24:   $x[n] = xi[n] \cdot (x_{\max P} - x_{\min P}) / [(100 - D) - (S - J)/2] + x_{\min P}$ 
25: end for

```

Source: Based on Kano et al. (2004).

The Kano parameters are related to Stribeck curve and valve parameters:

$$\begin{aligned} S &= \frac{2 F_s}{(P_{\max} - P_{\min}) \cdot S_a} \cdot 100 \\ J &= \frac{F_s - F_c}{(P_{\max} - P_{\min}) \cdot S_a} \cdot 100 \\ D &= \frac{F_{\text{init}}/S_a - P_{\min}}{P_{\max} - P_{\min}} \cdot 100. \end{aligned} \quad (3.31)$$

The main difference from the relationships shown in Eq. (3.31) and the ones proposed by Uehara, Garcia and Romano (2008) is that the latter considered that when the stem is moving, the friction force is F_c . However, this is not true if one analyzes the Stribeck curve, as when the valve velocity is close to zero, the friction force is close to F_s , leading to the equivalence equation presented in Eq. (3.31).

3.4 Diaphragm Valve Simulation

To ensure that the discrete models are equivalent to their continuous counterparts, simulations were performed and the results of the continuous and discrete models were compared, using a sampling time $T_s = 10 \mu\text{s}$, except for the Kano model, which employed $T_s = 1 \text{ ms}$. The valve and the friction parameters used in the simulations are presented in Tables 3.1 and 3.2.

Table 3.1 – Valve parameters used in the simulations.

Parameter	Value
$\tau_{I/P}$ (s)	1/0.28
S_a (m ²)	$445 \cdot 10^{-4}$
$P_{\max}$ (Pa)	180000
$P_{\min}$ (Pa)	41368
m (kg)	1.6
k (N/m)	210490
F_{init} (N)	2550
$x_{\min}$ (m)	0
$x_{\max}$ (m)	0.029
$x_{\min P}$ (m)	0
$x_{\max P}$ (m)	0.029

Source: from Author.

Table 3.2 – Friction parameters used in the simulations.

Parameter	Value	Parameter	Value
F_c (N)	700	α_1	0.75
F_s (N)	780	α_2	0.2
F_v (Ns/m)	$1.25 \cdot 10^5$	α_3	0.05
v_s (m/s)	$5 \cdot 10^{-4}$	κ_1 (N/m)	$F_s \alpha_1 / 2 \cdot 10^{-5}$
DV (m/s)	$v_s / 100$	κ_2 (N/m)	$F_s \alpha_2 / 10^{-5}$
σ_0 (N/m)	$F_s / 3 \cdot 10^{-5}$	κ_3 (N/m)	$F_s \alpha_3 / 5 \cdot 10^{-6}$
σ_1 (Ns/m)	$4\sqrt{\sigma_0}$	ν_1 (Ns/m)	$\sqrt{k + \kappa_1 + \kappa_2 + \kappa_3} / 3$
S (%)	25.29	ν_2 (Ns/m)	$\sqrt{k + \kappa_1 + \kappa_2 + \kappa_3} / 6$
J (%)	1.2968	ν_3 (Ns/m)	$\sqrt{k + \kappa_1 + \kappa_2 + \kappa_3} / 2$
D (%)	11.50	C (rad/s)	20.00

Source: from Author.

The simulation excitation signal, OP, consisted in a sequence of ramps with random velocities and magnitudes, as shown in Figure 3.11.

Figure 3.11 – Excitation signal used in the simulations.

Source: from Author.

The Karnopp, LuGre and GMS discrete and continuous simulation results are presented in Figure 3.12, where no visual difference is distinguished from any of the six simulations. The Kano simulation result is compared to the Karnopp model as shown in Figure 3.13, where it is possible to verify that the models present similar results, except for a variable offset.

Figure 3.12 – Comparison of continuous and discrete valve models with Kano, Karnopp, LuGre and GMS friction models.

Source: from Author.

Figure 3.13 – Simulation of the valve using the Kano model and comparison with the Karnopp model.

Source: from Author.

For a better evaluation of the discretization, the quantitative *fit* index is calculated, defined as:

$$fit = 100 \cdot \left(1 - \frac{\sqrt{\sum_{n=1}^{n_f} (x_c[n] - x[n])^2}}{\sqrt{\sum_{n=1}^{n_f} (x_c[n] - \mu(x_c))^2}} \right), \quad (3.32)$$

where $x_c[n]$ is the continuous model stem position at timestep n , $\mu(x_c)$ is the mean value of x_c and n_f is the final time step. As per Eq. (3.29), the Karnopp sampling time can be lower, the *fit* was calculated with $T_s = 10^{-4}$ s, as well. The quantitative comparison is presented in Table 3.3, where it is possible to conclude that the discretization is successful. The simulation time shows a huge difference between the data driven and first principle models, being the former much more computationally efficient.

Table 3.3 – Continuous and discrete valve models comparison.

Model	<i>fit</i>	Simulation Time (s)
Kano ($T_s = 10^{-3}$ s)	–	0.1
Karnopp ($T_s = 10^{-4}$ s)	97.68%	1.9
Karnopp ($T_s = 10^{-5}$ s)	100%	15.4
LuGre ($T_s = 10^{-5}$ s)	100%	20.3
GMS ($T_s = 10^{-5}$ s)	100%	25.0

Source: from Author.

4 Open Loop Parameters Estimation

This chapter addresses the design of an open loop diaphragm valve parameters estimation method. In this case, the valve stem position is allowed to move at will, as it is not being used in a control loop or is in a maintenance bench.

By evaluating the valve model of Eq. (3.1), one can easily identify the parameters that have to be estimated: the diaphragm cross sectional area, S_a , the moving parts mass, m , the spring constant, k , the initial force, F_{init} , the I/P converter model parameters and the friction parameters, F_f , depending on the selected friction model (Section 3.2). Regarding the Kano data driven model (Section 3.3), the estimated parameters are related to the I/P converter model, valve deadband, S , slip band, J , initial force, D and maximum and minimum observed stem positions, x_{minP} and x_{maxP} , respectively.

Estimating the valve and friction parameters can be accomplished by minimizing the difference between the measured and simulated stem position, e.g. calculating the mean squared error of a given dataset:

$$\{\hat{S}_a, \hat{m}, \hat{k}, \hat{F}_{\text{init}}, \hat{\theta}_{\text{I/P}}, \hat{\theta}_f\} = \arg \min_{S_a, m, k, F_{\text{init}}, \theta_{\text{I/P}}, \theta_f} V_{n_f}(S_a, m, k, F_{\text{init}}, \theta_{\text{I/P}}, \theta_f), \quad (4.1)$$

here the caret denotes estimated parameter, $\theta_{\text{I/P}} \in \mathbb{R}^3$ is a vector with the discrete I/P model parameters, $\theta_f \in \mathbb{R}^{d_f}$ is the friction model parameters vector, whose dimension (d_f) depends on which model is used in the simulation, n_f is the number of samples and V_{n_f} is defined as the mean squared prediction error (some function arguments are omitted for simplicity):

$$V_{n_f}(S_a, m, k, F_{\text{init}}, \theta_{\text{I/P}}, \theta_f) = \frac{1}{n_f} \sum_{n=1}^{n_f} e_x(n, \text{OP}[n], \theta_{\text{I/P}}, P[0], x[0], \dot{x}[0], S_a, m, k, F_{\text{init}}, \theta_f)^2, \quad (4.2)$$

where $\text{OP}[n]$ is the controller output, $P[0]$ is the initial diaphragm pressure, $x[0]$ is a vector with initial stem position and initial internal friction states position, when applicable, $\dot{x}[0]$ is a vector with initial stem velocity and initial internal friction states velocity, when applicable. The prediction error is calculated as:

$$e_x(n) = \hat{x}(n, \text{OP}[n], \theta_{\text{I/P}}, P[0], x[0], \dot{x}[0], S_a, m, k, F_{\text{init}}, \theta_f) - x[n], \quad (4.3)$$

here $\hat{x}(n, \text{OP}[n], \theta_{\text{I/P}}, P[0], x[0], \dot{x}[0], S_a, m, k, F_{\text{init}}, \theta_f)$ is the simulated stem position, using a given valve and friction model and $x[n]$ is the measured stem position.

As mentioned in Chapter 2, the diaphragm pressure is a measured variable, therefore the I/P model parameters can be estimated separately:

$$\hat{\theta}_{\text{I/P}} = \arg \min_{\theta_{\text{I/P}}} \frac{1}{n_f} \sum_{n=1}^{n_f} (\hat{P}(n, \text{OP}[n], P[0], \theta_{\text{I/P}}) - P[n])^2, \quad (4.4)$$

where $\hat{P}(n, OP[n], P[0], \theta_{I/P})$ is the simulated diaphragm pressure and $P[n]$ is the measured diaphragm pressure.

As the valve moving parts mass and diaphragm section area can be informed by the vendor and tends to be constant during the valve life time, these parameters are considered to be known. Therefore, Eq. (4.1) can be simplified to:

$$\{\hat{k}, \hat{F}_{\text{init}}, \hat{\theta}_f\} = \arg \min_{k, F_{\text{init}}, \theta_f} V_{nf}(S_a, m, k, F_{\text{init}}, \theta_f), \quad (4.5)$$

with the prediction error reduced to:

$$e_x(n) = \hat{x}(n, P[n], x[0], \dot{x}[0], S_a, m, k, F_{\text{init}}, \theta_f) - x[n], \quad (4.6)$$

It is worth noting that in the proposed estimation framework, $\hat{x}$ is independent from past stem measurements, leading to free simulation prediction minimization.

Despite solving Eq. (4.5) lead to the parameters estimation, there are many open questions that need to be answered beforehand. The optimization dimension is high, resulting in, at most, 16 estimated parameters, thus is it possible to estimate some of said parameters *a priori* to lower the complexity? Which excitation signal to use for estimating the parameters? Is it possible to define search space for the parameters? Lastly, which optimization method to use, since it is potentially a nonlinear, discontinuous and non convex set? Those questions are to be addressed in subsequent sections.

4.1 A Priori Estimation of Parameters

An initial estimate of the valve deadband, S_0 , can be obtained by increasing OP to 90% and then decreasing it linearly, with a low rate of change until it is observed a negative stem position velocity. The suggested OP rate of change is 1%/s, since slower variations may lead to time consuming experiments and faster may lead to delays between *OP* and the diaphragm pressure. The parameter S is the difference between 90% and the controller output at the moment which the valve movement is detected, as presented in Algorithm 4.1. Preferably, the normalized diaphragm pressure should be used in this estimation. This parameter is easy to identify and can be useful for designing the excitation signals and deriving a first initial guess (S_0) for the other model friction parameters. A simulated example is shown in Figure 4.1.

Algorithm 4.1 – S_0 detection.

-
- 1: Increase OP to 90% in 60 seconds
 - 2: Wait 40 seconds for stabilization
 - 3: Calculate the stem position measurement (x) standard deviation ($\text{std}(x)$) and mean value ($\mu(x)$) from the previous 10 seconds
 - 4: $p1 \leftarrow$ save the normalized diaphragm pressure value in this instant
 - 5: Reduce OP with a 1%/s rate
 - 6: When $\mu(x) - x > 8 \cdot \text{std}(x)$, return the difference between $p1$ and the actual normalized P value, which is S_0
-

Figure 4.1 – Simulated example for estimating S_0 a priori.

Source: from Author.

The I/P converter parameters can be estimated by minimizing the difference between the measured and the simulated diaphragm pressure as presented in Eq. (4.4), such that the latter is calculated using the discrete model given by Eq. (3.20). The solution for Eq. (4.4) is easily given using the one step ahead prediction minimization Least Squares Estimator (LSE) (LJUNG, 1999). However, it is preferable to use the infinite steps ahead prediction error minimization with an unconstrained optimization method to estimate the parameters vector. In this work, it was used the Simplex optimization method (NELDER; MEAD, 1965), with $\tau_{I/P} = 1$ s and $P_{\min}$ and K_{Pg} the same as the valve vendor manual as an initial guess. As the valve mechanical system dynamics tends to be faster than the I/P converter, the valve bandwidth can be approximated by the I/P bandwidth ($1/\tau_{I/P}$ rad/s), that can be calculated from the estimated discrete filter parameters using Eq. (3.21). Even though the first order filter is simple to simulate and easy to estimate, it must be noted that it is not perfect for a precise I/P converter simulation (MARQUES; GARCIA, 2019). For example, the I/P dynamics tends to be faster when excited with ramp signals than using steps and presents overshoot for positive steps but not for negative steps, as shown in Figure 4.2.

Figure 4.2 – I/P converter dynamics experimental data using the graphite gasket valve.

Source: from Author.

It is suggested to use both step and ramp signals for estimating the valve I/P model parameters. The step signal is rectangular with 80 s period, 60% magnitude, starting with 20%, as in Figure 4.2a. The I/P time constant obtained with the step signal, τ_{I/P_s} , is the one used for excitation signals and filters design. The time constant obtained using the ramp signals, τ_{I/P_r} , can be estimated using the excitation signal used for estimate k and F_{init} that is presented in the following paragraphs. Even though the two estimated models are not perfect and reflect the linear approximation of the I/P converter in the experiment, the model imprecision is not of great importance, as it is used mainly for secondary objectives and to detect faults in the I/P converter system.

The valve k and F_{init} can be estimated *a priori* also, reducing the number of estimated parameters of Eq. (4.5). The valve k and F_{init} parameters estimation technique suggested in this thesis is inspired in previous works (GARCIA, 2007; ROMANO; GARCIA, 2007) and is based on the diaphragm valve model analysis when the stem presents a constant velocity. If the valve is excited with a ramp signal, the result is an approximately constant stem velocity, therefore, Eq. (3.1) reduces to:

$$0 = S_a P(t) - k x(t) - F_f(\dot{x}) - F_{\text{init}}. \quad (4.7)$$

In steady state, $F_f(\dot{x})$ is constant, therefore Eq. (4.7) reduces to:

$$S_a P(t) = k x(t) + F_{b_l}(\dot{x}_{b_l}), \quad (4.8)$$

here $F_{b_l}(\dot{x}_{b_l}) = F_f(\dot{x}_{b_l}) + F_{\text{init}}$ is a constant force, $\dot{x}_{b_l}$ is a constant velocity, corresponding to a dataset $l \in \mathbb{N}$, which only contains data with a certain constant stem velocity. Therefore, estimating k and $F_{b_l}(\dot{x}_{b_l})$, is reduced to an algebraic linear regression estimation problem:

$$\mathbf{F}_{d_l} = \Phi_l \theta_l, \quad (4.9)$$

where $\mathbf{F}_{d_l} \in \mathbb{R}^{N_{b_l}}$ is the diaphragm force column vector of dataset l , containing N_{b_l} experimental observations, calculated using measured diaphragm pressure, $\theta_l = [k_l \quad F_{b_l}]^\top \in \mathbb{R}^2$ a parameter column vector, $\Phi_l = [\mathbf{x}_l \quad \mathbf{v}_u] \in \mathbb{R}^{N_{b_l} \times 2}$ the regression matrix, $\mathbf{x}_l \in \mathbb{R}^{N_{b_l}}$ the stem position experimental observations and $\mathbf{v}_u \in \mathbb{R}^{N_{b_l}}$ a vector of unitary values. Using the LSE, Eq. (4.9) solution is given by:

$$\hat{\theta}_l = (\Phi_l^\top \Phi_l)^{-1} \Phi_l^\top \mathbf{F}_{d_l}. \quad (4.10)$$

By exciting the valve with l_n constant velocities (at least 2 positive and 2 negative), it is possible to draw a Stribeck curve using the previous step calculated velocity and friction force. Therefore, it is possible to obtain an initial estimation of the Stribeck curve parameters and the initial force, by minimizing the following error equation:

$$\{\hat{F}_s, \hat{F}_c, \hat{F}_v, \hat{v}_s, \hat{F}_{\text{init}}\} = \arg \min_{F_s, F_c, F_v, v_s, F_{\text{init}}} \sum_{l=1}^{l_n} [\hat{F}_{b_l}(\dot{x}_{b_l}) - F_b(F_s, F_c, F_v, F_{\text{init}}, v_s, \dot{x}_{b_l})]^2, \quad (4.11)$$

where $\hat{F}_{b_l}(\dot{x}_{b_l})$ is estimated with Eq. (4.10), $\dot{x}_{b_l}$ is the stem velocity of dataset l and the F_b function is defined as:

$$F_b(F_s, F_c, F_v, F_{\text{init}}, v_s, \hat{x}_{b_i}) = F_d(F_s, F_c, F_v, v_s, \hat{x}_{b_i}) + F_{\text{init}}. \quad (4.12)$$

The Eq. (4.11) solution can be obtained using a derivative free optimization method, such as the Simplex. Note that this method provides an initial Stribeck curve parameters estimation, which should not be reliable, due to the low number of data points. The valve stem velocity can be approximated applying the backward differentiation. To minimize the measurement noise, the diaphragm pressure and stem position are filtered with a zero phase, second order linear filter, with 0.9 damping ratio and natural frequency $1/\tau_{I/P_s}$ (KORMYLO; JAIN, 1974).

For estimating k and F_{init} , the ideal excitation signal is a series of ramps, covering a wide range of velocities, ideally it should involve much lower and much higher velocities than the Stribeck, i.e. lower than 10^{-5} m/s and higher than 0.1 m/s (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994). However, the valve may impose constraints, specially at high velocities. The most evident constraint is the trade-off between the maximum valve stroke and the maximum stem velocity, as it is necessary to maintain the same excitation signal for more than $5 \tau_{I/P}$ s to achieve a constant stem velocity. An example of excitation signal is presented in Figure 4.3. Note that in this example, the valve deadband, which is roughly 26%, is compensated in the excitation signal, starting from this value before any ramp is applied, so that the experiment does not take too long with low velocity ramps. The signal with constant velocity is maintained during $20 \cdot \tau_{I/P}$ seconds or until the maximum stroke is achieved. The minimum velocity corresponds to a velocity of 1 $\mu\text{m/s}$, which in OP variation is:

$$v_{\text{OP min}_R} = \frac{10^{-6} \cdot 100}{x_{\text{max}} - x_{\text{min}}}, \quad (4.13)$$

and the maximum velocity is calculated to ensure that the signal is maintained constant until it reaches the maximum or minimum stem position in at least $5 \tau_{I/P}$:

$$v_{OP \max_R} = \frac{(100 - 2 \cdot S_0)}{5 \tau_{I/P}}. \quad (4.14)$$

The signal is generated to cover logarithmically the range between $v_{OP \min_R}$ and $v_{OP \max_R}$. Note that the ramps are applied to the upper and lower extrema of the valve stem stroke. It is useful to save the time interval in which the valve is excited with ramps, for latter data processing.

Figure 4.3 – Example of excitation signal used to estimate k and F_{init} a priori.
Source: from Author.

Algorithm 4.2 presents a scheme for estimating k and F_{init} . This method leads to a distribution of $\hat{k}$ estimations for many different valve velocities and stem positions, and it is possible to calculate the mean value of $\hat{k}$ estimations, $\mu(\hat{k})$. The standard deviation of those estimates, $\text{std}(\hat{k})$, is an indicative of the estimation quality. If the standard deviation is high, e.g. the following equation is true:

$$\frac{\mu(\hat{k}) + 2 \text{std}(\hat{k})}{\mu(\hat{k})} \cdot 100 - 100 > 2, \quad (4.15)$$

then it is preferable to estimate k and F_{init} together with the remaining friction parameters, otherwise the prediction may be poor, as the friction parameters may be used to compensate the flaws in this estimation. If it is necessary to estimate k and F_{init} together with θ_f , their search space is:

$$\begin{aligned} ub_s &= \max \left(1.1, \frac{\mu(k) + 2 \text{std}(k)}{\mu(k)} \right) \\ lb_s &= \min \left(0.9, \frac{\mu(k) - 2 \text{std}(k)}{\mu(k)} \right), \\ ub_k &= ub_s \cdot \mu(k) & lb_k &= lb_s \cdot \mu(k) \\ ub_{F_{\text{init}}} &= ub_s \cdot \hat{F}_{\text{init}} & lb_k &= lb_s \cdot \hat{F}_{\text{init}}, \end{aligned} \quad (4.16)$$

here ub_k and $ub_{F_{\text{init}}}$ are the upper bounds of the k and F_{init} search space, and lb_k and $lb_{F_{\text{init}}}$ are its respective lower bounds. Even if the proposed method results in poor estimates, it is still advantageous, since it delivers a search space and an initial guess for k and F_{init} .

Algorithm 4.2 – Algorithm for estimating k and F_{init} .

- 1: Filter the diaphragm pressure and stem position and calculate the stem velocity
 - 2: Separate the experimental data in l_n datasets, each with a given constant stem velocity
 - 3: **for** each dataset l_n **do**
 - 4: Calculate the velocity mode, $\dot{x}_{b_l}$
 - 5: Select the biggest period of time with the stem position velocity approximately equal to the dataset mode (3% deviation from the velocity mode)
 - 6: Calculate $\hat{k}_l$ and $\hat{F}_{b_l}(\dot{x}_{b_l})$, as in Eq. (4.10)
 - 7: **end for**
 - 8: Calculate F_{init} by solving Eq. (4.12)
 - 9: Return $\mu(k)$, $\text{std}(k)$ and $\hat{F}_{\text{init}}$
-

If the Kano model is used instead of estimating k and F_{init} , it is necessary to obtain $x_{\min P}$ and $x_{\max P}$, which are easily obtained by obtaining x when $OP = 0$ and $OP = 100$, respectively.

4.2 Open Loop Friction Parameters Estimation

Assuming that S_0 , $\hat{\theta}_{I/P}$, $\hat{k}$ and $\hat{F}_{\text{init}}$ were estimated successfully, it remains to estimate the friction model parameters:

$$\hat{\theta}_f = \arg \min_{\theta_f} V_{n_f}(S_a, m, \hat{k}, \hat{F}_{\text{init}}, \theta_f) + p(\theta_f), \quad (4.17)$$

where $p(\theta_f) : \mathbb{R}^{d_f} \mapsto \mathbb{R}^+$ is a penalty function, used when it is necessary to impose parameter constraints. As a reminder, if the a priori estimation of $\hat{k}$ and $\hat{F}_{\text{init}}$ is considered unsatisfactory, then it must be solved Eq. (4.5) instead.

An important aspect of the friction parameters estimation is the excitation signal. It should evidence information related to all friction phenomena discussed in Subsection 3.1.1 (SWEVERS et al., 2000). A sinusoidal velocity signal is able to expose the sliding state characteristics and a ramp signal during presliding may reveal the varying breakaway force and presliding displacement. The presliding hysteresis is neglected purposely in the excitation signal design, since the stem position sensor usually does not have micrometric resolution. The sinusoidal velocity signal is defined as:

$$v_{s_j}(t) = \frac{v_{s_{\max}} - v_{s_{\min}}}{2} + v_{s_{\min}} - \frac{v_{s_{\max}} - v_{s_{\min}}}{2} \cos \left(\frac{2\pi}{T_{s_j}} t \right), \quad (4.18)$$

where $v_{s_j}(t)$ is the instantaneous velocity of the j th sinusoidal excitation signal, $v_{s_{\max}}$ and $v_{s_{\min}}$ are the maximum and minimum stem velocities, respectively and T_{s_j} is the j th signal

period. Ideally, it should be generated a series of sinusoidal excitation signals, using high and low velocities and periods. Unfortunately, this is not possible, since the valve has a limited passband and stroke constraints. As the valve is a low-pass system, the minimum period is suggested as:

$$T_{s_{min}} = \frac{2 \pi \hat{\tau}_{I/P}}{20} \quad (4.19)$$

and for the maximum period, to excite the valve with at least half period, one obtains:

$$T_{s_{max}} = \frac{2 (100 - S_0)}{(v_{s_{max}} - v_{s_{min}}) / 2 + v_{s_{min}}}. \quad (4.20)$$

The minimum and maximum velocities should be $v_{s_{min}} < 10^{-5}$ m/s and $v_{s_{max}} > 10^{-1}$ m/s. As there is a trade-off between $v_{s_{max}}$ and $T_{s_{max}}$, it is suggested a maximum period of 40 s, since higher periods will not evidence relevant friction characteristics. The ramp signals, with velocities between $v_{s_{min}}$ and $v_{s_{max}}$ should be used when the system is in presliding regime until the stem starts moving. Figure 4.4 presents an example of such excitation signal, with 5 different periods T_{s_j} ($j = 1 \dots 5$), and 10 different breakaway velocities (tested in lower and upper stroke). Note that at first, the OP increases rapidly until $OP = 0.9 S_0$, then the proposed breakaway velocity test is applied until $OP = 1.1 S_0$. After a short period of stabilization, the sinusoidal velocity signal is applied. Finally, as the velocities and periods span orders of magnitude, it is a good measure to create the test grid using logarithmically spaced points.

Figure 4.4 – Example of excitation signal for estimating friction parameters ($S_0 \approx 25\%$).

Source: from Author.

The parameters search space and constraints are other features that have an impact on the estimation performance. To avoid optimization outside the search space, the following penalty function is used (ARORA, 2015):

$$p(\theta_f) = \sum_{d=1}^{d_f} \max(0, lb_d - \theta_{f_d}) \cdot 10^{10} + \max(0, \theta_{f_d} - ub_d) \cdot 10^{10}, \quad (4.21)$$

here the subscript d denotes the selection of the d th element of a vector, $\mathbf{lb} \in \mathbb{R}^{d_f}$ and $\mathbf{ub} \in \mathbb{R}^{d_f}$, which are the lower and upper parameters bounds vector, respectively. Further analysis for defining the search space bounds and eventually other constraints in the search space is carried out for every friction model as follows.

4.2.1 Kano Search Space Analysis

As presented in Section 4.1, the valve deadband can be easily estimated. This initial estimation, defined as S_0 , can be used to derive the Kano parameter bounds, as presented in Table 4.1. The slip band is allowed to reach up to 30% of S_0 and the initial force can be up to 30% as well, which is wide enough to model valves with extremely poor performance. If S_0 is lower than 2%, then it is suggested that the upper bound is calculated considering that S_0 is 2% and the lower bound considering that S_0 is 0%.

Table 4.1 – Kano parameter bounds.

Parameter	ub_d	lb_d
S	$1.3 S_0$	$0.7 S_0$
J	$0.3 S_0$	0
D	30	0

4.2.2 Karnopp Search Space Analysis

Given S_0 , it is possible to calculate F_{s_0} , by rearranging Eq. (3.31):

$$F_{s_0} = (P_{\max} - P_{\min}) \cdot S_a \cdot (S_0/200). \quad (4.22)$$

It is assumed that the maximum absolute estimation error of F_{s_0} is at most 30%.

The Coulomb friction parameter is derived by noting that $F_c \leq F_s$ and assuming that $F_c \geq 0.7 F_s$.

As the viscous friction parameter may span a wide range, it is suggested to deliver its upper bound as a hundred times higher than F_{s_0} with maximum stem velocity, calculated as presented in Eq. (3.28). The lower bound is derived similarly, by assuming that the viscous friction is a hundredth of F_{s_0} at the maximum stem velocity.

The Stribeck velocity parameter search space should span from 10^{-5} to 10^{-1} m/s, which are the limits obtained from experimental data, as presented in Subsection 3.1.1. Since the v_s search space is wide, it may decrease the optimization technique performance. An experimental evidence that can reduce the search space is the stick-slip behavior when exciting the valve with certain constant velocities. Consider the linear approximation, for $\dot{x} > 0$, of the valve with Karnopp friction model in the Laplace domain:

$$\frac{\delta x(s)}{\delta P(s)} = \frac{S_a}{s^2 + H_k(\dot{x}_0)s + k/m}, \quad (4.23)$$

here δ denotes an incremental variable, e.g. $\delta x(t) = x(t) - x_0$, x_0 is a linearization point, and $H_k(\dot{x}_0)$ is the first derivative of the Stribeck curve with respect to $\dot{x}$, divided by m :

$$H_k(\dot{x}_0) = \frac{1}{m} \left[F_v - 2 \cdot (F_s - F_c) e^{-(\dot{x}_0/v_s)^2} \frac{\dot{x}_0}{v_s^2} \right], \quad (4.24)$$

where $\dot{x}_0$ is the linearization velocity. What can be concluded from Eqs. (4.23) and (4.24) is that the Stribeck effect decreases the system damping. If the velocity is such that the damping is lower than 1, then the linear approximation presents an overshoot, which corresponds to a velocity reversal, switching the valve to the presliding state, leading to a stick-slip behavior. The system damping is calculated as:

$$\xi_K(\dot{x}) = \frac{H_k(\dot{x})}{2\sqrt{mk}}, \quad (4.25)$$

where ξ_K is the valve with Karnopp friction model damping.

To obtain the velocity in which occurs the largest damping decrease, it is necessary to obtain the derivative of Eq. (4.24) and equaling to zero:

$$0 = -(F_s - F_c) e^{-(\dot{x}_{0_{pk}}/v_s)^2} \left(\frac{2}{v_s^2} - \frac{4\dot{x}_0^2}{v_s^4} \right), \quad (4.26)$$

$$\dot{x}_{0_{pk}} = v_s/\sqrt{2}$$

where $\dot{x}_{0_{pk}}$ is the highest decrease in the system damping. If the stick-slip behavior is detected for some velocity range, being v_{sl_1} and v_{sl_2} the lower and upper bounds of this range, then the Stribeck velocity is certainly $v_s \in [v_{sl_1}/10, 10v_{sl_2}]$. If no stick-slip behavior is detected, then it indicates that F_s is close to F_c , or F_v is much higher than any decrease in the system damping, or the Stribeck velocity is higher than the stem velocities tested.

As an example, consider a valve with the same parameters as in Tables 3.1 and 3.2, except for $F_s = 800$ N and $F_v = 50000$ Ns/m. Figure 4.5 presents the behavior of ξ_K for given stem velocities. Note that the predicted stick-slip behavior is within $[6 \cdot 10^{-5}, 8 \cdot 10^{-4}]$ m/s.

Figure 4.5 – ξ_K variation with respect to the stem velocity, for $v_s = 5 \cdot 10^{-4}$ m/s.

Source: from Author.

The system simulation is presented in Figures 4.6 to 4.8. The tested velocities are: 10^{-6} , $1.56 \cdot 10^{-6}$, $2.43 \cdot 10^{-6}$, $3.80 \cdot 10^{-6}$, $5.92 \cdot 10^{-6}$, $9.24 \cdot 10^{-6}$, $1.44 \cdot 10^{-5}$, $2.25 \cdot 10^{-5}$, $3.51 \cdot 10^{-5}$, $5.47 \cdot 10^{-5}$, $8.54 \cdot 10^{-5}$, $1.33 \cdot 10^{-4}$, $2.08 \cdot 10^{-4}$, $3.24 \cdot 10^{-4}$, $5.06 \cdot 10^{-4}$ and $7.89 \cdot 10^{-4}$ m/s. The stick-slip prediction is correct for low velocities, but it must be pointed out that given the I/P bandwidth, it was not possible to test higher stem velocities. A better visualization of the stick-slip behavior can be seen in Figure 4.8.

Figure 4.6 – Stick-slip stem position behavior simulation using valve with the Karnopp model.

Source: from Author.

Figure 4.7 – Stick-slip stem velocity behavior simulation using valve with the Karnopp model.

Source: from Author.

Figure 4.8 – Stick-slip behavior simulation, with focus in excitation signals of $5.47 \cdot 10^{-5}$ m/s and $8.54 \cdot 10^{-5}$ m/s.

Source: from Author.

This analysis is an approximation of the physical behavior, as the model complexity was simplified by a linearization and the Karnopp model itself neglects many friction characteristics and the I/P model is more complex. However, some stick-slip behavior can be seen in the experimental data of the graphite gasket valve, as presented in Figures 4.9 to 4.12.

Figure 4.9 – No stick-slip from velocities lower than $1.26 \cdot 10^{-4}$ m/s.

Source: from Author.

Figure 4.10 – Slip phenomenon found at certain velocities.

Source: from Author.

Figure 4.11 – Slip and stick-slip phenomenon found at certain velocities.

Source: from Author.

Figure 4.12 – No stick-slip from velocities higher than $1.86 \cdot 10^{-3}$ m/s.

Source: from Author.

A generic search space for the Karnopp friction parameters is presented in Table 4.2. The v_s search space range can be smaller if any stick–slip behavior is detected, however the safest choice is to search the entire proposed v_s space, as detecting stick–slip behavior without visual inspection is a difficult task. If S_0 is lower than 2%, then it is suggested that the upper and lower bounds of F_c , F_s and F_v are calculated assuming that S_0 is 2% and 0%, respectively.

Table 4.2 – Karnopp parameter bounds.

Parameter	ub_d	lb_d
F_c	$1.3 F_{s_0}$	$0.49 F_{s_0}$
F_s	$1.3 F_{s_0}$	$0.7 F_{s_0}$
F_v	$100 \cdot F_{s_0}/v_{max}$	$(F_{s_0}/100)/v_{max}$
v_s	10^{-1}	10^{-5}

Source: from Author

To avoid the case $F_c > F_s$, Eq. (4.21) is augmented:

$$p_k(\theta_f) = p(\theta_f) + \max\left(0, \theta_{f_1} - \theta_{f_2}\right) \cdot 10^{10}, \quad (4.27)$$

where $\theta_{f_1} = F_c$, $\theta_{f_2} = F_s$ and $p_k(\theta_f)$ is the penalty function for Karnopp friction parameters estimation.

4.2.3 LuGre Search Space Analysis

As the LuGre model is also based on the Stribeck curve, the Karnopp search space derived in the previous subsection can be readily applied. However, the LuGre has some additional parameters, one to control the presliding displacement (σ_0) and the other controls the friction damping (σ_1), which is able to modify the overall system damping, possibly avoiding the stick–slip behavior even with a high difference between F_s and F_c . This occurs because $\dot{z}$ is positive when the velocity is reducing towards 0^+ m/s, increasing the system damping.

Olsson et al. (1998) suggest that it is possible to obtain an estimate of the system damping by linearizing around $\dot{x} = 0^+$ and $z = 0^+$. At this point, the linear approximation of the valve model, Eq. (3.1), with the LuGre friction model, Eqs. (3.9) and (3.10), in Laplace domain, are given by:

$$S_a \delta P(s) = m s^2 \delta x(s) + (F_v + \sigma_1) s \delta x(s) + (k + \sigma_0) \delta x(s). \quad (4.28)$$

Therefore, one can derive the system damping:

$$\xi_L = \frac{\sigma_1 + F_v}{2\sqrt{m(k + \sigma_0)}}, \quad (4.29)$$

where ξ_L is the valve with LuGre friction model damping. Thus, if stick-slip behavior is detected when exciting the valve with a ramp signal, not only information regarding v_s is given, but also may indicate that $\sigma_1 < 2\sqrt{m(k + \sigma_0)} - F_v$. However, this equation may not be taken as correct, given the simplifications applied in the analysis.

An example can be seen in Figures 4.13 and 4.14, where a valve with LuGre friction model was simulated with the parameters of Tables 3.1 and 3.2, except for: $F_s = 800$ N, $F_v = 50000$ Ns/m, $\sigma_0 = 10^6$ N/m and $\sigma_1 = 2 \cdot 10^3$ Ns/m, which corresponds to the same Stribeck curve parameters where stick-slip behavior is present in the valve with Karnopp friction model. However, σ_1 is high enough to prevent the stick-slip behavior in the LuGre model.

Figure 4.13 – Valve with LuGre model stem position simulation, with no stick-slip behavior.

Source: from Author.

Figure 4.14 – Valve with LuGre model stem velocity simulation, with no stick-slip behavior.

Source: from Author.

The generic search space is composed by the same values of Table 4.2, extended by the parameter bounds presented in Table 4.3. The assumption is that the minimum

and the maximum presliding displacement are 1 and 50 μm , respectively, when friction is equal to F_s . The friction damping parameter is allowed to reach high values, to model a wide range of experimental data. The penalty function is the same developed for the Karnopp model, as shown in Eq. (4.27).

Table 4.3 – LuGre parameter bounds, an extension of Table 4.2.

Parameter	ub_d	lb_d
σ_0	$1.3 F_{s_0} \cdot 10^6$	$0.014 F_{s_0} \cdot 10^6$
σ_1	$0.014 F_{s_0} \cdot 10^6$	500

Another issue with the LuGre model is determining the initial state of its internal variable z . In the open loop test, the valve always start from the lowermost position and to reach that state, z has to be at its minimum position, therefore:

$$z[0] = -\frac{F_s}{\sigma_0}. \quad (4.30)$$

4.2.4 GMS Search Space Analysis

Once more, the Karnopp search space can be used for the GMS model, as it is based on the Stribeck curve as well. In addition, the presliding displacement and friction damping for each massless Maxwell element is controlled by κ_i and ν_i , respectively. Yet, α_i determines how each Maxwell element contributes to the observed friction force and C defines the velocity to friction lag. Similarly to the LuGre model, the valve damping may be increased by the parameters ν_i .

The valve damping, in the presliding state, can be derived using the valve model, Eq. (3.1), and the presliding GMS model, given by Eqs. (3.12) and (3.13):

$$\xi_G = \frac{F_v + \sum_{i=1}^{N_{me}} \nu_i}{2\sqrt{m(k + \sum_{i=1}^{N_{me}} \kappa_i)}}, \quad (4.31)$$

where ξ_G is the valve with GMS model damping. Therefore, if stick-slip behavior is present, then it may be an indicator that $\sum_{i=1}^{N_{me}} \nu_i < 2\sqrt{m(k + \sum_{i=1}^{N_{me}} \kappa_i)} - F_v$, as well as imply the approximate value of v_s , as already discussed in Subsection 4.2.2.

As an example of how it is possible to control the stick-slip behavior with ν , a valve with GMS friction model was simulated using the same parameters of Tables 3.1 and 3.2, except for: $F_s = 800$ N and $F_v = 50000$ Ns/m. The results are presented in Figures 4.15 and 4.16, where despite the Stribeck parameters resulted in stick-slip behavior when the valve was simulated with Karnopp friction model, the stick-slip was not present in the GMS simulation due to ν additional damping.

Figure 4.15 – Valve with GMS model stem position simulation, with no stick-slip behavior.

Source: from Author.

Figure 4.16 – Valve with GMS model stem velocity simulation, with no stick-slip behavior.

Source: from Author.

The general GMS parameter search space, presented in Table 4.4, is an extension of the Karnopp bounds presented in Table 4.2. The premises used to derive the GMS κ_i and ν_i bounds are the same used for σ_0 and σ_1 definition in the LuGre model, respectively. The bounds for C are derived assuming that the velocity to friction lag may vary from 1 ms to 0.1 s (ARMSTRONG-HÉLOUVRY; DUPONT; CANUDAS de WIT, 1994).

Table 4.4 – GMS parameter bounds, an extension of Table 4.2.

Parameter	ub_d	lb_d
κ_i	$1.3 F_{s_0} \cdot 10^6$	$0.014 F_{s_0} \cdot 10^6$
ν_i	$0.014 F_{s_0} \cdot 10^6$	500
α_i	1	0
C	10^3	10

The penalty function used to estimate the GMS parameters is an extension of Eq. (4.27), to guarantee that $\sum_{i=1}^{N_{me}} \alpha_i = 1$:

$$p_g(\theta_f) = p_k(\theta_f) + \max \left(0, \left| \left(\sum_{i=1}^{N_{me}} \alpha_i \right) - 1 \right| \right) \cdot 10^{10}, \quad (4.32)$$

where $p_g(\theta_f)$ is the penalty function for the GMS friction parameters estimation.

For determining the initial internal states, ψ , the same reasoning used in the LuGre model is applied to the GMS model, therefore:

$$\psi_i[0] = -\alpha_i \frac{F_s}{\kappa_i}. \quad (4.33)$$

4.2.5 Optimization Method Selection

The friction models are nonlinear and discontinuous, which imposes difficulties for applying optimization methods that are based on the objective function differentiation, e.g. Steepest Descent or Newton–Raphson, as demonstrated by Marques and Garcia (2019). Therefore, the best option is to use a derivative free method with a fair capacity to avoid local minima. For that, some optimization techniques were tested to support the selection of a proper estimator.

This test is performed using the valve with LuGre friction model only, since it is the one with intermediate complexity between the models proposed in this thesis. The tests consists in identifying the friction parameters of a simulated valve model, without any measurement noise and with a perfect knowledge of m , k , S_a , F_{init} , x_{min} and x_{max} . Also, there is a perfect knowledge of $\tau_{I/P}$, which is used only to design the sinusoidal velocity excitation signal. The term S_0 was estimated previously using the Algorithm 4.1 and the search space is calculated as presented. The valve and friction parameters are the same shown in Tables 3.1 and 3.2. In summary, this test is an ideal case, with a perfect match between plant and model, without any measurement noise and a perfect knowledge of the valve parameters.

In the first three tests, three different residual function calculations were tested. The first is Mean Squared Error (MSE), as in Eq. (4.17). The second is the Integral Absolute Error (IAE), defined as:

$$V_{a_{n_f}}(\theta_f) = \sum_{n=1}^{n_f} |e_x(n, \theta_f)|. \quad (4.34)$$

The third is the Integral Root Absolute Error (IRAE), defined as:

$$V_{r_{n_f}}(\theta_f) = \sum_{n=1}^{n_f} \sqrt{|e_x(n, \theta_f)|}. \quad (4.35)$$

The mean squared error function maps the errors in a number using a quadratic equation, which amplifies or attenuates errors higher or lower than 1, respectively. On the other hand, the integral absolute error just adds the errors without any modification. Finally, the squared absolute residual has the reverse effect of the mean squared error function. The difference is numerical only, as all three functions will increase if any error occur, but each will do it with a different gain.

Some optimization techniques fail when the parameters differ many orders of magnitude, which is exactly the case in this thesis. Therefore, in the first three tested optimization algorithms, the parameters normalization, using the parameter lower and upper bounds, is tested.

4.2.5.1 Genetic Algorithm Optimization (GA)

The Genetic Algorithm is based on species evolution characteristics. The basic idea is to generate a random population of parameter vectors and to apply some evolutionary functions to the individuals (parameter vectors) to approximate the optimization problem solution. The scheme used in this thesis is presented in Algorithm A.1, from Appendix A, which is based on Ferragud (1999).

The results using the Genetic Algorithm optimization are presented in Tables 4.5 and 4.6. By analyzing the results, it is possible to conclude that the prediction performance is approximately the same, no matter what residual function is used or if the parameter normalization is performed or not. Another finding is that even with enormous errors in $\hat{v}_s$ and $\hat{\sigma}_1$, the overall friction prediction is quite good. This demonstrates that some parameters have low influence on the error function, making it difficult to estimate these parameters.

Table 4.5 – GA optimization LuGre parameter estimation results.

Function	Norm.	<i>fit</i> (%)	Run Time (h)	Func. Evals.
MSE	No	99.50	42.25	43860
IAE	No	99.47	33.93	36120
IRAE	No	99.49	33.61	36120
MSE	Yes	99.50	36.42	37800
IAE	Yes	99.46	23.10	24780
IRAE	Yes	99.42	22.50	24120

Norm.: indicates if the parameters are normalized (Yes) or not (No) and Func. Evals.: indicates to the number of objective function evaluations.

Source: from Author.

Table 4.6 – GA optimization LuGre parameter estimation error.

Residuals	Norm.	$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
MSE	No	11.16	-0.20	-38.88	$1.82 \cdot 10^4$	-12.51	$1.97 \cdot 10^2$
IAE	No	9.58	0.07	-42.65	$1.98 \cdot 10^4$	0.53	-88.11
IRAE	No	11.33	0.06	-40.47	$1.97 \cdot 10^4$	1.20	-97.29
MSE	Yes	10.85	-0.32	-38.14	$1.84 \cdot 10^4$	-14.01	-97.55
IAE	Yes	-5.54	0.08	-43.93	$1.78 \cdot 10^4$	0.94	$4.36 \cdot 10^2$
IRAE	Yes	9.82	0.07	-46.67	$1.69 \cdot 10^4$	0.50	$6.31 \cdot 10^2$

Source: from Author.

4.2.5.2 Differential Evolution Optimization (DE)

The differential evolution algorithm is based on generating a population of random parameters vectors and applying aleatory linear combinations on aleatory population members. The Algorithm A.2 from Appendix A summarizes the method, which is proposed by Storn and Price (1997).

The estimation results using DE algorithm are presented in Tables 4.7 and 4.8. It is possible to conclude that the *fit* and the estimation error performance is similar to the GA algorithm, however, the number of function evaluations and thus the run time, are significantly lower.

Table 4.7 – DE optimization LuGre parameters estimation results.

Residuals	Norm.	<i>fit</i> (%)	Run Time (h)	Func. Evals.
MSE	No	99.50	11.30	12121
IAE	No	99.47	11.48	12361
IRAE	No	99.46	13.79	14881
MSE	Yes	99.50	11.28	12121
IAE	Yes	99.47	11.26	12121
IRAE	Yes	99.46	12.18	13141

Norm.: indicates if the parameters are normalized (Yes) or not (No) and Func. Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 4.8 – DE optimization LuGre parameters estimation error.

Residuals	Norm.	$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
MSE	No	11.13	-0.27	-37.96	$1.86 \cdot 10^4$	-9.99	-97.53
IAE	No	11.50	0.06	-42.55	$1.81 \cdot 10^4$	0.47	$5.09 \cdot 10^2$
IRAE	No	-29.75	0.07	-44.07	$1.83 \cdot 10^4$	0.02	$6.38 \cdot 10^2$
MSE	Yes	11.13	-0.27	-37.96	$1.92 \cdot 10^4$	-9.98	-97.49
IAE	Yes	11.50	0.06	-42.56	$1.93 \cdot 10^4$	0.47	$5.10 \cdot 10^2$
IRAE	Yes	-20.51	0.07	-44.10	$1.99 \cdot 10^4$	0.15	$6.28 \cdot 10^2$

Source: from Author.

4.2.5.3 Monte Carlo with Simplex Optimization (MS)

As the estimator is failing due to local minima, as already seen in previous tests, it was selected a Monte Carlo method together with a Simplex optimization, which is synthesized in Algorithms A.3 and A.4, from Appendix A. This algorithm is based on selecting many aleatory points in the search space and evaluating its residuals. Then, the points with the best residuals are used as the starting point of a Simplex optimization.

The results are presented in Tables 4.9 and 4.10. This algorithm performance is better than the previous ones, specially when the MSE residual function is used, regardless of the parameter normalization. However, σ_1 estimation errors are still high. It is clear, though, that the best residual function choice until now is the MSE, which is the only used in succeeding tests. As no difference is perceived whether the parameters are normalized or not, future tests are performed only with non normalized parameters.

Table 4.9 – MS optimization LuGre parameter estimation results.

Residuals	Norm.	fit (%)	Run Time (h)	Func. Evals.
MSE	No	100.00	13.88	12986
IAE	No	99.47	14.80	13843
IRAE	No	99.46	9.52	9073
MSE	Yes	100.00	13.71	12843
IAE	Yes	99.47	13.40	12613
IRAE	Yes	99.46	6.00	5953

Norm.: indicates if the parameters are normalized (Yes) or not (No) and Func. Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 4.10 – MS optimization LuGre parameters estimation error.

Residuals	Norm.	$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
MSE	No	0.00	0.00	0.00	-0.01	0.05	-99.85
IAE	No	11.35	0.06	-42.56	$1.88 \cdot 10^4$	0.48	$1.85 \cdot 10^2$
IRAE	No	10.32	0.07	-44.00	$4.21 \cdot 10^3$	0.35	-96.66
MSE	Yes	-0.02	0.00	0.04	0.23	-0.36	$1.28 \cdot 10^2$
IAE	Yes	10.80	0.06	-42.58	$1.71 \cdot 10^4$	0.51	-82.20
IRAE	Yes	-19.47	0.05	-35.31	$9.36 \cdot 10^3$	0.25	34.48

Source: from Author.

4.2.5.4 Successive Nonlinear Linear Regression (SNL)

This method is suggested by Rizos and Fassois (2009), which consists in separating the optimization problem in a linear part and a nonlinear part to estimate the LuGre parameters. The difference from the proposed algorithm is that F_f is not a measured variable, which imposes higher difficulties in estimating the parameters, which has to be done with x only. The algorithm scheme is presented in Algorithm A.5 from Appendix A.

The friction force can be calculated by rearranging Eq. (3.1):

$$F_f[n] = S_a P[n] - \hat{k} x[n] - \hat{F}_{\text{init}} - \hat{m} \hat{x}[n], \quad (4.36)$$

where $\hat{x}$ is the estimated valve acceleration, using backward differencing of the measured stem position. Note that no noise is present in this test. The algorithm starts by testing aleatory points in the search space. The best residual from the previous step is used as the starting point. Then, the optimization cycle is initialized by optimizing the nonlinear parameters, F_c , F_s and v_s using GA, with fixed linear parameters, F_v , σ_0 and σ_1 . With the new nonlinear parameters, a valve with LuGre model is simulated and by noting that:

$$F_f[n] = \sigma_0 \hat{z}[n] + \sigma_1 \dot{\hat{z}}[n] + F_v \hat{x}[n], \quad (4.37)$$

the linear parameters are easily estimated using LSE. The cycle is then restarted and continues until the finishing criteria is met.

This algorithm results are presented in Table 4.11 and 4.12. The results are quite similar to the GA and DE algorithms, which is not surprising, as this algorithm uses the GA to estimate the nonlinear parameters. One explanation for this inability to find the residual function minimum is an inherent difficulty, due to the low parameter sensitivity and local minima, and the problem separation, which lowers the search dimension, is not enough to overcome the problem. Despite this algorithm can perform better if the estimator parameters are tuned, this algorithm is not suitable for practical applications, since the friction force calculation would be imprecise, due to measurement noise and indirect variables calculation.

Table 4.11 – SNL optimization LuGre parameter estimation results.

fit (%)	Run Time (h)	Func. Evals.
99.50	19.43	18281

Source: from Author.

Func. Evals.: refers to the number of objective function evaluations.

Table 4.12 – SNL optimization LuGre parameter estimation error.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
11.11	-0.28	-37.72	$1.97 \cdot 10^4$	-10.22	-97.55

Source: from Author.

4.2.5.5 Grid Search with Differential Evolution and Simplex Optimization (GDES)

The first stage of this algorithm is an initial evaluation of the search space, which is done with by selecting just a few points for every parameter, since a more refined search would lead to computationally impossible problems. The best residuals are then used as an input for a DE optimization, which result is used for a further Simplex optimization, for a

more precise estimation of the minima. This algorithm scheme is presented in Algorithm A.6 from Appendix A.

As this is the selected algorithm for estimating the friction parameters, all models are tested, and the results are shown in Tables 4.13 to 4.17. The Kano, Karnopp and LuGre models presented a perfect *fit* index, even though the σ_1 LuGre parameter is estimated with an error of 1%. The GMS model parameters, however, were estimated with high errors, specially for κ , ν and α . Even though there were high errors in the estimations, the *fit* is notably high, evidencing the high complexity in estimating the GMS parameters, as its sensitivities are low to the overall valve stem position prediction. Despite the errors regarding the GMS model, this is the algorithm with the best performance so far and it is selected as the estimator, since trying to refine the GMS estimations would lead to eventually a change in the GMS model, to improve identifiability or to use an estimator that would result in far more function evaluations than this estimator.

Table 4.13 – GDES estimation results.

Model	<i>fit</i> (%)	Run Time (h)	Func. Evals.
Kano	100.00	0.06	4585
Karnopp	100.00	14.53	16058
LuGre	100.00	39.40	45107
GMS	99.97	225.53	133575

Source: from Author.

Func. Evals.: refers to the number of objective function evaluations.

Table 4.14 – GDES Kano parameter estimation error.

$\hat{S}$ (%)	$\hat{J}$ (%)	$\hat{D}$ (%)
0.00	0.00	0.00

Source: from Author.

Table 4.15 – GDES Karnopp parameter estimation error.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)
0.00	0.00	0.00	0.02

Source: from Author.

Table 4.16 – GDES LuGre parameter estimation error.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
0.00	0.00	0.00	0.00	0.00	1.01

Source: from Author.

Table 4.17 – GDES GMS parameter estimation error.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\kappa}_1$ (%)	$\hat{\kappa}_2$ (%)	$\hat{\kappa}_3$ (%)
1.45	0.00	0.36	-4.63	52.06	25.18	$2.64 \cdot 10^3$
$\hat{v}_1$ (%)	$\hat{v}_2$ (%)	$\hat{v}_3$ (%)	$\hat{a}_1$ (%)	$\hat{a}_2$ (%)	$\hat{a}_3$ (%)	$\hat{C}$ (%)
$3.77 \cdot 10^3$	$6.59 \cdot 10^2$	$3.71 \cdot 10^3$	-31.06	$1.40 \cdot 10^2$	-94.34	23.03

Source: from Author.

4.3 Simulated Tests

Some tests were performed to guarantee that the proposed open loop parameter estimation method is feasible under influence of measurement noise. In this test, the plant is the simulated valves with parameters presented in Tables 3.1 and 3.2, but with a noise addition that results in a 25dB (signal mean around 316 times higher than the noise standard deviation) Signal to Noise Ratio (SNR) in measured variables (x and P).

To estimate S_0 , the test is performed using the valve with Karnopp friction model, and it is performed exactly as described in Section 4.1. The diaphragm pressure and stem position used in this test are presented in Figure 4.17.

Figure 4.17 – Signals used for testing the S_0 estimation algorithm.

Source: from Author.

Analogously, the I/P converter parameters are estimated using the excitation signal and algorithm proposed in Section 4.1. The test signals are presented in Figure 4.18.

Figure 4.18 – Signals used for testing the I/P parameter estimation algorithm.

Source: from Author.

To estimate k and F_{init} , the valve with Karnopp friction model is used. Again, the test is performed exactly as suggested in Section 4.1 and the signals used in the estimation are presented in Figure 4.19.

Figure 4.19 – Signals used for testing the k and F_{init} estimation algorithm.

Source: from Author.

The results are presented in Table 4.18. For comparison purposes, the algorithms were run in a case without measurement noise, as well. It is possible to verify that the results are very consistent, with a slightly increase in the estimation error as the noise increases. The S_0 algorithm has an inherent error, which is necessary to avoid incorrect stem movement detection due to measurement noise.

Table 4.18 – Open loop valve parameters estimation error in simulated case.

Parameter	Without noise est. error (%)	25dB SNR est. error (%)
S_0	0.97	0.97
$\hat{P}_{\min}$	-0.01	-0.02
$\hat{K}_{P_g}$	-0.02	-0.01
$\hat{\tau}_{I/P}$	0.01	-0.07
$\hat{k}$	0.00	-0.01
$\hat{F}_{\text{init}}$	-0.01	0.03

As for the friction estimation test, the GDES estimator was used with non normalized parameters. The excitation signal and the search space were designed according Section 4.2 guidelines. The diaphragm pressure and stem position are filtered using a zero phase second order linear filter with 0.9 relative damping and $100/\tau_{I/P}$ natural frequency. Additionally, the diaphragm pressure is filtered using a Kalman filter with a plant model as in Eq. (3.20), measurement variance estimated by the difference between simulated and measured diaphragm pressure during the I/P converter parameter estimation algorithm and the model variance assumed to be 50 times lower than the measurement variance. The Kalman filter is defined as:

$$\begin{aligned}
L_p[n] &= M[n-1] - \frac{M[n-1]^2}{M[n-1] + \sigma_{\text{meas}}^2} \\
L_c[n] &= \frac{L_p[n]}{\sigma_{\text{meas}}} \\
P_{\text{priori}}[n] &= P_{\text{filt}}[n-1] + L_c[n] (\bar{P}[n-1] - P_{\text{filt}}[n-1]) \\
P_{\text{filt}}[n] &= \hat{a}_0 P_{\text{priori}}[n] + \hat{b}_1 \text{OP}[n-1] \\
M[n] &= \hat{a}_0^2 \cdot L_p[n] + \sigma_{\text{mod}}^2 \quad \text{with} \quad M[0] = 1,
\end{aligned} \tag{4.38}$$

where $\bar{P}[n] = P[n] - P_{\min}$, is the incremental diaphragm pressure, σ_{meas}^2 is the measurement variance, σ_{mod}^2 is the model variance and $P_{\text{filt}}[n]$ is the Kalman filtered diaphragm pressure. The estimation results are presented in Tables 4.19 to 4.23.

Table 4.19 – Friction parameter estimation test with simulated data results.

Model	<i>fit</i> (%)	Run Time (h)	Func. Evals.
Kano	99.26	0.09	8010
Karnopp	99.99	17.54	19322
LuGre	99.92	34.01	39167
GMS	99.98	182.48	112240

Source: from Author.

Func. Evals.: refers to the number of objective function evaluations.

Table 4.20 – Kano parameter estimation error, test with simulated data.

$\hat{S}$ (%)	$\hat{J}$ (%)	$\hat{D}$ (%)
-2.62	-57.16	0.15
Source: from Author.		

Table 4.21 – Karnopp parameter estimation error, test with simulated data.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)
0.04	0.02	-0.30	0.12
Source: from Author.			

Table 4.22 – LuGre parameter estimation error, test with simulated data.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
0.10	0.19	-0.48	-1.86	24.27	$3.88 \cdot 10^2$
Source: from Author.					

Table 4.23 – GMS parameter estimation error, test with simulated data.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\kappa}_1$ (%)	$\hat{\kappa}_2$ (%)	$\hat{\kappa}_3$ (%)
-2.79	0.02	-0.51	6.59	-10.71	23.65	$2.23 \cdot 10^2$
$\hat{\nu}_1$ (%)	$\hat{\nu}_2$ (%)	$\hat{\nu}_3$ (%)	$\hat{\alpha}_1$ (%)	$\hat{\alpha}_2$ (%)	$\hat{\alpha}_3$ (%)	$\hat{C}$ (%)
$2.30 \cdot 10^3$	$2.78 \cdot 10^3$	$1.00 \cdot 10^2$	-5.68	46.30	-99.98	-26.68
Source: from Author.						

The Kano model is highly affected by measurement noise, presenting significantly higher errors when compared to the ideal case test. The main reason for that is because this model lacks any dynamics, responding to any frequency, even for small measurement noises. Had the pressure not been filtered, the results would be worst, as presented in Figure 4.20.

Figure 4.20 – Deterioration of Kano model performance due to noise.

Source: from Author.

Excellent performance is hold by the Karnopp model, even in the presence of measurement noise. The LuGre model still presents a great performance, but the noise resulted in poorer estimates for σ_0 and σ_1 , which did not affect considerably the *fit* index. One practical aspect that is worth mentioning is that the LuGre model imprecision regarding presliding displacement may lead to a drift in the system position, which is not physically plausible, as can be seen in Figure 4.21. This problem is not present in GMS models, as shown in Figure 4.22.

Figure 4.21 – Presliding displacement imprecision of LuGre model is negatively affected by measurement noise.

Source: from Author.

Figure 4.22 – GMS with good precision in predicting presliding displacement even in the presence of noise.

Source: from Author.

Surprisingly, the GMS model presented a slightly higher *fit* index than in the case without noise. Even some parameters were estimated with lower error than in the ideal case. Therefore, the GMS friction parameter estimation presents good performance, even in the presence of measurement noise.

4.4 Experimental Tests

The experimental tests are performed using the valves presented in Chapter 2, applying the algorithms and guidelines suggested in Sections 4.1 and 4.2.

The valves were excited with a trapezoidal signal to estimate S_0 , as shown in Figure 4.23 and the results are presented in Table 4.24.

Figure 4.23 – Valve deadband estimation in open loop.

Source: from Author.

The I/P parameter estimation results are presented in Figures 4.24 and 4.25, and in Table 4.24. It is possible to verify that the I/P converter time constant is very different depending on the excitation signal used, as already discussed.

Figure 4.24 – Measured and estimated diaphragm pressure, using rectangular excitation.

Source: from Author.

Figure 4.25 – Measured and estimated diaphragm pressure, using velocity excitation.

Source: from Author.

Table 4.24 – Open loop valve parameter estimation with experimental data.

Parameter	Graphite	Teflon
S_0 (%)	23.72	0.52
$\hat{P}_{\min}$ (Pa)	41276.40	41861.85
$\hat{K}_{P_g}$ (Pa/%)	1666.49	1726.54
$\hat{\tau}_{I/P_s}$ (s)	0.933	0.979
$\hat{\tau}_{I/P_r}$ (s)	0.425	0.438
$\hat{k}$ (N/m)	204670.89	383911.56
$\text{std}(\hat{k})$ (N/m)	8682.26	193.62
$\hat{F}_{\text{init}}$ (N)	2619.43	-1.58

To estimate k and F_{init} , $v_{\text{OP min}_R}$ and $v_{\text{OP max}_R}$ were calculated using Eqs. (4.13) and (4.14) and $\hat{\tau}_{I/P_s}$, resulting in the experimental data presented in Figures 4.26 to 4.29. Note that only a few points were considered valid for the F_{init} estimation, due to non stable stem velocities, but as the interest is estimating the initial force, the number of points is sufficient for a proper estimation.

Figure 4.26 – Normalized diaphragm pressure and stem position for experimental open loop k and F_{init} estimation.

Source: from Author.

Figure 4.27 – Graphite gasket stem velocity during experiment for estimating k and F_{init} in open loop.

Source: from Author.

Figure 4.28 – Teflon gasket stem velocity during experiment for estimating k and F_{init} in open loop.

Source: from Author.

Figure 4.29 – Stribeck curve obtained for open loop F_{init} estimation, used to solve Eq. (4.11).

Source: from Author.

The friction parameters were estimated accordingly to the simulated open loop tests presented in Section 4.3. However, as graphite gasket valve spring constant estimation presented a high standard deviation, k and F_{init} were estimated concomitantly with the friction parameters, with the search space calculated using Eq. (4.16). The excitation signal was designed using the guidelines of Section 4.2, with $T_{s_{\text{max}}} = 40$ s and $v_{s_{\text{min}}} = 10^{-6}$ m/s, S_0 as in Table 4.24 and $T_{s_{\text{min}}}$ and $v_{s_{\text{max}}}$ calculated as in Eqs. (4.19) and (4.20). The signals used for the friction parameters estimation are presented in Figures 4.30 and 4.31.

Figure 4.30 – Filtered signals used for estimating the graphite gasket valve friction parameters, k and F_{init} .

Source: from Author.

Figure 4.31 – Filtered signals used for estimating the teflon gasket valve friction parameters.

Source: from Author.

To validate the models with a different dataset, the fit index is also evaluated using a ramp signal with aleatory velocity as excitation signal. The estimation results are presented in Tables 4.25 to 4.30. With respect to the graphite gasket valve, it is possible to verify that the Kano model has the lowest performance. The Karnopp, LuGre and GMS efficiencies are very good and have similar fit indexes. It is interesting to note that the $\hat{F}_s$ values are close to each other, as expected. As for the teflon gasket valve, once more the Kano model presented the worst performance, whereas the other models show outstanding prediction abilities either for the estimation or validation datasets.

Table 4.25 – Open loop graphite gasket valve model estimation performance.

Model	fit (%)	fit val. (%)	Run Time (h)	Func. Evals.
Kano	97.76	94.82	0.01	2515
Karnopp	99.11	96.83	26.20	37019
LuGre	99.11	96.83	37.57	52253
GMS	99.08	96.74	76.10	60744

fit val.: indicates to the fit index evaluated using the validation dataset and Func. Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 4.26 – Open loop teflon gasket valve model estimation performance.

Model	fit (%)	fit val. (%)	Run Time (h)	Func. Evals.
Kano	97.93	97.78	0.01	2368
Karnopp	99.13	99.35	1.03	4914
LuGre	99.15	99.37	3.30	13398
GMS	99.16	99.40	26.94	80012

fit val.: indicates to the fit index evaluated using the validation dataset and Func. Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 4.27 – Open loop Kano estimated parameters.

	$\hat{S}$ (%)	$\hat{J}$ (%)	$\hat{D}$ (%)
Graphite	27.13	0.75	14.36
Teflon	0.86	0.00	0.00

Source: from Author.

Table 4.28 – Open loop Karnopp estimated parameters.

	$\hat{k}$ (N/m)	$\hat{F}_{init}$ (N)	$\hat{F}_c$ (N)	$\hat{F}_s$ (N)	$\hat{F}_v$ (Ns/m)	$\hat{v}_s$ (m/s)
Graphite	203527.8	2577.6	717.9	938.3	54836.8	$4.23 \cdot 10^{-3}$
Teflon	–	–	0	0	5780.47	$3.87 \cdot 10^{-2}$

Source: from Author.

Table 4.29 – Open loop LuGre estimated parameters.

	$\hat{k}$ (N/m)	$\hat{F}_{init}$ (N)	$\hat{F}_c$ (N)	$\hat{F}_s$ (N)	$\hat{F}_v$ (Ns/m)	$\hat{v}_s$ (m/s)
Graphite	203495.8	2578.3	623.7	939.5	46624.4	$6.42 \cdot 10^{-3}$
Teflon	–	–	1.65	2.05	3534.69	$1.41 \cdot 10^{-5}$

Model	$\hat{\sigma}_0$ (N/m)	$\hat{\sigma}_1$ (Ns/m)
Graphite	$1.07 \cdot 10^9$	110182.2
Teflon	$3.61 \cdot 10^5$	527.46

Source: from Author.

Table 4.30 – Open loop GMS estimated parameters.

Model	$\hat{k}$ (N/m)	$\hat{F}_{\text{init}}$ (N)	$\hat{F}_c$ (N)	$\hat{F}_s$ (N)	$\hat{F}_v$ (Ns/m)	$\hat{v}_s$ (m/s)
Graphite	203719.4	2579.5	638.3	949.3	19215.7	$8.98 \cdot 10^{-2}$
Teflon	–	–	0.37	1.37	2111.78	$9.82 \cdot 10^{-4}$

Model	$\hat{\kappa}_1$ (N/m)	$\hat{\kappa}_2$ (N/m)	$\hat{\kappa}_3$ (N/m)	$\hat{\nu}_1$ (Ns/m)	$\hat{\nu}_2$ (Ns/m)	$\hat{\nu}_3$ (Ns/m)
Graphite	$8.93 \cdot 10^8$	$2.53 \cdot 10^8$	$9.83 \cdot 10^8$	$8.96 \cdot 10^4$	$3.01 \cdot 10^4$	$2.20 \cdot 10^5$
Teflon	$9.66 \cdot 10^6$	$1.25 \cdot 10^6$	$2.50 \cdot 10^7$	1837.59	4916.41	500.29

Model	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{C}$ (rad/s)
Graphite	0.0012	0.0026	0.9962	963.7
Teflon	$2.13 \cdot 10^{-4}$	$1.32 \cdot 10^{-5}$	$9.9977 \cdot 10^{-1}$	10.01

Source: from Author.

4.4.1 Graphite Gasket Model Prediction Analysis

For a qualitative analysis of the prediction efficiency of the graphite gasket valve models, the results are presented in Figures 4.32 to 4.43. It is possible to note that the Kano model presented the higher residual values. The other model residuals are very similar with a few visible differences. As the system velocity is important for friction compensation, as it evidence the stick–slip phenomena that is able to induce limit cycles, the comparison between the measured and estimated stem velocity is presented, as well. The Kano velocity prediction is poor, as it presented stick–slip motion that is not visible in the experimental data. Once more, the other models showed quite good stem velocity prediction precisions, with the only visible difference being a higher noise at low velocity prediction, regarding the GMS model.

Figure 4.32 – Kano model graphite gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.33 – Karnopp model graphite gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.34 – LuGre model graphite gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.35 – GMS model graphite gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.36 – Kano model graphite gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.37 – Karnopp model graphite gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.38 – LuGre model graphite gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.39 – GMS model graphite gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.40 – Kano model graphite gasket valve stem velocity prediction (450 s to 600 s) using the validation dataset.

Source: from Author.

Figure 4.41 – Karnopp model graphite gasket valve stem velocity prediction (450 s to 600 s) using the validation dataset.

Source: from Author.

Figure 4.42 – LuGre model graphite gasket valve stem velocity prediction (450 s to 600 s) using the validation dataset.

Source: from Author.

Figure 4.43 – GMS model graphite gasket valve stem velocity prediction (450 s to 600 s) using the validation dataset.

Source: from Author.

As another resource for analyzing the graphite gasket valve model prediction efficiency, the residual distribution is presented in Figures 4.44 to 4.46. From the error distribution with the estimation dataset plots, it is possible to verify that the Karnopp, LuGre and GMS model residuals presented a Gaussian like distribution, which is desirable because it indicates that the residual is approximately an aleatory variable. The distributions show a slight bias, though, which may indicate a constant error, probably due to k or F_{init} errors. The Kano distribution is not symmetric and presents three modes, which implies that the model is not able to predict the plant behavior perfectly.

Figure 4.44 – Kano and Karnopp graphite gasket valve prediction error distribution using the estimation dataset.

Source: from Author.

Figure 4.45 – LuGre and GMS graphite gasket valve prediction error distribution using the estimation dataset.

Source: from Author.

Figure 4.46 – Kano graphite gasket valve prediction error distribution using the estimation dataset, with no scaling in x axis.

The correlation coefficient, defined as:

$$r(a, b) = \frac{\sum_{n=1}^{n_f} (a[n] - \mu(a)) (b[n] - \mu(b))}{\sqrt{\sum_{n=1}^{n_f} (a[n] - \mu(a))^2} \sqrt{\sum_{n=1}^{n_f} (b[n] - \mu(b))^2}}, \quad (4.39)$$

is calculated to determine the correlation of some variable combinations, as shown in Table 4.31. Low values of $r(e_x, \hat{x})$ and $r(e_x, \dot{x})$ are indications of successful parameter estimation. As already observed in the visual analysis, the Kano model has the worst correlation coefficients, and $r(\hat{x}, \dot{x})$ shows that the Kano model has a poor performance for predicting the stem velocity. The other models presented pretty good and similar correlation coefficients between the measured and simulated stem position and velocity.

Table 4.31 – Statistical measures of the graphite gasket valve prediction.

Model	$r(x, \hat{x})$	$r(e_x, \hat{x})$	$r(e_x, \hat{\hat{x}})$	$r(\hat{\hat{x}}, \dot{x})$
Kano	0.99976	0.1859	0.2424	0.8586
Karnopp	0.99996	0.1484	-0.1621	0.9951
LuGre	0.99996	0.1285	-0.1615	0.9947
GMS	0.99996	0.0543	0.0256	0.9945

Model	$r(x, \hat{x})$ val.	$r(e_x, \hat{x})$ val.	$r(e_x, \hat{\hat{x}})$ val.	$r(\hat{\hat{x}}, \dot{x})$ val.
Kano	0.99913	0.5905	0.0064	0.3700
Karnopp	0.99954	0.0345	-0.2568	0.9901
LuGre	0.99954	0.0398	-0.2544	0.9899
GMS	0.99955	-0.0203	-0.1599	0.9884

val.: indicates to a statistical quantity calculated using the validation dataset.

Source: from Author.

4.4.2 Teflon Gasket Model Prediction Analysis

The teflon gasket valve is used only for algorithm benchmark, to check that the proposed algorithms are able to estimate good models when the valve presents low friction index. Analogously to the graphite gasket valve, Figures 4.47 to 4.58 show the teflon gasket valve model prediction accuracy. The Kano model has higher residuals, whereas the other models presented visually similar residuals. The other models presented visually similar residuals and exhibited similar responses, apart from a few localized differences. Regarding the stem velocity prediction, all models are very accurate and present pretty similar results.

Figure 4.47 – Kano model teflon gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.48 – Karnopp model teflon gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.49 – LuGre model teflon gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.50 – GMS model teflon gasket valve residual using the estimation dataset.

Source: from Author.

Figure 4.51 – Kano model tefflon gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.52 – Karnopp model tefflon gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.53 – LuGre model tefflon gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.54 – GMS model tefflon gasket valve residual using the validation dataset.

Source: from Author.

Figure 4.55 – Kano model tefflon gasket valve stem velocity prediction (220s to 300 s) using the validation dataset.

Source: from Author.

Figure 4.56 – Karnopp model tefflon gasket valve stem velocity prediction (220s to 300 s) using the validation dataset.

Source: from Author.

Figure 4.57 – LuGre model tefflon gasket valve stem velocity prediction (220s to 300 s) using the validation dataset.

Source: from Author.

Figure 4.58 – GMS model tefflon gasket valve stem velocity prediction (220s to 300 s) using the validation dataset.

Source: from Author.

The error distribution is presented in Figures 4.59 and 4.60. The more well behaved residual distributions are provided by the Karnopp, LuGre and GMS models. Regarding the Kano model, the error distribution deviates from a Gaussian distribution, which indicates that the estimation can be improved. This deviation is likely to occur due to an estimation error regarding the $\hat{x}_{\min_P}$ and $\hat{x}_{\max_P}$ parameters, as the residual seems to be correlated to the stem position, as seen in Figures 4.47 and 4.51.

Figure 4.59 – Kano and Karnopp tefflon gasket valve prediction error distribution using the estimation dataset.

Source: from Author.

Figure 4.60 – LuGre and GMS teflon gasket valve prediction error distribution using the estimation dataset.

Source: from Author.

The correlation coefficients between some variables of the teflon gasket valve models are presented in Table 4.32. The stem position and velocity prediction correlation coefficient is very high for every model and dataset, which is a good indicator of successful estimations. The Kano model, however, presented high correlation coefficients between residuals and the stem position, which indicates that the estimation could be improved (or that the model does not have a structure that is able to reproduce the plant perfectly).

Table 4.32 – Statistical measures of the teflon gasket valve prediction.

Model	$r(x, \hat{x})$	$r(e_x, \hat{x})$	$r(e_x, \hat{\dot{x}})$	$r(\hat{\dot{x}}, \dot{x})$
Kano	0.99995	-0.8456	-0.3453	0.9909
Karnopp	0.99997	-0.3886	-0.2687	0.9911
LuGre	0.99998	-0.3929	-0.1670	0.9910
GMS	0.99998	-0.3999	-0.0288	0.9904

Model	$r(x, \hat{x})$ val.	$r(e_x, \hat{x})$ val.	$r(e_x, \hat{\dot{x}})$ val.	$r(\hat{\dot{x}}, \dot{x})$ val.
Kano	0.99983	-0.3935	-0.4853	0.9752
Karnopp	0.99998	-0.3000	-0.4050	0.9812
LuGre	0.99998	-0.2750	-0.2975	0.9821
GMS	0.99998	-0.2995	-0.1086	0.9808

val.: indicates to a statistical quantity calculated using the validation dataset.

Source: from Author.

5 Closed Loop Parameter Estimation

This chapter is devoted to design algorithms to estimate the valve and friction parameters during the normal operation of valves with digital positioners, that is, the valve stem position is controlled by an embedded control system, whose stem position Set Point (SP) is given by the process Digital Control System (DCS).

Figure 5.1 presents a scheme for the diaphragm valve with a digital positioner, where exc is an external excitation signal that can be used to estimate the valve and friction parameters, C_p is the stem position controller and C_H is the hydraulic system controller, that is implemented in the DCS.

Figure 5.1 – Scheme of the diaphragm valve with digital positioner.

Source: from Author.

In this case, the valve stem is not able to move freely for obtaining the parameter estimates, which increases the estimation difficulty. Solving Eq. (4.5) also is a solution for the closed loop case. However, as in the open loop case, this optimization dimension is large, which demands studying possible simplifications.

5.1 Valve Diagnostics and Friction Detection

Assuming that the valve is delivered by the maintenance personal or the valve manufacturer with a good model, estimated in open loop, then identifying problems in the valve is a matter of comparing the measured and simulated signals, as presented in Figure 5.2.

Figure 5.2 – Scheme of valve diagnostics by analyzing the difference between measured and simulated variables.

Source: from Author.

Having the standard *fit* index for the I/P converter and the valve models, obtained during the valve maintenance procedure or by the manufacturer, the valve signals can be stored in a memory with a long time window, e.g. 20 minutes, and the actual *fit* indexes can be compared to the standard ones. If a deviation occurs, then a problem in the valve is detected, and it is possible to define if it is in the I/P converter or in the valve mechanical system.

When a problem is detected in the I/P converter or the valve mechanical system, then it is possible to reinitialize the model to check if the problem is related to the model simulation. To do so, one may notice that the models have internal states that have to be initialized accordingly to the valve. This may be achieved by switching C_p to manual, increasing OP so just the stem position increases and waiting $5 \cdot \tau_{I/P_s}$ s, to restart the model simulation with new initial conditions and switch the controller to automatic again. In this case, it is possible to determine all initial model states, since the valve is in the presliding state with constant position and zero velocity. For all models, the initial stem position used to restart the simulation is obviously the valve measured position immediately before the controller is switched to automatic again. For the Kano model, it is also necessary to obtain the input when the valve stopped moving, OPs from Algorithm 3.1 and the direction the valve was moving before the stem stopped, which is obviously upward ($d = 1$). The other first principle models need to be informed of the initial stem velocity, which is zero. Finally, the LuGre and GMS models need the initial internal state position, which is calculated as in Eqs. (4.30) and (4.33), but with reversed signal. The I/P model only needs to be informed of the initial diaphragm pressure, $P[0]$. At every moment during this procedure, the controller logic should switch back to automatic if the DCS SP varies drastically, to avoid affecting the control loop performance.

If even after restarting the model and evaluating the *fit* between measured and simulated variables are still high, then it is likely to have a problem with the I/P converter or the valve mechanical system.

As for a problem with the I/P converter, it should not influence the valve mechanical model, as it uses the measured diaphragm pressure as input. However, it is possible to estimate the I/P model parameters again and refine the C_p tuning. Estimating the I/P parameters in closed loop is addressed in Section 5.2 and updating the valve controller is discussed in the next chapter.

The stem position residual can be evaluated as well, to detect defects. As a test, consider the plant as a valve with GMS friction model simulation in closed loop, with model parameters as presented in Tables 3.1 and 3.2, unless said otherwise, controlled by a parallel Proportional Integral Derivative Controller (PID) with $K_p = 0.72$, $K_i = 0.43$ rep/s, $K_d = 6.74$ s and derivative filter time constant $\tau_{df} = 278$ s. Then, the signals generated by this plant are used to excite the valve model, with the same parameters as in Tables 3.1 and 3.2. Figure 5.3a shows the residual distribution of a valve with factory performance, i.e. the plant and the model have the same parameters and structure, so the residual can be considered a Gaussian random variable, due to the measurement noise. Figures 5.3b, 5.4a and 5.4b present the test cases when the plant has a problem with a 10% increase in k , 10% increase in F_{init} and increase in several friction parameters. It is possible to notice that when a deviation occurs, the most apparent modification in the residual distribution is a mean value drift.

Figure 5.3 – Residual distribution for plant with factory performance and deviation in k .

Source: from Author.

Figure 5.4 – Residual distribution for plant with deviation in F_{init} and friction parameters.

Source: from Author.

Table 5.1 presents some statistical measures of the cases of test residuals. When there is a deviation in k , the mean value drifts from the ideal case, as well as the correlations between residual and simulated stem position and velocity. Besides these three parameters deviation, when F_{init} deviates, then there is an increase in the distribution standard deviation and skewness as well, $\mu_3(e_x)$, which is defined as:

$$\mu_3(e_x) = \frac{1}{n_f} \sum_{n=1}^{n_f} (e_x[n] - \mu(e_x))^3. \quad (5.1)$$

The friction deviation may affect every statistical measure, depending on which parameter is affected, but in general it should have a less strong correlation between residuals and the stem position, since friction is independent of x . Therefore, these statistical measures may be calculated periodically and if drifts are detected, then it may be used to classify which problem is occurring in the valve mechanical system.

Table 5.1 – Statistical measures of simulated defective valves of Figures 5.3a to 5.4b.

Case	$\mu(e_x)$	$\text{std}(e_x)$	$\mu_3(e_x)$	$r(e_x, \hat{x})$	$r(e_x, \hat{\dot{x}})$
No defect	$2.2 \cdot 10^{-8}$	$4.6 \cdot 10^{-5}$	$4.6 \cdot 10^{-16}$	0.0044	-0.0058
k deviation	0.0015	$9.5 \cdot 10^{-5}$	$-8.4 \cdot 10^{-12}$	0.8707	-0.6323
F_{init} deviation	0.0009	0.0012	$7.9 \cdot 10^{-9}$	0.9378	-0.4519
Friction deviation	$-3.4 \cdot 10^{-5}$	$5.9 \cdot 10^{-5}$	$1.8 \cdot 10^{-13}$	-0.2267	0.3102

Source: from Author.

Another measure to determine if the valve mechanical system has deviated, is the valve deadband. If it has changed, when compared to its standard value, then it is

likely that the friction has deviated over time. Estimating the valve deadband can be accomplished by noting that the valve signature curve tends to present a trapezoidal shape, as already noted by Kano et al. (2004), Choudhury et al. (2006). If two lines are fitted to the valve operational data containing only nonzero stem velocities, then the distance between these lines corresponds to the valve deadband. The procedure for obtaining a S_0 estimation is presented in Algorithm 5.1. The estimated parameters are calculated easily, with minimal valve deviation from the desired position SP, and may be important for defining which parameters are responsible for the valve performance measure deviation and designing excitation signals.

Algorithm 5.1 – Closed loop valve deadband estimation.

- 1: Switch C_p to manual, but if a large variation in DCS SP occurs at any time, interrupt the algorithm and switch C_p back to automatic
- 2: Wait $5 \cdot \tau_{I/P}$ s
- 3: Start data collection of P and x data
- 4: Wait 1 s
- 5: Switch C_p back to automatic
- 6: Collect 5 minutes of data
- 7: $w_c \leftarrow 1000$
- 8: **for** $ct = 1 : 100$ **do**
- 9: Filter the stem position with a zero phase, second order linear filter with 0.9 damping ratio and w_c passband and calculate the $\dot{x}$
- 10: $\text{std}(\dot{x}_{1s}) \leftarrow$ Calculate the standard deviation of $\dot{x}$ using only the first second of data
▷ the stem should be still
- 11: **if** $\text{std}(\dot{x}_{1s}) < 5 \cdot 10^{-5}$ **then**
- 12: Exit for loop
- 13: **end if**
- 14: $w_c \leftarrow w_c/2$
- 15: **end for**
- 16: Exclude data point n if $\dot{x}[n] < \max(10^{-4}, 4 \cdot \text{std}(\dot{x}_{1s}))$
- 17: Fit two parallel lines to data points, $x_1[n] = l_{inc} \cdot P[n] + x_{1b}$ and $x_2[n] = l_{inc} \cdot P[n] + x_{2b}$, by minimizing the criterion:

$$V_{l_{n_f}}(l_{inc}, x_{1b}, x_{2b}) = \frac{1}{n_f} \sum_{n=1}^{n_f} \min(|x[n] - x_1[n]|, |x[n] - x_2[n]|)$$

- 18: $x_{01} \leftarrow -x_{1b}/l_{inc}$
 - 19: $x_{02} \leftarrow -x_{2b}/l_{inc}$
 - 20: $S_0 \leftarrow (\max(x_{01}, x_{02}) - \min(x_{01}, x_{02}))/K_{P_g}$
-

Algorithm 5.2 presents a conceptual framework to detect defects in the valve and start the necessary procedures to estimate new model parameters and update C_p . If the Kano model is used, then the algorithm should be changed to estimate $x_{\min P}$ and $x_{\max P}$, instead of k and F_{init} .

Algorithm 5.2 – Conceptual closed loop valve defect detection.

```

1: if Diaphragm pressure prediction fit index deviates 5% from the standard value then
2:   Set maintenance system alarm
3:   Reinitialize the model and calculate new fit index
4:   if fit index deviation persists then
5:     Estimate new I/P model parameters as in Section 5.2
6:     Reset the standard value
7:     Tune  $C_p$  parameters as presented in Chapter 4
8:   end if
9: end if
10: if The stem position prediction fit index deviates 5% from the standard value or any
    statistical measure deviates 10% from the standard values then
11:   Set the maintenance system alarm
12:   Reinitialize the model and calculate new fit index and statistical measures
13:   if Deviation persists then
14:     if  $\mu(e_x)$  deviates 10% from the standard value and  $r(e_x, \hat{x}) > 0.6$  then
15:       Estimate  $k$  and  $F_{\text{init}}$  (or  $x_{\max P}$ ,  $x_{\min P}$ ), as in Section 5.2
16:       if The fit and the statistical measures are about the same as the standard
          value then
17:         Reset the standard fit value and the statistical measures
18:         Tune  $C_p$  parameters as presented in Chapter 4
19:       else
20:         Estimate  $S_0$ 
21:         Estimate  $k$ ,  $F_{\text{init}}$  and  $\theta_f$  altogether (or  $x_{\max P}$ ,  $x_{\min P}$  and  $\theta_f$ ), as in Section
          5.2
22:         Reset the standard fit value and the statistical measures
23:         Tune  $C_p$  parameters as presented in Chapter 4
24:       end if
25:     else
26:       Estimate  $S_0$ 
27:       Estimate the friction parameters, as in Section 5.2
28:       if The fit and the statistical measures are about the same as the standard
          value then
29:         Reset the standard fit value and the statistical measures
30:         Tune  $C_p$  parameters as presented in Chapter 4
31:       else
32:         Estimate  $k$ ,  $F_{\text{init}}$  and  $\theta_f$  altogether (or  $x_{\max P}$ ,  $x_{\min P}$  and  $\theta_f$ ) , as in
          Section 5.2
33:         Reset standard fit value and statistical measures
34:         Tune  $C_p$  parameters as presented in Chapter 4
35:       end if
36:     end if
37:   end if
38: end if

```

5.2 Closed Loop Parameter Estimation

To estimate the I/P converter parameters, it is enough to apply a rectangular excitation signal in *exc*, with amplitude $1.5 \cdot S_0$ and 80 s period, very similar to the open loop case. Of course, the *exc* signal will be highly attenuated by C_p , which is desirable, so to decrease the perturbations in the control loop. However, as the overall signal is not rectangular and the I/P converter has nonlinear dynamics, it is not expected that the parameters will be the same as in the open loop estimation, but it is enough to accommodate defective or drifting I/P converter dynamics. The parameters can be estimated exactly as described in Section 4.1.

As the valve and the friction parameter estimation is carried out with an infinite steps ahead simulation of the valve, once again the biggest challenge is to determine the initial states of the valve to initialize the simulation. This can be accomplished with the exact procedure of simulation reinitialization from Section 5.1. After C_p is switched to automatic again, the excitation signal *exc* can be started, as well as the estimation data collection.

With respect to the excitation signal design, the most important aspect for estimating friction is to collect data from a wide range of stem velocities and from presliding and sliding states. This may not be informative enough with just the SP excitation from DCS, therefore the need for the perturbation signal *exc*. The suggested *exc* is an aleatory velocity ramp signal, with range from 10^{-5} to $3 \cdot 10^{-3}$ m/s and aleatory magnitude from 0.7 to 1.2 times S_0 . The *exc* signal is corrected by C_p , so there are no large disturbances in the stem position, which is desirable for maintaining the process controlled, but it is disadvantageous for obtaining valve information. However, it should be enough to obtain fair estimates to update the model if the valve behavior varies with time. Figure 5.5 presents an example of excitation signal with $S_0 = 25.7$.

Figure 5.5 – Closed loop excitation signal example.

Source: from Author.

To estimate k and F_{init} only, the residual function to be minimized is:

$$\{\hat{k}, \hat{F}_{\text{init}}\} = \arg \min_{k, F_{\text{init}}} \sqrt{\sum_{n=1}^{n_f} \left(x[n] - \hat{x}(n, \text{OP}[n], x[0], \hat{m}, k, F_{\text{init}}, \hat{\theta}_f) \right)^2}. \quad (5.2)$$

To estimate the friction parameters, the residual function is exactly as in Eq. (4.17). Finally, to estimate all parameters it is just a matter of augmenting Eq. (4.17) with k and F_{init} , as suggested in the open loop case. If the Kano model is used in the estimation, then it is necessary to augment Eq. (4.17) with $x_{\max P}$ and $x_{\min P}$, instead.

The search space and penalty functions for the friction parameters can be calculated as described in Section 4.2, using the closed loop S_0 estimate. The k and F_{init} search space should be created by allowing a deviation of $\pm 50\%$ from the previous estimate, which is a very conservative criterion. Regarding the Kano model, the $x_{\max P}$ and $x_{\min P}$ also should be allowed to vary $\pm 50\%$ from the previous value. To solve the estimation problem, the GDES optimization method is used and the measured variables filtering should be addressed as in the open loop case.

When estimating parameters in closed loop, there is a problem with parameter bias due to correlation between the measurement noise and the system input. This problem is addressed in the following section.

5.3 Stochastic Parameters Estimation Analysis

In this section, the residual function stochastic analysis is performed to ensure that the expected values for the estimated parameters are equal to the plant parameters.

The first principle valve model is given by the following difference equation, as seen in Section 3.2:

$$x[n] = \frac{T_s^2 q^{-1} + 2q^{-2} + q^{-3}}{4} \frac{F_{\text{res}}[n]}{1 - 2q^{-1} + q^{-2}} \frac{1}{m}. \quad (5.3)$$

Expanding the term F_{res} , multiplying both sides by the denominator and rearranging, one obtains:

$$4x[n] + \left(\frac{T_s^2 k}{m} - 8 \right) x[n-1] + \left(4 + \frac{2T_s^2 k}{m} \right) x[n-2] + \frac{T_s^2 k}{m} x[n-3] = \frac{T_s^2}{m} (q^{-1} + 2q^{-2} + q^{-3}) (S_a P[n] - F_f[n] - F_{\text{init}}). \quad (5.4)$$

For a further analysis, it is necessary to expand the term $F_f[n]$ for each friction model, which is done in the following sections.

5.3.1 Karnopp Friction Model

The Karnopp model calculates the friction force using three equations, that are switched depending on the velocity and resultant force of the system. If the stem velocity

is zero and $|F_r[n]| \leq F_s$, the friction force is:

$$F_f[n] = S_a P[n] - k x[n] - F_{\text{init}}. \quad (5.5)$$

Substituting Eq. (5.5) into Eq. (5.4) and simplifying it, the stem position equation is reduced to:

$$x[n] = 2x[n-1] - x[n-2]. \quad (5.6)$$

However, as in this case the stem velocity is forced to zero, the valve equation is simply:

$$x[n] = x[n-1], \quad (5.7)$$

which means that the stem position does not change.

If the stem velocity is zero and $|F_r[n]| > F_s$, then:

$$F_f[n] = F_s. \quad (5.8)$$

Substituting Eq. (5.8) into Eq. (5.4) and rearranging the terms, the valve model is reduced to:

$$x[n] = \left(\frac{T_s^2}{4m} \right) \frac{q^{-1} + 2q^{-2} + q^{-3}}{1 + \left(\frac{T_s^2 k}{4m} - 2 \right) q^{-1} + \left(1 + \frac{T_s^2 k}{2m} \right) q^{-2} + \frac{T_s^2 k}{4m} q^{-3}} (S_a P[n] - F_s - F_{\text{init}}). \quad (5.9)$$

Note that Eq. (5.9) represents a mechanical system composed of mass and spring and therefore the linear discrete equation tends to be marginally stable, as no damping is active. This equation is used only in one time step each time the valve switches from sliding to presliding state.

Lastly, if the stem velocity is different from zero:

$$F_f[n] = \left[F_c + (F_s - F_c) \exp \left(-(\dot{x}[n]/v_s)^2 \right) \right] \text{sgn}(\dot{x}[n]) + F_v \dot{x}[n]. \quad (5.10)$$

Using the concept of Generalized Gradient Theorem (CLARKE et al., 1998), that states that if a function is Lipschitz near the discontinuous point and it is defined over domain subsets, such that the union of these subsets spans the real space, and the intersection of these subsets is null, then the function is differentiable and its derivative lies anywhere in the convex hull formed by the gradient of the function at every subset limit, it is possible to calculate the first order partial differential equation of Eq. (5.10), with respect to $\dot{x}[n]$, around the stem velocity $\dot{x}_L$:

$$F_L(\dot{x}_L) = \left. \frac{\partial F_f[n]}{\partial \dot{x}[n]} \right|_{\dot{x}[n]=\dot{x}_L} = -2 (F_s - F_c) \exp \left(-(\dot{x}_L/v_s)^2 \right) \frac{\dot{x}_L}{v_s^2} \text{sgn}(\dot{x}_L) + F_v. \quad (5.11)$$

Note that the generalized derivative of the signal function is zero. The valve model with linearized friction force model is:

$$x[n] \left[4 + \left(\frac{T_s^2 k}{m} - 8 \right) q^{-1} + \left(4 + \frac{2 T_s^2 k}{m} \right) q^{-2} + \frac{T_s^2 k}{m} q^{-3} \right] = \frac{T_s^2}{m} (q^{-1} + 2 q^{-2} + q^{-3}) \left(S_a P[n] - F_d(\dot{x}_L) - F_L(\dot{x}_L) \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}} x[n] - F_{\text{init}} \right). \quad (5.12)$$

Rearranging the terms, Eq. (5.12) is rewritten as:

$$x[n] \left[4 + A_{LK1}(\dot{x}_L) q^{-1} + A_{LK2} q^{-2} + A_{LK3}(\dot{x}_L) q^{-3} \right] = \frac{T_s^2}{m} (q^{-1} + 2 q^{-2} + q^{-3}) (S_a P[n] - F_d(\dot{x}_L) - F_{\text{init}}), \quad (5.13)$$

with:

$$\begin{aligned} A_{LK1}(\dot{x}_L) &= \frac{T_s^2 k}{m} + \frac{2 T_s}{m} F_L(\dot{x}_L) - 8 \\ A_{LK2} &= 4 + \frac{2 T_s^2 k}{m} \\ A_{LK3}(\dot{x}_L) &= \frac{T_s^2 k}{m} - \frac{2 T_s}{m} F_L(\dot{x}_L). \end{aligned} \quad (5.14)$$

It is clear from Eqs. (5.9) and (5.13) that the valve model, when in sliding state or in presliding with $|F_r[n]| > F_s$, can be approximated by a transfer function with variable parameters, given the linearization point:

$$x[n] = G_{LK}(q, \dot{x}_L) (S_a P[n] - F_d(\dot{x}_L) - F_{\text{init}}). \quad (5.15)$$

As already mentioned in Chapter 4, the valve model with Karnopp friction model is a filter with variable gain and poles, given the stem velocity. The friction force decreases or increases the overall system damping when the stem velocity is lower, higher than the Stribeck velocity, respectively.

5.3.2 LuGre Friction Model

Given Eq. (3.9), the LuGre model friction force is:

$$F_{fL}[n] = \sigma_0 z[n] + \sigma_1 \dot{z}[n] + F_v \dot{x}[n]. \quad (5.16)$$

Using the average bristle deflection equations, Eqs. (3.24) and (3.25), it is possible to find the difference equation relationship between $\dot{x}$ and z :

$$z[n] = \frac{T_s}{2} \left[\dot{x}[n-1] + \dot{x}[n-2] + \left(\frac{2}{T_s} - \frac{|\dot{x}[n-1]|}{g(\dot{x}[n-1])} \right) z[n-1] + \frac{|\dot{x}[n-2]|}{g(\dot{x}[n-2])} z[n-2] \right]. \quad (5.17)$$

Considering that the the generalized derivative of the absolute function at the discontinuous point is zero (it lies in the convex hull $[-1, 1]$, however the imprecision is considered tolerable in this work), the first order partial derivative of $z[n]$ with respect to the input variables are:

$$\begin{aligned}\frac{\partial z[n]}{\partial \dot{x}[n-1]} &= \frac{T_s}{2} \left[1 + \left(\frac{|\dot{x}[n-1]|}{g([n-1])^2} \frac{\partial g(\dot{x}[n-1])}{\partial \dot{x}[n-1]} - \frac{\text{sgn}(\dot{x}[n-1])}{g(\dot{x}[n-1])} \right) z[n-1] \right] \\ \frac{\partial z[n]}{\partial \dot{x}[n-2]} &= \frac{T_s}{2} \left[1 + \left(\frac{|\dot{x}[n-2]|}{g([n-2])^2} \frac{\partial g(\dot{x}[n-2])}{\partial \dot{x}[n-2]} - \frac{\text{sgn}(\dot{x}[n-2])}{g(\dot{x}[n-2])} \right) z[n-2] \right] \\ \frac{\partial z[n]}{\partial z[n-1]} &= 1 - \frac{|\dot{x}[n-1]|}{g([n-1])} \frac{T_s}{2} \\ \frac{\partial z[n]}{\partial z[n-2]} &= -\frac{|\dot{x}[n-2]|}{g([n-2])} \frac{T_s}{2},\end{aligned}\tag{5.18}$$

with:

$$\frac{\partial g(\dot{x}[n])}{\partial \dot{x}[n]} = -2 \frac{F_s - F_c}{\sigma_0} \exp\left(-(\dot{x}[n]/v_s)^2\right) \frac{\dot{x}[n]}{v_s^2}.\tag{5.19}$$

The linearized difference equation that maps the stem velocity into an average bristle deflection can be written as:

$$\delta z[n] = A_{LL1} \delta \dot{x}[n-1] + A_{LL2} \delta \dot{x}[n-2] + A_{LL3} \delta z[n-1] + A_{LL4} \delta z[n-2]\tag{5.20}$$

where:

$$\begin{aligned}A_{LL1} &= \left. \frac{\partial z[n]}{\partial \dot{x}[n-1]} \right|_{\substack{\dot{x}[n-1]=\dot{x}_{L1} \\ z[n-1]=z_{L1}}} & A_{LL2} &= \left. \frac{\partial z[n]}{\partial \dot{x}[n-2]} \right|_{\substack{\dot{x}[n-2]=\dot{x}_{L2} \\ z[n-2]=z_{L2}}} \\ A_{LL3} &= \left. \frac{\partial z[n]}{\partial z[n-1]} \right|_{\dot{x}[n-1]=\dot{x}_{L1}} & A_{LL4} &= \left. \frac{\partial z[n]}{\partial z[n-2]} \right|_{\dot{x}[n-2]=\dot{x}_{L2}},\end{aligned}\tag{5.21}$$

and δ denotes the linearization point incremental variable, e.g. $\delta z[n-1] = z[n-1] - z_{L1}$. Therefore, the average bristle deflection can be rewritten in a transfer function form:

$$\delta z[n] = G_{zL}(q, \dot{x}_{L1}, \dot{x}_{L2}, z_{L1}, z_{L2}) \delta \dot{x}[n].\tag{5.22}$$

The friction force, Eq. (5.16), can be written as a function of $\delta \dot{x}[n]$ and the linearization point (which is omitted in the transfer function for simplicity):

$$\delta F_{fL}[n] = \left(F_v + \sigma_0 G_{zL}(q) + \sigma_1 G_{zL}(q) \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}} \right) \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}} \delta x[n].\tag{5.23}$$

Then, the valve model, Eq. (5.4), is written as:

$$\begin{aligned}4 \delta x[n] + \left(\frac{T_s^2 k}{m} - 8 \right) \delta x[n-1] + \left(4 + \frac{2 T_s^2 k}{m} \right) \delta x[n-2] + \frac{T_s^2 k}{m} \delta x[n-3] = \\ \frac{T_s^2}{m} \left(q^{-1} + 2 q^{-2} + q^{-3} \right) \left(S_a \delta P[n] - \delta F_{fL}[n] \right).\end{aligned}\tag{5.24}$$

Eq. (5.24) can be reduced to a transfer function form (omitting the linearization point terms), which tends to be overall stable, as the valve is obviously designed to be bounded input, bounded output stable:

$$\delta x[n] = G_{LL}(q) \delta P[n]. \quad (5.25)$$

5.3.3 GMS Friction Model

Given Eq. (3.12), the GMS model friction force is:

$$F_{f_G}[n] = \sum_{i=1}^{N_{Me}} F_i[n] + F_v \dot{x}[n], \quad (5.26)$$

where:

$$F_i[n] = \kappa_i \psi_i[n] + \nu_i \dot{\psi}_i[n]. \quad (5.27)$$

If all Maxwell elements are in presliding state, using the GMS model definition in Eq. (3.26), then Eq. (5.4) is rewritten as:

$$4x[n] + \left(\frac{T_s^2 k}{m} - 8 \right) x[n-1] + \left(4 + \frac{2T_s^2 k}{m} \right) x[n-2] + \frac{T_s^2 k}{m} x[n-3] = \frac{T_s^2}{m} (q^{-1} + 2q^{-2} + q^{-3}) (S_a P[n] - F_{f_{Gp}}[n] - F_{\text{init}}), \quad (5.28)$$

with:

$$F_{f_{Gp}}[n] = \sum_{i=1}^{N_{Me}} \kappa_i x[n] + \nu_i x[n] \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}}. \quad (5.29)$$

Eq. (5.28) can be reduced to a transfer function form:

$$\delta x[n] = G_{LGp}(q) \delta P[n], \quad (5.30)$$

that is defined used incremental variables only to guarantee the notation consistency with the following analysis, since Eq. (5.28) is already linear.

With regard to the sliding state, using Eq. (3.26), the Maxwell elements virtual position are governed by the following difference equation:

$$\frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}} \psi_i[n+1] = \frac{C\alpha_i}{\kappa_i} \left(\text{sgn}(\dot{x}[n]) - \frac{\kappa_i \psi_i[n] + \nu_i \dot{\psi}_i[n] \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}}}{\alpha_i s(\dot{x}[n])} \right). \quad (5.31)$$

Rearranging the terms of Eq. (5.31), one obtains:

$$\begin{aligned} \psi_i[n+1] = & \frac{T_s C\alpha_i}{2 \kappa_i} \text{sgn}(\dot{x}[n]) + \frac{T_s C\alpha_i}{2 \kappa_i} \text{sgn}(\dot{x}[n-1]) + \\ & \left(1 - \frac{T_s C}{2 s(\dot{x}[n])} - \frac{C\nu_i}{\kappa_i s(\dot{x}[n])} \right) \psi_i[n] - \frac{C\nu_i}{\kappa_i s(\dot{x}[n-1])} \psi_i[n-1]. \end{aligned} \quad (5.32)$$

By applying the generalized derivative theorem, the first order partial derivatives of ψ_i with respect to the input variables are:

$$\begin{aligned}\frac{\partial \psi_i[n]}{\partial \psi_i[n-1]} &= 1 - \frac{T_s}{2} \frac{C}{s(\dot{x}[n-1])} - \frac{C\nu_i}{\kappa_i s(\dot{x}[n-1])} \\ \frac{\partial \psi_i[n]}{\partial \psi_i[n-2]} &= -\frac{C\nu_i}{\kappa_i s(\dot{x}[n-2])} \\ \frac{\partial \psi_i[n]}{\partial \dot{x}[n-1]} &= \left(\frac{T_s}{2} \frac{C}{s(\dot{x}[n-1])^2} \frac{\partial s(\dot{x}[n-1])}{\partial \dot{x}[n-1]} + \frac{C\nu_i}{\kappa_i s(\dot{x}[n-1])^2} \frac{\partial s(\dot{x}[n-1])}{\partial \dot{x}[n-1]} \right) \psi_i[n-1] \\ \frac{\partial \psi_i[n]}{\partial \dot{x}[n-2]} &= \frac{C\nu_i}{\kappa_i s(\dot{x}[n-2])^2} \frac{\partial s(\dot{x}[n-2])}{\partial \dot{x}[n-2]} \psi_i[n-2].\end{aligned}\quad (5.33)$$

Thus, the linearized difference equation that maps the stem velocity into a Maxwell element i displacement is:

$$\delta \psi_i[n] = A_{LG1} \delta \dot{x}[n-1] + A_{LG2} \delta \dot{x}[n-2] + A_{LG3} \delta \psi_i[n-1] + A_{LG4} \delta \psi_i[n-2], \quad (5.34)$$

where:

$$\begin{aligned}A_{LG1} &= \left. \frac{\partial \psi_i[n]}{\partial \dot{x}[n-1]} \right|_{\substack{\dot{x}[n-1]=\dot{x}_{L1} \\ \psi_i[n-1]=\psi_{iL1}}} & A_{LG2} &= \left. \frac{\partial \psi_i[n]}{\partial \dot{x}[n-2]} \right|_{\substack{\dot{x}[n-2]=\dot{x}_{L2} \\ \psi_i[n-2]=\psi_{iL2}}} \\ A_{LG3} &= \left. \frac{\partial \psi_i[n]}{\partial \psi_i[n-1]} \right|_{\dot{x}[n-1]=\dot{x}_{L1}} & A_{LG4} &= \left. \frac{\partial \psi_i[n]}{\partial \psi_i[n-2]} \right|_{\dot{x}[n-2]=\dot{x}_{L2}}.\end{aligned}\quad (5.35)$$

As in the LuGre model case, the Maxwell elements displacement in sliding state is a nonlinear filter of stem velocity, with variable gain and poles, depending on the previous stem velocities and Maxwell elements displacement. Therefore, it is possible to define a linearized transfer function to calculate the Maxwell element displacement, given the stem velocity:

$$\delta \psi[n] = G_{\psi_i G}(q, \dot{x}_{L1}, \dot{x}_{L2}, \psi_{iL1}, \psi_{iL2}) \delta \dot{x}[n]. \quad (5.36)$$

With Eqs. (5.36) and (5.27), the linearized valve model with GMS friction model in sliding state is:

$$\begin{aligned}4 \delta x[n] + \left(\frac{T_s^2 k}{m} - 8 \right) \delta x[n-1] + \left(4 + \frac{2 T_s^2 k}{m} \right) \delta x[n-2] + \frac{T_s^2 k}{m} \delta x[n-3] = \\ \frac{T_s^2}{m} (q^{-1} + 2 q^{-2} + q^{-3}) (S_a \delta P[n] - \delta F_{f_{Gs}}[n]),\end{aligned}\quad (5.37)$$

with:

$$\delta F_{f_{Gs}}[n] = \sum_{i=1}^{N_{Me}} \left(\kappa_i + \nu_i \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}} \right) \frac{2}{T_s} \frac{1 - q^{-1}}{1 + q^{-1}} G_{\psi_i G}(q) \delta x[n]. \quad (5.38)$$

Note that the linearization point of $G_{\psi_i G}(q)$ is omitted for simplicity. Eq. (5.37) can be rearranged into a transfer function form:

$$\delta x[n] = G_{LGs}(q) \delta P[n]. \quad (5.39)$$

5.3.4 Kano Valve Model

This model is rather simple, as there is no dynamics, as seen in Algorithm 3.1. If the valve is in the presliding state, then:

$$x[n] = x[n-1]. \quad (5.40)$$

If the valve is in the sliding state, then the stem position is the scaled valve input, depending on previous values of x (the movement direction):

$$x[n] = G_K(q) P[n-1]. \quad (5.41)$$

5.3.5 A Generalized Valve Model

From the previous sections it can be noted that the valve model maps the diaphragm pressure into stem position using nonlinear filters. It may be assumed that the valve model can be approximated by allowing time variations of the difference equation coefficients, reflecting a linearized valve model, with updated linearization point at each time step:

$$\begin{cases} \zeta[n+1] = \Theta[n] \zeta[n] + \Gamma[n] P[n] \\ x[n] = \Omega \zeta[n], \end{cases} \quad (5.42)$$

where $\zeta[n] \in \mathbb{R}^{d_\zeta \times 1}$ is the internal state vector whose dimension depends on the valve model, $P[n] \in \mathbb{R}$ is the diaphragm pressure, $\Theta[n] \in \mathbb{R}^{d_\zeta \times d_\zeta}$, $\Gamma[n] \in \mathbb{R}$ are bounded operator sequences (e.g. $\sup\{\|\Theta[n]\| < \infty \mid n \in \mathbb{N}\}$) and $\Omega \in \mathbb{R}^{1 \times d_\zeta}$.

Solving Eq. (5.42), one obtains (HALANAY; IONESCU, 1994):

$$x[n] = \Omega S_m(n-1, 0) \zeta[0] + \sum_{i=1}^n \Omega S_m(n-i, 0) \Gamma[n-i] P[n-i], \quad (5.43)$$

where $S_m : \mathbb{R}^{d_\zeta \times 1} \mapsto \mathbb{R}^{d_\zeta \times 1}$ is defined as:

$$S_m(i, j) = \begin{cases} I, & \text{if } i = j \\ \Theta[i] \Theta[i-1] \dots \Theta[j], & \text{if } i > j \\ 0, & \text{if } i < j, \end{cases} \quad (5.44)$$

here I is the identity matrix. Therefore, from Eq. (5.43), the stem position can be approximated by a time varying function that depends on the friction parameter vector:

$$x[n] = T(n, \theta_f, P[n]). \quad (5.45)$$

5.3.6 Open Loop Parameter Estimation Analysis

Even though estimating the parameters of an open loop system usually does not lead to estimation bias, its stochastic analysis is carried out as an introduction for the

closed loop systems analysis. In Chapter 4 the measured variables are considered perfectly known, which is an assumption that does not hold in practical cases. Frequently, the measured variables are considered corrupted by measurement noise that is usually modeled as an additive white noise with zero mean and a given variance:

$$\begin{aligned} x_m[n] &= x[n] + w_x[n], & w_x &\sim \mathcal{N}(0, \sigma_{w_x}^2) \\ P_m[n] &= P[n] + w_P[n], & w_P &\sim \mathcal{N}(0, \sigma_{w_P}^2). \end{aligned} \quad (5.46)$$

The random variables w_x and w_P are considered independent, as the measurement systems are not coupled in any way. Using Eq. (5.46), the mean squared prediction error, defined in Eqs. (4.2) and (4.3), can be updated (omitting some parameters for simplification):

$$V_{n_f}(\hat{\theta}_f) = \frac{1}{n_f} \sum_{n=1}^{n_f} \left(\hat{x}(n, \hat{\theta}_f) - x_m[n] \right)^2 = \frac{1}{n_f} \sum_{n=1}^{n_f} e_{x_m}[n]^2. \quad (5.47)$$

Assuming that the plant and model have the same structure, the residual, $e_{x_m}[n]$, is calculated as:

$$e_{x_m}[n] = T(n, \hat{\theta}_f, P[n] + w_P[n]) - \left(T(n, \theta_f, P[n]) + w_x[n] \right). \quad (5.48)$$

Expanding the squared residual, one obtains:

$$e_{x_m}[n]^2 = \Delta T[n]^2 - 2\Delta T[n] + w_x[n]^2, \quad (5.49)$$

with:

$$\Delta T[n] = T(n, \hat{\theta}_f, P[n] + w_P[n]) - T(n, \theta_f, P[n]). \quad (5.50)$$

Let E denote the expectation and averaging operator (LJUNG, 1999), then:

$$V_{n_f}(\hat{\theta}_f) = E \left(\Delta T[n]^2 \right) - 2 E \left(\Delta T[n] w_x \right) + E \left(w_x^2 \right). \quad (5.51)$$

By using the T definition, from Eq. (5.43), the first term of Eq. (5.51) can be expanded:

$$E \left(\Delta T[n]^2 \right) = E \left((\Delta x[n])^2 \right) + 2 E \left(\Delta x[n] G_S[n] w_P[n] \right) + E \left((G_S[n] w_P[n])^2 \right), \quad (5.52)$$

with:

$$\begin{aligned} \Delta x[n] &= \hat{\Omega} \hat{S}(n-1, 0) \hat{\zeta}[0] + \sum_{i=1}^n \hat{\Omega} \hat{S}(n-i, 0) \hat{\Gamma}[n-i] P[n-i] - \\ &\quad \Omega S(n-1, 0) \zeta[0] - \sum_{i=1}^n \Omega S(n-i, 0) \Gamma[i] P[n-i] \end{aligned} \quad (5.53)$$

and

$$G_S[n] w_P[n] = \sum_{i=1}^n \hat{\Omega} \hat{S}(n-i, 0) \hat{\Gamma}[n-i] w_P[n-i]. \quad (5.54)$$

From Eq. (5.54), one may note that $E(G_S[n] w_P[n]) = E(w_P[n]) = 0$, as the term $G_S[n]$ acts as a linear filter of the random variable (assuming the stability of $\hat{S}$). The variance, however, is affected by $G_S[n]$ transformation. If the state-transition operator, $\hat{S}$, is stable, then it follows that $E(\Delta x[n] G_S[n] w_P[n]) = 0$. It is reasonable to assume that the state-transition operator is stable, since the valves are designed to be stable and an unstable $\hat{S}$ would readily be discarded by the estimator, due to its high mean squared prediction error. Yet, perfect valve and friction parameters estimation lead to $E(\Delta x[n] G_S[n] w_P[n]) = 0$, as well. The second term can be expanded as well:

$$E(\Delta T[n] w_x[n]) = E\left(\left[\hat{\Omega} \hat{S}(n-1, 0) \hat{\zeta}[0] + \sum_{i=1}^n \hat{\Omega} \hat{S}(n-i, 0) \hat{\Gamma}[n-i] (P[n-i] + w_P[n]) - \Omega S(n-1, 0) \zeta[0] - \sum_{i=1}^n \Omega S(n-i, 0) \Gamma[n-i] P[n-i]\right] w_x\right). \quad (5.55)$$

By noting that the random variables have zero mean and are independent, then Eq. (5.55) reduces to:

$$E(\Delta T[n] w_x[n]) = \hat{\Omega} \hat{S}(n, 0) \hat{\zeta}[0] - \Omega S(n, 0) \zeta[0]. \quad (5.56)$$

The term $E(\Delta T[n] w_x) = 0$, given the conditions already discussed (state-transition operators stability and a perfect estimation of valve and friction parameters).

From the previous analysis, Eq. (5.51) is reduced to:

$$V_{n_f}(\hat{\theta}_f) = E(\Delta x[n]^2) + \sigma_{w_x}^2 + E(G_S[n] w_P[n]^2). \quad (5.57)$$

Eq. (5.57) shows that when $\hat{\theta}_f = \theta_f$, $V_{n_f}(\hat{\theta}_f)$ is at its minimal value, which means that the open loop estimation method is unbiased, even in presence of measurement noise.

5.3.7 Closed Loop Parameter Estimation Analysis

From Figure 5.1, it is possible to calculate the functions that map deviations from the desired set point to the position controller output. The OP can be calculated from SP and x_m :

$$\text{OP}[n] = C_p(q, x_m[n-1], \text{SP}[n-1]). \quad (5.58)$$

A generic function can be used to map OP into P :

$$P[n] = f_{I/P}(\text{OP}[n], \theta_{I/P}, q). \quad (5.59)$$

The analysis is essentially the same as in Subsection 5.3.6, however the diaphragm pressure is now correlated to the stem position measurement noise.

The difference from the open loop case lies on the terms $E(\Delta T[n] w_x[n])$ and $E(\Delta x[n] G_S[n] w_P[n])$, which are not zero, because $E(P[n] w_x[n]) \neq 0$. The state-transition

operator acts as a filter and may even amplify the correlation between these variables. In closed loop, the resulting mean squared prediction error is:

$$V_{n_f}(\hat{\theta}_f) = E(\Delta x[n]^2) - 2 E(\Delta T[n] w_x[n]) + 2 E(\Delta x[n] G_S[n] w_P[n]) + \sigma_{w_x}^2 + E[(G_S[n] w_P[n])^2]. \quad (5.60)$$

From Eq. (5.60) it is possible to conclude that in the closed loop case, the parameter estimation is biased, since when $\hat{\theta}_f = \theta_f$, $V_{n_f}(\hat{\theta}_f)$ is not at its minimal value, as shown by Hagenblad, Ljung and Wills (2008).

A solution for this problem is to lower the correlation between P and w_x , by using a position controller with low gain and no integrator during the parameter estimation experiment. By doing so, the term $2 E(\Delta T[n] w_x[n])$ tends to be minimized, improving the estimation performance.

Assume that the stem position and SP are normalized to 0–100%. Then, if $C_p = 0.1$ during the excitation period, a 10% correction is applied in OP when the stem position error is 100%, which is not acceptable. To ensure that the overall valve performance is fair, the SP may be modified to:

$$SP[n] = 20 (SP_H[n] - 50), \quad (5.61)$$

where SP_H is the output from the hydraulic system controller, C_H . Therefore, $SP \in [-1000, 1000]$ and $OP \in [-100, 100]$. Note that OP has to compensate the *exc* signal, the reason why its lower range is -100 .

5.4 Simulated Tests

In this test, C_p is a discrete P controller with 10^{-3} s sampling time and proportional gain, $K_p = 0.1$. The hydraulic system is considered the same as presented by Hidalgo and Garcia (2017), which corresponds to a Wiener system with a linear dynamic system:

$$\frac{x_w(s)}{x(s)} = \frac{1}{3.375 s + 1}, \quad (5.62)$$

and nonlinear static function:

$$Q(x_w(t)) = -100442.87 x_w(t)^2 - 630.57 x_w(t) + 101.54. \quad (5.63)$$

Note that the flow rate Q is normalized. The hydraulic system controller (C_H) is a parallel digital PI controller with 10^{-3} s sampling time, proportional gain $K_H = 0.675$ and $K_{iH} = 0.2$ rep/s, which is calculated to result in a closed loop time constant 50% higher than the process time constant, which represents a system with low natural excitation. The SP (output of C_H) is modified as presented in Section 5.3.

The valve stem position and diaphragm pressure measurements are considered corrupted by white noise, resulting in 25dB SNR. The valve flow rate set point, SP_Q , is considered a white noise signal with 60% mean, 0.25% standard deviation and a sampling time of 120 s, which represents a valve that does not exhibit rich information during normal operation (the worst case). The valve and friction parameters (plant) are the ones shown in Tables 3.1 and 3.2.

The valve deadband is estimated as presented in Algorithm 5.1 and the I/P model parameters are estimated as suggested in Section 5.2, using the valve with Karnopp friction model simulated data as the plant. The signals used for the estimation are presented in Figures 5.6 and 5.7, and the results are shown in Table 5.2. It is possible to verify that the I/P model parameter estimation performance is excellent. Despite the fact that the valve deadband estimation is much less precise, it is still tolerable, since the search space admits an error of 30% in this estimation.

Table 5.2 – Closed loop I/P and valve signature curve parameters estimation in the simulated case.

Parameter	Est. Error (%)
S_0	4.84
$\hat{P}_{\min}$	-0.12
$\hat{K}_{P_g}$	-0.02
$\hat{\tau}_{I/P}$	0.02

Figure 5.6 – Signals used to estimate the I/P model parameters and S_0 in the simulated closed loop case.

Source: from Author.

Figure 5.7 – Valve signature curve with only nonzero stem velocities used to estimate S_0 in the simulated closed loop case.

Source: from Author.

The signals used to estimate k , F_{init} and θ_f are shown in Figure 5.8. Note that the valve stem position does not deviate substantially.

Figure 5.8 – Signals used to estimate k , F_{init} and θ_f in the simulated closed loop case.

Source: from Author.

To estimate k and F_{init} , it is assumed that the parameters have deviated 10% from the original value and the friction parameters are perfectly known. The results are satisfactory, as can be seen in Table 5.3.

Table 5.3 – Friction parameters estimation test with simulated data results.

Model	Est. error (%)	
	$\hat{k}$	$\hat{F}_{\text{init}}$
Karnopp	-0.029	0.026
LuGre	-0.219	0.156
GMS	-0.139	0.132

Source: from Author.

Finally, to estimate θ_f , the k and F_{init} parameters are considered known. The estimation results are presented in Tables 5.4 to 5.8. The best performance is provided by the GMS model, even though the parameter estimation errors were high, which may indicate that the model is over-parameterized, since even the Karnopp model, with almost perfect estimates, is not able to reach the same efficiency. As for the LuGre model, the performance is fair and the estimation error is similar to the open loop simulated case. Finally, the Kano model has the lower prediction efficiency and presented high parameter errors, specially regarding J parameter, which is a pattern already observed, with less severity, in the open loop simulated case.

Table 5.4 – Closed loop friction parameter estimation test results with simulated data.

Model	fit (%)	Run Time (h)	Func. Evals.
Kano	98.19	0.43	7885
Karnopp	99.10	42.7	21922
LuGre	98.55	217.9	34887
GMS	99.49	312.7	97614

Func. Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 5.5 – Closed loop Kano parameter estimation error in a test with simulated data.

$\hat{S}$ (%)	$\hat{J}$ (%)	$\hat{D}$ (%)	$\hat{x}_{\min P}$ (%)	$\hat{x}_{\max P}$ (%)
-4.41	-98.12	-6.31	-0.03	-0.49

Source: from Author.

Table 5.6 – Closed loop Karnopp parameter estimation error in a test with simulated data.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)
-0.01	-0.01	-0.41	0.41

Source: from Author.

Table 5.7 – Closed loop LuGre parameter estimation error in a test with simulated data.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\sigma}_0$ (%)	$\hat{\sigma}_1$ (%)
-0.32	-0.16	0.64	1.73	17.60	-97.5

Source: from Author.

Table 5.8 – Closed loop GMS parameters estimation error, test with simulated data.

$\hat{F}_c$ (%)	$\hat{F}_s$ (%)	$\hat{F}_v$ (%)	$\hat{v}_s$ (%)	$\hat{\kappa}_1$ (%)	$\hat{\kappa}_2$ (%)	$\hat{\kappa}_3$ (%)
-16.83	-0.26	1.58	$1.55 \cdot 10^4$	-30.16	60.83	44.99
$\hat{v}_1$ (%)	$\hat{v}_2$ (%)	$\hat{v}_3$ (%)	$\hat{\alpha}_1$ (%)	$\hat{\alpha}_2$ (%)	$\hat{\alpha}_3$ (%)	$\hat{C}$ (%)
$2.00 \cdot 10^3$	$7.61 \cdot 10^3$	70.96	-27.53	112.48	-36.92	-88.17

Source: from Author.

5.5 Experimental Tests

The experimental data is obtained using the FPP presented in Chapter 2. The valve position controller, C_p , is a proportional gain with $K_p = 0.1$, as already discussed in Sections 5.4 and 5.3.

The hydraulic system dynamics is approximated by a first order plus dead time transfer function, estimated with data obtained using rectangular signal excitation, resulting in:

$$\frac{Q(s)}{x(s)} = \frac{-1.124}{1.815s + 1} e^{-0.14s}. \quad (5.64)$$

The hydraulic system controller, C_H , is calculated using the Direct Synthesis (DS) method, to result in a closed loop time constant response 50% slower than the open loop time constant, which is a PI controller with proportional gain $K_H = 0.564$ and integral gain $K_{iH} = 0.31$. The flow rate set point SP_Q is the same shown in Section 5.4.

The I/P model parameters and the valve deadband are estimated using the proposed method shown in Section 5.2 and Algorithm 5.1. The results are summarized in Table 5.9 and the signals used for the estimations are shown in Figures 5.9 to 5.11. Once again, the S_0 estimation precision is poor, however the search space is wide enough to accommodate such errors (note that the teflon deadband is lower than 2% and its error is negative). Note the different pattern in deviations from the open loop I/P model parameter estimation, regarding the graphite and teflon gasket valves, as the former presents better estimates for $P_{\min}$ and K_{P_g} , while the latter shows a better accuracy for τ_{I/P_r} . This happens because the graphite gasket takes longer to overcome the *exc* signal, resulting in an excitation signal that is similar to ramps, with only a few high velocity variations, whereas the teflon gasket valve is able to readily compensate *exc* and therefore the resulting excitation signal is approximately constant with a few spikes. These imprecisions do not influence significantly the friction estimation, as it is used only for designing the signal filters in the closed loop method. As the I/P converter is highly nonlinear, it is suggested that the filters use τ_{I/P_s} obtained in the open loop case, regardless of the new closed loop estimates, as the passband is wide enough. Also, the experimental findings indicate that the *fit* threshold has to be low in order to detect I/P model defects (e.g. lower than 50%).

Table 5.9 – Closed loop I/P model and S_0 parameter estimation deviation from the open loop case.

Parameter	Dev. Open Loop (%)	
	Graphite	Teflon
S_0	10.53	−32.31
$\hat{P}_{\min}$	0.34	−14.64
$\hat{K}_{P_g}$	−2.98	9.96
$\hat{\tau}_{I/P_r}$	−81.66	−11.76

Source: from Author.

Figure 5.9 – Signals used to estimate the graphite gasket valve I/P model parameters and S_0 .

Source: from Author.

Figure 5.10 – Signals used to estimate the teflon gasket valve I/P model parameters and S_0 .

Source: from Author.

Contrary to the closed loop parameter estimation in the simulated tests, in the experimental case, k and F_{init} parameters were estimated together with θ_f , as this scenario was not tested in the simulated tests.

The estimation performance and comparison to the open loop estimated parameters are presented in Tables 5.10 to 5.15. With respect to the graphite gasket valve, in general,

Figure 5.11 – Valves signature curves with only nonzero stem velocities used to estimate S_0 .

Source: from Author.

the *fit* value calculated using the validation dataset decreased roughly 2% for every model, when compared to the open loop estimated parameters, except for the Kano model, which has a similar *fit* index. It is interesting to note that the validation dataset has a *fit* index higher than the estimation dataset. This characteristic occurred because the *fit* index penalizes more rigorously the prediction errors that are close to the dataset mean value, which is the case of the estimation dataset, since it presents a low stem position standard deviation, as can be seen in the following subsection. The spring constant and the initial force were pretty consistent when compared to the open loop case. The Karnopp, LuGre and GMS model, presented a consistent decrease in the F_s value, whereas F_c and v_s varied without a visible pattern. It must be pointed out that pretty similar results can be obtained with several different combinations of F_c and v_s , as can be inferred from the Stribeck curve. The σ_1 from LuGre model, and κ_i , ν_i and α_i , from GMS model, also presented high deviations, however, these parameters have low influence in the overall valve behavior (as already discussed in Section 4.3). As previously observed in the open loop test, the Kano model presents a relevant underestimation of J parameter, as well as high deviations in S and D parameters. Note that a high $x_{\min P}$ deviation is not so relevant, as this value is close to zero.

Regarding the teflon gasket valve, the estimation performance in closed loop is excellent. The *fit* index using the validation dataset is very close to those obtained when the parameters are estimated in open loop, except for the Kano model, in which its *fit* index increased. This increase is explained by the fact that in closed loop, the maximum and minimum observed stem positions are estimated altogether with the friction parameters, improving the overall estimation performance. The huge closed loop parameter deviations from the open loop estimates are not alarming, as the teflon gasket valve has numerically small friction parameters, that do not affect substantially the overall stem

position prediction.

Table 5.10 – Closed loop graphite gasket valve model estimation performance.

Model	fit (%)	fit val. (%)	Run Time (h)	Func. Evals.
Kano	92.18	94.29	0.02	7037
Karnopp	93.29	94.80	56.21	32728
LuGre	93.16	94.90	93.51	45878
GMS	93.48	94.89	138.43	38193

fit val.: indicates to the fit index evaluated using the open loop validation dataset and Func.

Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 5.11 – Closed loop teflon gasket valve model estimation performance.

Model	fit (%)	fit val. (%)	Run Time (h)	Func. Evals.
Kano	98.18	98.69	0.04	15834
Karnopp	98.95	99.39	44.81	26288
LuGre	98.95	99.39	60.96	33862
GMS	98.95	99.39	161.40	49553

fit val.: indicates to the fit index evaluated using the validation dataset and Func. Evals.: refers to the number of objective function evaluations.

Source: from Author.

Table 5.12 – Closed loop Kano parameter estimation deviation from open loop tests.

	$\hat{S}$	$\hat{J}$	$\hat{D}$	$\hat{x}_{\min P}$	$\hat{x}_{\max P}$
Graphite (%)	-11.23	-99.89	-24.3	-42.86	-1.11
Teflon (%)	-96.17	-97.95	100.00	3.41	1.37

Source: from Author.

Table 5.13 – Closed loop Karnopp parameter estimation deviation from open loop tests.

	$\hat{k}$	$\hat{F}_{\text{init}}$	$\hat{F}_c$	$\hat{F}_s$	$\hat{F}_v$	$\hat{v}_s$
Graphite (%)	0.17	-1.91	-40.89	-7.2	-13.56	82.34
Teflon (%)	-0.06	-49.86	100.00	100.00	-83.77	-98.23

Source: from Author.

Table 5.14 – Closed loop LuGre parameter estimation deviation from open loop tests.

	$\hat{k}$	$\hat{F}_{\text{init}}$	$\hat{F}_c$	$\hat{F}_s$	$\hat{F}_v$	$\hat{v}_s$
Graphite (%)	-0.13	-1.48	-24.73	-6.87	-10.19	27.71
Teflon (%)	-0.06	-49.87	-27.61	-41.82	-99.49	$6.29 \cdot 10^5$

Model	$\hat{\sigma}_0$	$\hat{\sigma}_1$
Graphite (%)	5.58	147.1
Teflon (%)	-25.50	$7.02 \cdot 10^3$

Source: from Author.

Table 5.15 – Closed loop GMS parameter estimation deviation from open loop tests.

Model	$\hat{k}$	$\hat{F}_{\text{init}}$	$\hat{F}_c$	$\hat{F}_s$	$\hat{F}_v$	$\hat{v}_s$
Graphite (%)	0.33	-2.31	4.12	-7.61	41.45	-26.08
Teflon (%)	-0.06	-47.47	-3.36	11.41	-95.09	-65.48

Model	$\hat{\kappa}_1$	$\hat{\kappa}_2$	$\hat{\kappa}_3$	$\hat{\nu}_1$	$\hat{\nu}_2$	$\hat{\nu}_3$
Graphite (%)	13.13	-35.65	2.11	-90.77	-43.43	179.1
Teflon (%)	$1.81 \cdot 10^3$	-77.36	-96.03	$1.01 \cdot 10^3$	138.91	1.25

Model	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{C}$
Graphite (%)	-58.15	12767.66	20959.04	0.56
Teflon (%)	$2.79 \cdot 10^5$	$2.67 \cdot 10^3$	-4.26	-0.07

Source: from Author.

5.5.1 Graphite Gasket Model Prediction Analysis

The model predictions, using the closed loop estimated parameters, are compared to the estimation dataset (closed loop) and validation dataset (open loop), as presented in Figures 5.12 to 5.23. Visually, the Kano model has a slight higher residuals and the worst stem velocity prediction accuracy, as it presented stick and slip behavior, where it is not visible in the measured dataset. The other models presented pretty similar efficiency.

Figure 5.12 – Kano model graphite gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.13 – Karnopp model graphite gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.14 – LuGre model graphite gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.15 – GMS model graphite gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.16 – Kano model graphite gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.17 – Karnopp model graphite gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.18 – LuGre model graphite gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.19 – GMS model graphite gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.20 – Kano model graphite gasket valve stem velocity prediction (450 s to 600 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Figure 5.21 – Karnopp model graphite gasket valve stem velocity prediction (450 s to 600 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Figure 5.22 – LuGre model graphite gasket valve stem velocity prediction (450 s to 600 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Figure 5.23 – GMS model graphite gasket valve stem velocity prediction (450 s to 600 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

The correlation coefficient of some variables are presented in Table 5.16. The correlation coefficients between measured and simulated stem position and velocity are slightly lower for the Kano model, while the other models presented pretty similar results. In general, the stem position and velocity prediction accuracies are very good, for all models. The correlation coefficient between the residual and the simulated stem position and velocity can be considered appropriate, even though some models present higher values in certain cases.

Table 5.16 – Statistical measures of the graphite gasket valve prediction using parameters estimated in closed loop.

Model	$r(x, \hat{x})$	$r(e_x, \hat{x})$	$r(e_x, \hat{\dot{x}})$	$r(\hat{\dot{x}}, \dot{x})$
Kano	0.9971	-0.2145	0.4949	0.9481
Karnopp	0.9979	-0.2856	0.0146	0.9876
LuGre	0.9978	-0.2741	0.0111	0.9897
GMS	0.9981	-0.3216	-0.0165	0.9899

Model	$r(x, \hat{x})$ val.	$r(e_x, \hat{x})$ val.	$r(e_x, \hat{\dot{x}})$ val.	$r(\hat{\dot{x}}, \dot{x})$ val.
Kano	0.9989	0.3259	0.4978	0.9236
Karnopp	0.9993	0.4603	0.2781	0.9817
LuGre	0.9993	0.5044	0.2735	0.9820
GMS	0.9992	0.3993	0.2789	0.9812

val.: indicates to a statistical quantity calculated using the validation dataset.

Source: from Author.

5.5.2 Teflon Gasket Model Prediction Analysis

The model predictions, using the closed loop estimated parameters, are compared to the estimation dataset (closed loop) and validation dataset (open loop), as presented in Figures 5.24 to 5.35. It is possible to verify visually that the Kano model presented higher residuals at the beginning of the validation dataset, whereas the other models presented

very similar stem position prediction precisions. The Karnopp and LuGre models are the less precise for predicting the stem velocity, as the former has a stick-slip behavior and the latter has some spikes, that are not visible in the dataset.

Figure 5.24 – Kano model teflon gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.25 – Karnopp model tefflon gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.26 – LuGre model tefflon gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.27 – GMS model tefflon gasket valve residual with model parameters estimated in closed loop using the estimation dataset.

Source: from Author.

Figure 5.28 – Kano model tefflon gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.29 – Karnopp model tefflon gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.30 – LuGre model tefflon gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.31 – GMS model teflon gasket valve residual with model parameters estimated in closed loop using the validation dataset.

Source: from Author.

Figure 5.32 – Kano model teflon gasket valve stem velocity prediction (220 s to 300 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Figure 5.33 – Karnopp model teflon gasket valve stem velocity prediction (220 s to 300 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Figure 5.34 – LuGre model teflon gasket valve stem velocity prediction (220 s to 300 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Figure 5.35 – GMS model teflon gasket valve stem velocity prediction (220 s to 300 s) with model parameters estimated in closed loop using the open loop validation dataset.

Source: from Author.

Table 5.17 presents some statistical measures that are used to analyze the prediction precision of the teflon gasket valve model, when its parameters are estimated in closed loop. It is possible to verify that the stem prediction is excellent for every model and dataset. In the estimation dataset, one may note an increase in the correlation coefficient between the residuals and stem position, indicating that the estimation performance could be improved. The most precise models, with respect to the stem velocity prediction, are the Kano and GMS.

Table 5.17 – Statistical measures of the graphite gasket valve prediction using parameters estimated in closed loop.

Model	$r(x, \hat{x})$	$r(e_x, \hat{x})$	$r(e_x, \hat{\dot{x}})$	$r(\hat{\dot{x}}, \dot{x})$
Kano	0.99990	-0.6206	-0.0208	0.9596
Karnopp	0.99996	-0.4717	-0.0252	0.9329
LuGre	0.99996	-0.4720	-0.0264	0.9333
GMS	0.99996	-0.4748	0.0229	0.9595

Model	$r(x, \hat{x})$ val.	$r(e_x, \hat{x})$ val.	$r(e_x, \hat{\dot{x}})$ val.	$r(\hat{\dot{x}}, \dot{x})$ val.
Kano	0.99992	-0.1880	0.0258	0.9797
Karnopp	0.99998	-0.2665	0.0353	0.9702
LuGre	0.99998	-0.2514	0.0686	0.9632
GMS	0.99998	-0.2598	0.1025	0.9792

val.: indicates to a statistical quantity calculated using the validation dataset.

Source: from Author.

5.6 Valve Model Selection

The models presents very similar overall characteristics to predict the valve stem position, but each have singularities. In this section the results obtained so far are discussed and a valve model is selected for the rest of this work.

The Kano model is very sensitive to noise, because it has a flat passband, responding to every excitation frequency (limited by the model sampling time), as seen in Figure 4.20. If the Kano model has slip band, then it is inevitable that it presents stick-slip behavior if the excitation signal has noise. This is undesirable, since it may affect negatively the C_p design, as the slip band is a major player in inducing control loops limit cycles (MOHAMMAD; HUANG, 2012). The great advantage of using Kano model is the computational efficiency.

The Karnopp model presents an overall good stem position prediction, but it may predict a stick-slip behavior when it is not present in the plant. Although the Karnopp model holds the good stem velocity prediction indexes, visually some imprecisions can be seen even in simple cases (with low friction index), as shown in Figure 5.21. Therefore, the same drawback regarding C_p design with Kano model is applied to the Karnopp model. This drawback, however, has less severity for the Karnopp model, since there are parameter combinations that may eliminate the stick-slip behavior. One Karnopp model advantage

is the possibility to use a higher time step than LuGre and GMS models, improving the computational efficiency, however, it would deteriorate even more the stick-slip prediction accuracy.

The LuGre model is very precise to model pneumatic diaphragm valves when the excitation signal is filtered and with high signal to noise ratio. However, this model has a high risk of presenting terrible predictions if the input signal is deteriorated, as seen in Figure 4.21. It is prohibitive to use a model which has an increased mathematical complexity, when compared to the Kano and Karnopp models, that may fail if some combination of events happen.

The GMS model is very precise in every experimental tests that were carried out, but its high number of parameters, some of them with extremely low sensitivity for the stem position prediction, prevents a perfect estimation even in the ideal case. Also, estimating this model parameters is the most time consuming, among the tested models. It is worth mentioning, though, that the computational performance can be greatly improved by using Field Programmable Gate Array (FPGA) and fixed point calculations. It is possible to simulate 1 ms with one FPGA clock, which is around 100 MHz. Therefore, a 30 min simulation would take 0.018 s, which is significantly lower than the needed 50 s to simulate using a personal computer.

The selected models, to be used for the automatic friction compensation part of this thesis, are the Kano, Karnopp and GMS models. The Kano model certainly has its limitations, however, so does the Karnopp and LuGre models, therefore it is reasonable to select the most computationally efficient model among these three. The Karnopp model is selected as it has consistent estimation performance and has better predictions than the Kano model. With respect to the GMS model, it is selected as it has pretty good stem position and velocity prediction precision and it is robust with respect to diaphragm pressure measurement noise. In the following developments of this thesis, it will be possible to verify if the added precision of the GMS model produces more efficient valve position controllers, when compared to the Kano and Karnopp models.

6 Automatic Friction Compensation

In this chapter, the estimated valve models obtained in Chapters 4 and 5 are used in an Adaptive Inverse Control (AIC) framework, where the control system parameters are tuned using an optimization algorithm that runs offline, as presented in Figure 6.1. The idea is to tune the C_p parameters so that the plant has the same closed loop response as the reference model.

Figure 6.1 – Adaptive Inverse Control framework example for the diaphragm valve position controller tuning.

Source: based on Widrow and Walach (2008).

If the plant corresponds to a stable linear time invariant system, then Widrow and Walach (2008) show that it is possible to invert the plant dynamics using a Finite Impulse Response Filter, with parameters tuned using the Recursive Least Squares algorithm. However, if the plant is nonlinear, then there is not a fixed generic structure that is able to deliver a controller that can approximate any plant to the desired closed loop response (x_d). Widrow and Walach (2008) suggest that, for nonlinear systems, the controller can be a Volterra filter or a neural network, however, as there are many control structures that were suggested in the friction compensation literature, some of these compensators are employed instead.

6.1 The AIC framework

One aspect that is very important to construct a good AIC framework is to select a proper reference model, in a sense that the valve model is able to exhibit such output response with C_p . In the diaphragm control valve case, the reference model is easily derived, as the plant does not present any substantial dead time and it is a stable system. The reference model is designed to be a first order filter of the excitation signal, as it is not desirable that the valve presents any movement reversal, since it would mean that C_p would have to overcome the friction force more than once to reach the desired response. The first order filter time constant is chosen to be 50% lower than the I/P model time constant. This choice is based on the trade-off between a fast valve response and the control effort, as faster desired valve responses mean higher control efforts.

The excitation signal is also very important to obtain a good C_p tuning. It has to present the characteristics in which the controller is expected to perform during its regular operation. As the diaphragm valve with digital positioner is a cascade control loop, the excitation signal is rather stochastic and depends on how the hydraulic system and C_H are designed. Therefore, the excitation signal is a series of random ramps (commonly found in integrative controllers) and steps. The ramp velocities, $v_{exc C_p}$, is given by a Gaussian random variable, with a standard deviation of:

$$\text{std}(v_{exc C_p}) = \frac{50}{5 \hat{\tau}_{I/P}}, \quad (6.1)$$

with zero mean and a sampling time of:

$$T_{v_{exc C_p}} = \frac{S_0/2}{\text{std}(v_{exc C_p})}. \quad (6.2)$$

The steps have a mean value of 50% and a standard deviation of $0.1 S_0$. Additionally, the excitation signal is kept constant for 200 seconds at the end of this aleatory excitation signal, so that the limit cycles can be mitigated by C_p . Figure 6.2 presents an example of excitation signal for $S_0 = 24$ and the respective desired stem position x_d . Notice that this excitation signal forces many movement reversals, which is the worst case that has to be compensated by C_p .

Figure 6.2 – Example of the excitation signal used to obtain the optimal parameters of C_p .

Source: from Author.

Another important characteristic regarding the AIC framework is to select a cost function. Even though Figure 6.1 shows that only the difference between the simulated and the desired stem positions is used to tune C_p , in practice this is not desirable, since it may lead to extremely high control efforts or an attempt to vigorously correct any measurement noise that the sensors may present. Therefore, the AIC cost function used in this work encompass the control effort as well, which is usual for many optimal control techniques:

$$J_C(\theta_p) = \sum_{n=1}^{n_f} g_x \left(\hat{x}(n, \theta_p) - x_d[n] \right)^2 + g_u \left(\hat{O}P[n-1] - \hat{O}P[n] \right)^2 + \text{pen}(\theta_p), \quad (6.3)$$

where θ_p is the C_p parameter vector, g_x is the stem position deviation gain, g_u is the controller output difference gain and $\text{pen}(\theta_p)$ is a function used to force the optimization to be inside a predefined search space, that is implemented as presented in Chapter 4. The values of g_x and g_u were selected empirically as 1 and 0.1, respectively, which tends to result in a controller tuning that follows the desired dynamics regardless the control effort. The optimal controller tuning, θ_p^* , is calculated as:

$$\theta_p^* = \arg \min_{\theta_p} J_C(\theta_p). \quad (6.4)$$

The optimization algorithm used to obtain the minimum of $J_C(\theta_p)$ is the same used to estimate the friction parameters in Chapter 4, the GDES.

Additionally, the stem position measurement noise is simulated in the AIC framework as an additive Gaussian random variable with zero mean and a variance that results in a SNR of 25 dB.

The controller sampling time is potentially different from the integration time of the valve model, therefore, the AIC framework has to account for this difference, by using a zero order hold in the C_p output. In this work, the controller sampling time is 20 ms, as it is not possible to obtain lower values with the current hardware configuration of the FPP.

6.2 A First Test with PID control

The PID controller is defined as:

$$\begin{aligned}
 P_{C_p}[n] &= K_p \hat{e}[n] \\
 I_{C_p}[n] &= K_i \frac{T_{s_{C_p}}}{2} (\hat{e}[n] + \hat{e}[n-1]) + I_{C_p}[n-1] \\
 D_{C_p}[n] &= \frac{K_d (\hat{x}[n] - \hat{x}[n-1]) + \tau_{df} D_{C_p}[n-1]}{\tau_{df} + T_{s_{C_p}}} \\
 \hat{O}P[n] &= P_{C_p}[n] + I_{C_p}[n] + D_{C_p}[n],
 \end{aligned} \tag{6.5}$$

where $\hat{e}[n] = ES[n] - \hat{x}[n]$, ES is the AIC framework excitation signal (or SP in the practical applications), $T_{s_{C_p}} = 20$ ms is the controller sampling time and a back calculation technique is used to ensure that the integral action, $I_{C_p}[n]$, stops integrating errors outside the actuator range. The PID controller parameter search space is presented in Table 6.1.

Table 6.1 – PID controller parameter search space.

Parameter	ub_d	lb_d
K_p	50	0.1
K_i	$10/\hat{\tau}_{I/P}$	0
K_d	$10 \hat{\tau}_{I/P}$	0
τ_{df}	$100 \hat{\tau}_{I/P}$	0

This test is performed using the graphite gasket valve with estimated valve model as presented in Chapters 4 and 5. Unlike the algorithms to estimate the parameters of valve and friction models, the I/P model time constant is very important when tuning the valve position controller, as it may be the system dominant time constant. Thus, in this test, the controllers are tuned using open and closed loop estimated Kano, Karnopp and GMS valve models. Even though the closed loop estimated valve model has only one numerical value for the I/P model time constant, the open loop estimated models have the possibility to use the step or ramp ($\hat{\tau}_{I/P_s}$ and $\hat{\tau}_{I/P_r}$) I/P model estimated time constants. Table 6.2 presents the optimal PID parameter tuning for each estimated valve model. Notice that the optimal tuning varies greatly, depending on the estimated valve model and the I/P model time constant used in the AIC framework.

Table 6.2 – PID tunings for each estimated model used in the AIC framework.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*
Kano OL, $\hat{\tau}_{I/P_r}$	5.9	11.3	4.2	2.9
Kano OL, $\hat{\tau}_{I/P_s}$	5.8	9.4	9.1	3.1
Kano CL	4.0	14.2	2.3	1.9
Karnopp OL, $\hat{\tau}_{I/P_r}$	8.8	22.7	4.2	1.3
Karnopp OL, $\hat{\tau}_{I/P_s}$	6.9	8.7	9.3	3.4
Karnopp CL	7.0	11.9	0.6	0.1
GMS OL, $\hat{\tau}_{I/P_r}$	7.1	15.5	4.2	2.5
GMS OL, $\hat{\tau}_{I/P_s}$	6.3	7.0	8.8	3.9
GMS CL	5.2	16.3	2.3	1.3

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

The hydraulic circuit controller, C_H , is a PI, with proportional gain $K_H = 0.564$ and integral gain $K_{iH} = 0.31$, calculated as presented in Section 5.5.

For each PID tuning, three tests are performed: a servo, a regulatory and an aleatory. The servo test consists in maintaining SP_Q constant at a given value and modifying it using a step function at 300 s and 600 s. In the regulatory test, the SP_Q is kept constant during the test, but the perturbation valve (FY-13) position is modified at 300 s and 600 s, using a step function. In the aleatory test, SP_Q is modified using a stream of aleatory velocity ramps, similar to the excitation signal used to obtain the optimal C_p parameters, and it is maintained constant at the last 300 seconds of the test. Some examples are presented in Figures 6.3 to 6.5.

Figure 6.3 – Servo test example, using the PID controller tuned with the Kano OL and τ_{I/P_r} estimated model.

Source: from Author.

Figure 6.4 – Regulatory test example, using the PID controller tuned with the Karnopp OL and τ_{I/P_s} estimated model.

Source: from Author.

Figure 6.5 – Aleatory test example, using the PID controller tuned with the GMS CL estimated model.

Source: from Author.

Note that in every test it is possible to observe that the hydraulic circuit flow rate (Q) presents limit cycle. When using cascaded control loops, which is the case when using a digital positioner, the system tends to be more oscillatory in presence of high friction, as can be seen in the works of Hidalgo and Garcia (2017) and Baeza and Garcia (2018). This happens due to an accumulation of errors between the cascaded controller integrators, which makes it very difficult to eliminate the limit cycles in such systems by tuning C_p only.

For comparison purposes, a first order plus dead time model is estimated for the valve, using a step excitation signal, resulting in the following transfer function, in the Laplace domain:

$$\frac{OP(s)}{x(s)} = \frac{0.8243}{1.073s + 1} e^{-0.56s}. \quad (6.6)$$

Applying the DS method to obtain a closed loop time constant 50% faster than the model time constant, a PI controller is calculated as $K_p = 1.2$ and $K_i = 1.1$.

To compare the tuning performance, it is possible to calculate the integral absolute flow rate error (iae_Q) and stem position error (iae_x) indexes, that are defined as:

$$\text{iae}_Q = \sum_{n=0}^{n_f} |\text{SP}_Q[n] - Q[n]| \quad (6.7)$$

$$\text{iae}_x = \sum_{n=0}^{n_f} |\text{SP}[n] - x[n]|. \quad (6.8)$$

Grouping the experiment performance indexes into types of estimated models used in the AIC framework, it is possible to create a box plot, as presented in Figure 6.6. It is possible to verify that it is more likely to obtain better results when the open loop estimated valve model with $\hat{\tau}_{I/P_r}$ or the closed loop estimated valve model are used in the AIC framework. When $\hat{\tau}_{I/P_s}$ is used in the open loop estimated valve model, the tunings tend to be worst. The DS tuned PI controller performances are not shown, as its lower indexes are $\text{iae}_Q = 110421$ and $\text{iae}_x = 107265$, much higher than any PID tuned using the AIC framework.

(a) Comparison of the iae_Q .

(b) Comparison of the iae_x .

Figure 6.6 – Comparison of the tuning performance of the AIC method in the initial PID test, grouping data by model estimation type.

Source: from Author.

The comparison of performance between the estimated valve models used in the AIC framework are presented in Figures 6.7 to 6.9, where the controller output standard deviation index, $\text{std}(\text{OP})$, is introduced, which is calculated over periods of the experiment in which the SP_Q is maintained stable, therefore it indicates whether the control loop has a limit cycle, as this index should be close to zero when SP_Q is kept constant. It is possible to verify that the PID tuning has the best overall performance when open loop estimated Karnopp model is used together with $\hat{\tau}_{I/P_r}$, in the AIC framework. The GMS model, however, holds the best indexes when the valve model parameters are estimated in closed loop. From the performance indexes, it is possible to verify that the GMS model is pretty consistent with the friction parameters estimated either in closed or open loop, provided that the $\hat{\tau}_{I/P_r}$ time constant is used in the open loop valve model.

Figure 6.7 – Comparison of iae_Q , among the estimated friction models.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.8 – Comparison of iae_x , among the estimated friction models.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.9 – Comparison of $std(OP)$, among the estimated friction models.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

For a time domain performance comparison, an extract of the aleatory experiment

is presented in Figures 6.10 and 6.11. Note that even though the numerical performance indexes indicate differences among the tunings, the time domain comparison presents very similar responses, with a few visual differences.

Figure 6.10 – Aleatory experiment extract using PID tuned with open loop estimated Karnopp and GMS models in the AIC framework (with $\hat{\tau}_{I/P_r}$ as the I/P model time constant).

Source: from Author.

Figure 6.11 – Aleatory experiment extract using PID tuned with open loop estimated Kano and GMS models in the AIC framework (with $\hat{\tau}_{I/P_r}$ as the I/P model time constant).

Source: from Author.

6.3 A Robustness Test

As the I/P model time constant seems to play a major role regarding the controller performance, some tests are carried out to verify if the proposed AIC framework is able to deliver good controllers even if τ_{I/P_s} is used for the I/P model time constant, and yet it is assumed that this parameter is estimated with a +100% error.

In this test, besides the PID controller, some other usual friction compensation techniques are used as well, such as the control freezing, the knocker, the constant reinforcement and the fuzzy PID controller, which are described in the following subsections.

The DS calculated PI controller is adjusted accordingly, to simulate a +100% error in the valve transfer function time constant estimation, resulting in: $K_p = 1.59$ and $K_i = 0.741$.

6.3.1 The Control Freezing Algorithm (CF)

In this method, the controller output is kept equal to the last value if the absolute error ($|\hat{e}[n]|$) is lower than e_l for t_{e_l} seconds and the controller starts to update its output again if the absolute error is higher than e_h for t_{e_h} seconds (SILVA; GARCIA, 2014). In this work, the algorithm is slightly modified, as only the integral action and the friction compensator algorithm of the controller are disabled, instead of freezing the controller output. This method is used together with a regular PID controller and it is intended to eliminate the control loop limit cycles.

These parameters are suggested to be tuned as $e_l = e_h = 0.5$, $t_{e_l} = 10$ s and $t_{e_h} = 2$ s (SILVA; GARCIA, 2014). However, after some empirical tests, it was verified that for the FPP, the best results are obtained by using $e_l = e_h = 1$.

The search space of the CF algorithm parameters, used in the AIC framework, is defined in Table 6.3. The negative lower bound of the e_l and e_h parameters is used to allow searching for tunings in which the CF algorithm is disabled.

Table 6.3 – CF method parameter search space.

Parameter	ub_d	lb_d
e_l	10	-1
e_h	10	-1
t_{e_l}	20	0
t_{e_h}	20	0

6.3.2 The Knocker Compensator

This compensator idea is to add or subtract a high frequency signal to the PID output, so that the friction force can be overcome without influencing significantly the control loop. The Knocker compensator signal has a period, t_{k_p} , a duty cycle, d_{k_p} and an amplitude, a_{k_n} . The suggested values for these parameters are $t_{k_p} = 5T_{s_{C_p}}$ s, $d_{k_p} = 0.4$ and $a_{k_n} = S_0/2$ (SILVA; GARCIA, 2014). In this work, the Knocker compensator is used combined with the PID and the CF algorithm.

The selection between adding or subtracting the Knocker signal to the controller output is determined by the equation:

$$\text{sig}_k = \text{sgn} \left(\hat{\text{OP}}[n] - \hat{\text{OP}}[n - t_{k_p}/T_{s_{C_p}}] \right), \quad (6.9)$$

such that if sig_k is positive, then the compensator signal is added to the PID output and if sig_k is negative, the compensator signal is subtracted, instead.

The search space of the Knocker compensator, used in the AIC framework, is presented in Table 6.4.

Table 6.4 – CF method parameter search space.

Parameter	ub_d	lb_d
t_{k_p}	$\hat{\tau}_{I/P}$	0
d_{k_p}	1	0
a_{kn}	100	0

6.3.3 The Constant Reinforcement Compensator (CR)

This compensator is simpler than the Knocker, as it simply adds or subtracts a constant from the PID controller output, such that the valve deadband can be neglected when tuning the PID controller. The only parameter of this algorithm is a constant, which is usually suggested as $a_{CR} = S_0/2$ (SILVA; GARCIA, 2014). Similarly to the Knocker, this compensator is used together with the PID and the CF algorithm.

The addition or subtraction of the CR signal constant to the PID output is calculated as:

$$\text{sig}_{CR} = \text{sgn} \left(\hat{\text{OP}}[n] - \hat{\text{OP}}[n - 1/T_{s_{C_p}}] \right), \quad (6.10)$$

where a_{CR} is added to the PID output if sig_{CR} is positive, and subtracted if sig_{CR} is negative.

The search space of this compensator parameter is: $a_{CR} \in [0, 100]$.

6.3.4 The Fuzzy PID Controller

This method idea is to have a PID controller with an integral gain that varies using fuzzy logic, as developed by Mishra, Kumar and Rana (2014). Since the limit cycles are generated by the integral action of the controllers, then the fuzzy logic may mitigate the limit cycle amplitude, by reducing the integral gain when the control loop error is low. This controller has two membership functions, to determine whether the error and its rate of change are zero:

$$\begin{aligned} m_{ez}(\hat{e}) &= \exp \left(-\frac{\hat{e}^2}{2sd_{\hat{e}}^2} \right) \\ m_{rz}(\dot{\hat{e}}) &= \exp \left(-\frac{\dot{\hat{e}}^2}{2sd_{\dot{\hat{e}}}^2} \right). \end{aligned} \quad (6.11)$$

The corresponding membership functions that determine whether the variables are nonzero are calculated as:

$$\begin{aligned} m_{enz}(\hat{e}) &= 1 - m_{ez}(\hat{e}) \\ m_{rnz}(\dot{\hat{e}}) &= 1 - m_{rz}(\dot{\hat{e}}). \end{aligned} \quad (6.12)$$

The integral gain is defined by the following rules:

Rule 1: If $\hat{e}$ is nonzero and $\dot{\hat{e}}$ is nonzero, then $K_{fi} = K_{i_1}$;

Rule 2: If $\hat{e}$ is zero and $\dot{\hat{e}}$ is nonzero, then $K_{fi} = K_{i_2}$;

Rule 3: If $\hat{e}$ is nonzero and $\dot{\hat{e}}$ is zero, then $K_{fi} = K_{i_3}$ and

Rule 4: If $\hat{e}$ is zero and $\dot{\hat{e}}$ is zero, then $K_{fi} = K_{i_4}$.

The crisp integral gain is calculated using a T-norm:

$$K_{fi} = \frac{m_{enz} m_{r nz} K_{i_1} + m_{ez} m_{r nz} K_{i_2} + m_{enz} m_{rz} K_{i_3} + m_{ez} m_{rz} K_{i_4}}{m_{enz} m_{r nz} + m_{ez} m_{r nz} + m_{enz} m_{rz} + m_{ez} m_{rz}}, \quad (6.13)$$

and the PID output is calculated as presented in Eq. (6.5), but with an integral gain that varies (K_{fi}).

The suggested parameters of this controller are $sd_{\hat{e}} = 1$, $sd_{\dot{\hat{e}}} = 0.15$, $K_{i_1} = K_i$, $K_{i_2} = K_{i_4} = K_i/1000$ and $K_{i_3} = 1.1 K_i$. To avoid noise differentiation, the error rate of change is calculated using a first order filter with $\hat{\tau}_{I/P}$ time constant.

The search space of the fuzzy PID compensator, used in the AIC framework, is presented in Table 6.5. Note that the derivative and proportional terms search space is the same presented in Table 6.1.

Table 6.5 – Fuzzy PID controller parameter search space.

Parameter	ub_d	lb_d
$sd_{\hat{e}}$	50	0
$sd_{\dot{\hat{e}}}$	50	0
$K_{i_1}, K_{i_2}, K_{i_3}$ and K_{i_4}	$10/\hat{\tau}_{I/P}$	0

6.3.5 Robustness Test Results

For each controller, the AIC tuning is performed using each open loop estimated valve model, considering that the time constant of the I/P model is $2\hat{\tau}_{I/P_s}$. The tunings for each model and control structure are presented in Tables 6.6 to 6.10. Regarding the PID with CF control structure, note that when using the Karnopp model for the tuning, e_h is negative, which in practice disables the CF algorithm after t_{e_h} seconds, whatever is the controller error. With respect to the PID with CF and Knocker controller structure, it is interesting to note that the AIC framework tunes the a_{kn} parameter with a much lower value than what is suggested in the literature, which means that the Knocker compensation algorithm is almost disabled. In regard to the PID with CF and CR controller structure, when the Kano and Karnopp models are used, the proportional gain of the controllers is almost disabled and the CR amplitude is higher than what is suggested in the literature,

whereas when the GMS model is used, the CR action is almost disabled. As for the Fuzzy PID control structure, the proportional and derivative parameters are similar to the tunings obtained for the PID control structure, but the integral terms differ substantially when a different estimated valve model is used in the AIC framework.

Table 6.6 – PID tunings in the robustness test.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*
Kano	3.5	1.8	23.4	13.5
Karnopp	3.5	2.0	23.5	12.8
GMS	3.3	1.9	23.5	12.8

Source: from Author.

Table 6.7 – PID with CF tunings in the robustness test.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*	e_l^*	e_h^*	$t_{e_l}^*$	$t_{e_h}^*$
Kano	4.1	3.0	23.4	11.1	9.7	0.2	1.8	1.0
Karnopp	3.2	2.5	23.1	15.1	7.7	-0.2	1.4	1.1
GMS	5.3	3.8	22.8	12.3	2.6	2.4	0.2	1.9

Source: from Author.

Table 6.8 – PID with CF and Klocker friction compensation tunings in the robustness test.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*	e_l^*	e_h^*	$t_{e_l}^*$	$t_{e_h}^*$	$t_{k_p}^*$	$d_{k_p}^*$	a_{kn}^*
Kano	3.0	1.1	3.3	9.4	3.1	1.8	0.002	0.1	1.7	0.4	4.9
Karnopp	5.8	4.2	21.2	11.9	9.4	1.1	2.0	2.2	1.0	0.01	1.0
GMS	5.0	4.2	23.1	14.3	2.2	2.5	0.08	2.2	0.2	0.5	1.7

Source: from Author.

Table 6.9 – PID with CF and CR friction compensation tunings in the robustness test.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*	e_l^*	e_h^*	$t_{e_l}^*$	$t_{e_h}^*$	a_{CR}^*
Kano	0.1	0.4	1.8	101.8	0.9	0.8	0.09	0.2	22.9
Karnopp	0.4	0.4	1.1	37.0	2.9	0.8	9.9	0.3	19.6
GMS	5.44	4.2	23.1	11.6	3.2	3.2	0.5	2.0	0.001

Source: from Author.

Table 6.10 – Fuzzy PID tunings in the robustness test.

Model	K_p^*	K_d^*	τ_{df}^*	$K_{i_1}^*$	$K_{i_2}^*$	$K_{i_3}^*$	$K_{i_4}^*$	$sd_{\hat{e}}^*$	$sd_{\hat{e}}^*$
Kano	3.85	21.9	11.6	0.3	0.4	1.9	0.02	0.9	13.5
Karnopp	3.24	23.3	16.0	3.2	1.6	4.2	0.9	9.7	0.7
GMS	3.51	23.4	14.7	1.0	4.1	2.9	0.01	2.4	1.3

Source: from Author.

The performed tests are the same ones presented in Section 6.2. Figure 6.12 shows the performance comparison, using box plot, grouping the results of the methods used to

tune the controllers parameters. In general, the AIC tuning provides better performances than the DS method. However, there are two outliers, with excellent results, when using the DS method, that are given by the PID with CF and CR controller structure.

Figure 6.12 – Comparison of tuning performance using DS or AIC methods, in the robustness test.

Source: from Author.

A performance comparison among the estimated valve models used in the AIC framework is presented in Figure 6.13. The GMS model tends to present better performances regarding the iae_Q and $std(OP)$ indexes, whereas the Kano and Karnopp models tend to perform better regarding iae_x . The Karnopp $std(OP)$ index indicates that the tuned controllers using the Karnopp friction model are more likely to result in loops that are more oscillatory than with the other models.

Figure 6.13 – Comparison of the AIC tuning performance when using different estimated models, in the robustness test.

Source: from Author.

The iae_Q index comparison when using different friction models in the AIC framework, grouped by experiment type, is shown in Figure 6.14. The controller tunings are

more likely to present better results when using the GMS friction model in AIC framework, however, the Kano and Karnopp result in very good tunings (shown as outliers), even better than when the GMS model is used, when the C_p is the PID with CF and CR.

(a) Comparison of the iae_Q , in the servo experiment. (b) Comparison of the iae_Q , in the regulatory experiment. (c) Comparison of the iae_Q , in the aleatory experiment.

Figure 6.14 – Comparison, for each experiment, of the friction models tuning performance, in the robustness test.

Source: from Author.

A performance comparison among the different control structures and compensators used in this test, for each estimated valve model used in the AIC framework, is presented in Figures 6.15 to 6.20. Once more, it is possible to verify that when the GMS model is used for tuning the controllers in the AIC framework, the results are more consistent, even though the best overall performances are from the Kano and Karnopp models, using the PID with CF and CR friction compensation. When the Karnopp model is used, it results in the highest $\text{std}(\text{OP})$ indexes. In general, the PID with CF and CR controller presents very good performance indexes.

Figure 6.15 – Comparison of the iae_Q index, using the GMS model in the AIC framework, for each controller, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.16 – Comparison of the iae_Q index, using the Kano model in the AIC framework, for each controller, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.17 – Comparison of the iae_Q index, using the Karnopp model in the AIC framework, for each controller, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.18 – Comparison of the $std(OP)$ index, using the GMS model in the AIC framework, for each controller, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.19 – Comparison of the std(OP) index, using the Kano model in the AIC framework, for each controller, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.20 – Comparison of the std(OP) index, using the Karnopp model in the AIC framework, for each controller, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

A comparison between the AIC and DS tuning methods are presented in Figures 6.21 to 6.23. In general, the DS method produces tunings that perform poorer when compared to the AIC tuning method, however, the PID with CF and CR is an exception, as the DS tuning method outperforms the AIC method in the regulatory experiment. Notice that even though using the GMS model produces very consistent tunings, with better overall indexes in many experiments, it is outperformed by the Karnopp and Kano models when the PID with CF and CR controller structure is used.

Figure 6.21 – AIC and DS tuning performance comparison of the PID and PID with CF control structures, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.22 – AIC and DS tuning performance comparison of the PID with CF and Klocker, and the PID with CF and CR, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.23 – AIC and DS tuning performance comparison of the fuzzy PID control structure, in the robustness test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

An extract of the aleatory experiment, using the PID with CF and CR controller structure, is presented in Figures 6.24 and 6.25. Note that this is the controller structure in which when the Kano and Karnopp friction models are used in the AIC framework, the performance is better than when the GMS friction model is used.

Figure 6.24 – Extract of the aleatory experiment using the PID with CF and CR friction compensation, tuned with the Karnopp and GMS models.

Source: from Author.

Figure 6.25 – Extract of the aleatory experiment using the PID with CF and CR friction compensation, tuned with the Kano and GMS models.

Source: from Author.

6.4 Test of the Sliding Mode Control and of the Feedforward PID with Integral Deadband Structure

In this test, the best control structure so far, the PID with CF and CR, is compared to two other control structures, the Integrative Sliding Mode Control (ISMC) and the Feedforward PID with Integral Deadband controller, which are defined in the following subsections.

6.4.1 The Integrative Sliding Mode Control (ISMC)

The ISMC control design starts by the definition of a sliding surface, that in the case of the diaphragm control valve, considering that the I/P converter can be modeled by

a gain, is:

$$s_{ismc}(t) = \dot{\tilde{x}}(t) + 2\lambda_{ismc}\tilde{x}(t) + \lambda_{ismc}^2 \int_{t_0}^t \tilde{x}(t) dt, \quad (6.14)$$

where $\tilde{x}(t) = \hat{x}(t) - \text{ES}(t)$, $\text{ES}(t)$ is the excitation signal of the AIC framework (or SP for the real valve control system) and λ_{ismc} is a control parameter that defines how fast the stem position tracking error, $\tilde{x}$, decays to zero, given that the system reaches the sliding surface. Taking the time derivative of Eq. (6.14), using the valve model from Eq. (3.1) and neglecting the spring initial force, one obtains:

$$\dot{s}_{ismc}(t) = \left(\frac{S_a K_{P_g}}{m} \hat{\text{OP}}(t) - \frac{k}{m} \hat{x}(t) - \frac{F_f(t)}{m} - \ddot{\text{ES}}(t) \right) + 2\lambda_{ismc}\dot{\tilde{x}}(t) + \lambda_{ismc}^2 \tilde{x}(t). \quad (6.15)$$

Then, a control law can be defined to ensure that the sliding surface is attractive. The most straightforward structure that can be used is the feedback linearization:

$$\begin{aligned} \hat{\text{OP}}(t) = \frac{\hat{k} \hat{x}(t) + \hat{F}_f(t)}{\hat{S}_a \hat{K}_{P_g}} + [\ddot{\text{ES}}(t) - 2\lambda_{ismc}\dot{\tilde{x}}(t) + \lambda_{ismc}^2 \tilde{x}(t)] \frac{\hat{m}}{\hat{S}_a \hat{K}_{P_g}} - \\ k_{ismc}(\hat{x}, \dot{\hat{x}}) \text{sat} \left(\frac{s_{ismc}}{\Phi_{ismc}} \right), \end{aligned} \quad (6.16)$$

where $k_{ismc}(\hat{x}, \dot{\hat{x}})$ is a gain that may vary with the stem position and velocity, Φ_{ismc} is used to build a dead zone around the sliding surface, to avoid chattering, and the saturation function is defined as:

$$\text{sat} \left(\frac{s_{ismc}}{\Phi_{ismc}} \right) = \begin{cases} 1, & \text{if } s_{ismc}/\Phi_{ismc} > 1 \\ -1, & \text{if } s_{ismc}/\Phi_{ismc} < -1 \\ s_{ismc}/\Phi_{ismc}, & \text{otherwise.} \end{cases} \quad (6.17)$$

To ensure that the created sliding surface is an attractor, the following equation has to be true:

$$\frac{1}{2} \frac{ds_{ismc}^2}{dt} < -\nu_{ismc} |s_{ismc}|, \quad (6.18)$$

where ν_{ismc} defines how fast the system reaches the sliding surface. Using Eq. (6.18) criterion, the sliding surface time derivative, Eq. (6.15), the control law, Eq. (6.16), and selecting a proper value for ν_{ismc} , one can derive analytically the value of $k_{ismc}(\hat{x}, \dot{\hat{x}})$, to ensure that the sliding surface is an attractor. Yet, if the mismatch between the plant and the model can be estimated ($\max(|F_f - \hat{F}_f|)$, for example), it can be used to ensure that the controller is robust with respect to the model inaccuracies. However, the AIC framework is used to tune the controller, instead of calculating the ISMC parameters using mathematical analysis, as the valve model, in the AIC framework, is considered a very good approximation of the real valve behavior. Yet, in this work, the ISMC gain, k_{ismc} , is considered constant.

The valve model parameters used in the ISMC control law are the ones estimated in Chapters 4 and 5. The friction model, however, is a simplified Stribeck curve, which is frequently employed to compensate diaphragm control valve friction, defined as (KAYIHAN; DOYLE III, 2000; HIDALGO; GARCIA, 2017; BAEZA; GARCIA, 2018):

$$\hat{F}_f(\dot{\hat{x}}) = \left[\hat{F}_c + (\hat{F}_s - \hat{F}_c) \exp \left\{ -(\dot{\hat{x}}/\hat{v}_s)^2 \right\} \right] \tanh(10000 \dot{\hat{x}}) + \hat{F}_v \dot{\hat{x}}. \quad (6.19)$$

The Stribeck curve parameters are given by the estimated friction model used in the AIC framework, when the Karnopp and GMS models are used. Instead, if the Kano model is used, then $\hat{F}_v = 0$ Ns/m and $\hat{v}_s = 10^{-6}$ m/s and the Coulomb and static friction parameters are calculated using the Kano parameters, as presented in Section 3.3.

Besides the ISMC parameters, k_{ismc} , λ_{ismc} and Φ_{ismc} , the control law relies on estimating the stem velocity, as shown in Eq. (6.16), which is calculated using a backward differentiation of the filtered stem position using a low pass first order filter, whose passband ($1/\tau_{ismc}$ rad/s) is also tuned using the AIC framework. It is worth mentioning that the valve set point has to be twice differentiable, therefore, it is filtered using a second order low pass filter, with unitary relative damping and natural frequency equal to $2/\hat{\tau}_{I/P}$ rad/s. The search space of the ISMC controller structure is presented in Table 6.11.

Table 6.11 – ISMC parameter search space.

Parameter	ub_d	lb_d
k_{ismc}	2000	1
λ_{ismc}	2000	10^{-3}
Φ_{ismc}	1	10^{-4}
τ_{ismc}	$\hat{\tau}_{I/P}$	$\hat{\tau}_{I/P}/100$

6.4.2 The Feedforward PID with Integral Deadband (FFPID) Controller

This control structure uses the same PID defined in Section 6.2, however, its integral action has a deadband, where only absolute errors higher than a certain threshold ($e_{I_{th}}$) are integrated. The integral deadband is widely used in the industry to reduce the control loop variability. Therefore, the integral term of the PID, defined in Eq. (6.5), is redefined to:

$$I_{C_p}[n] = \begin{cases} K_i \frac{T_s}{2} (\hat{e}[n] + \hat{e}[n-1]) + I_{C_p}[n-1] & , \text{ if } |\hat{e}[n]| > e_{I_{th}} \\ I_{C_p}[n-1] & , \text{ otherwise.} \end{cases} \quad (6.20)$$

The feedforward term is a function of ES, that is added directly to the PID output. As the valve model is known, it is possible to calculate the diaphragm pressure that is necessary to reach the desired ES[n]:

$$\hat{P}_{ff}[n] = \frac{1}{\hat{S}_a} \left[\hat{k} \text{ES}[n] + \hat{F}_f(n, \dot{\text{ES}}) + \hat{F}_{\text{init}} + \hat{m} \ddot{\text{ES}}[n] \right]. \quad (6.21)$$

As the friction models have some internal states that are hard to be estimated in practice, once more the friction force is modeled using the Stribeck curve:

$$\hat{F}_f(\dot{E}S[n]) = \left[\hat{F}_c + (\hat{F}_s - \hat{F}_c) \exp \left\{ - (\dot{E}S[n]/\hat{v}_s)^2 \right\} \right] \text{sgn}(\dot{E}S[n]) + \hat{F}_v \dot{E}S[n]. \quad (6.22)$$

As in the practical application the set point is given by C_H , it may propagate noise from the hydraulic controlled variable measurement system, then ES is filtered using a first order low pass filter with $5/\hat{\tau}_{I/P}$ rad/s passband. The normalized feed forward value, $\hat{O}P_{ff}[n]$, is easily derived from $\hat{P}_{ff}[n]$, considering that the I/P converter has instantaneous response:

$$\hat{O}P_{ff}[n] = \left(\frac{\hat{P}_{ff}[n]}{\hat{S}_a} - \hat{P}_{\min} \right) \frac{1}{\hat{K}_{P_g}} k_{ff}, \quad (6.23)$$

where k_{ff} is the feedforward gain, that is used to compensate some inaccuracies that the feedforward model has, such as the assumptions that the friction force can be modeled by the Stribeck curve and the I/P model instantaneous response.

The search space of the FFPID parameters is presented in Table 6.12, and as this structure is based on the PID controller, the search space shown in Table 6.1 is also applicable to the FFPID.

Table 6.12 – FFPID parameter search space.

Parameter	ub_d	lb_d
$e_{I_{th}}$	0.5	0
k_{ff}	1	0.5

6.4.3 Test Results

For each controller, the parameters are tuned using the AIC framework, using the open and closed loop estimated valve model. Unlike the PID tests, only $\hat{\tau}_{I/P_r}$ is used in the open loop valve model, as it has the best performance so far. The AIC tunings, for each control structure and valve model, are presented in Tables 6.13 to 6.15. Regarding the PID with CF and CR tunings, notice that when the closed loop estimated valve model in the AIC framework is used, the a_{CR} is closer to the analytical value that is suggested in the literature, whereas when the open loop estimated valve model is used instead, the CR action is almost inexistent. It is interesting to note the large controller tuning variance among the estimated models used in the AIC framework, for the ISMC and FFPID control structures.

Table 6.13 – PID with CF and CR friction compensation tunings in the ISMC and FFPID tests.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*	e_l^*	e_h^*	$t_{e_l}^*$	$t_{e_h}^*$	a_{CR}^*
Kano OL	5.78	11.89	4.23	2.51	3.00	1.76	0.13	0.04	2.13
Kano CL	2.63	10.94	2.33	2.17	2.31	1.58	9.16	0.75	11.40
Karnopp OL	8.34	23.48	4.23	1.16	6.43	0.11	0.10	0.08	0.01
Karnopp CL	4.24	7.32	0.36	0.09	9.99	1.05	0.14	0.01	11.60
GMS OL	7.48	19.57	4.02	1.65	-0.84	0.06	3.59	0.85	0.50
GMS CL	4.33	9.06	0.36	0.08	7.62	0.44	16.59	0.93	7.15

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

Table 6.14 – ISMC tunings in the ISMC and FFPID tests.

Model	k_{ismc}^*	λ_{ismc}^*	Φ_{ismc}^*	τ_{ismc}^*
Kano OL	5.28	1911.97	0.58	0.42
Kano CL	1.75	1353.64	0.07	0.22
Karnopp OL	1991.28	0.19	0.61	0.004
Karnopp CL	4.27	1994.28	0.81	0.23
GMS OL	1783.40	0.87	0.53	0.004
GMS CL	3.28	1950.57	0.99	0.22

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

Table 6.15 – FFPID tunings in the ISMC and FFPID tests.

Model	K_p^*	K_i^*	K_d^*	τ_{df}^*	$e_{I_{th}}^*$	k_{ff}^*
Kano OL	5.48	0.77	0.80	0.14	0.32	0.60
Kano CL	2.47	0.10	0.17	0.03	0.01	0.76
Karnopp OL	5.06	0.40	0.80	0.15	0.22	0.94
Karnopp CL	2.40	0.00	0.15	0.16	0.18	0.99
GMS OL	4.80	0.31	0.64	0.08	0.45	0.89
GMS CL	5.29	2.30	0.33	0.04	0.39	0.57

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

The same tests described in Section 6.2 are performed. A performance comparison between the open and closed loop estimated model parameters used in the AIC framework is presented in Figure 6.26. Using the open loop estimated parameters in the AIC framework, in general, results in slightly better performance indexes. However, this improved performance has a drawback, which is a higher control effort.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.26 – Comparison of tuning performance when the open and closed loop estimated valve models are used in the AIC framework.

Source: from Author.

A comparison among the AIC tuning performance, for when different estimated valve models are used, is presented in Figures 6.27 and 6.28. The GMS holds the best overall performance among the models, regarding the iae_Q index, whether the open or closed loop estimated valve models are used, however, in general, using the GMS and Karnopp models in the AIC framework result in similar performance indexes, as the first and third quartiles are close to each other. When the Kano model is used in the AIC framework, the hydraulic control performance tends to decrease.

(a) Comparison of the iae_Q . (b) Comparison of the iae_x . (c) Comparison of the $std(OP)$.

Figure 6.27 – Comparison of the controller tuning performance, for each open loop estimated friction model used in the AIC framework.

Source: from Author.

(a) Comparison of the iae_Q . (b) Comparison of the iae_x . (c) Comparison of the $std(OP)$.

Figure 6.28 – Comparison of the controller tuning performance, for each closed loop estimated friction model used in the AIC framework.

Source: from Author.

The AIC tuning performance, for each experiment type, when the open loop estimated valve models are used, is presented in Figure 6.29. The data shows that it is more likely to obtain better values of the iae_Q index when the GMS friction model is used in the AIC framework, specially regarding the servo and regulatory experiments.

(a) Comparison of the iae_Q , in the servo experiment. (b) Comparison of the iae_Q , in the regulatory experiment. (c) Comparison of the iae_Q , in the aleatory experiment.

Figure 6.29 – Comparison of the controller tuning performance, separated by experiment type, for each open loop estimated friction model used in the AIC.

Source: from Author.

Figures 6.30 to 6.35 present performance comparisons of the controller structures, for each estimated friction model used in the AIC framework. The ISMC structure has the higher control effort, whichever the friction model is used to tune its parameters and this increased control effort does not necessarily corresponds to a better hydraulic system control performance. When the GMS model is used, the best performance indexes are obtained using the PID with CF and CR control structure, even though the FFPID outperforms in the servo experiment when using the open loop estimated GMS model and

the ISMC outperforms in the servo experiment when using the closed loop estimated GMS model. When the Karnopp model is used, the best results are obtained with the FFPID and ISMC control structures, when the open or closed loop estimated valve model is used in the AIC framework, respectively. In general, the GMS and Karnopp models present similar patterns regarding the FFPID and ISMC controller structures, as when the open loop estimated friction models are used, the FFPID outperforms the ISMC, whereas when the closed loop estimated friction models are used, the ISMC outperforms the FFPID. The Kano model, however, presents a different pattern, since when the open loop estimated friction model is used, the best performance is given by the ISMC control structure, while when the closed loop estimated friction model is used, the best performance is given by the PID with CF and CR. What is impressive regarding the PID with CF and CR control structure is its high consistency, specially when the GMS and Karnopp estimated models are used in the AIC framework. It presents a very similar performance index than the more complex control structures, however its control effort is much lower than the other structures.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.30 – Comparison of the tuning performance when the open loop estimated GMS model is used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.31 – Comparison of the tuning performance when the open loop estimated Kano model is used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.32 – Comparison of the tuning performance when the open loop estimated Karnopp model is used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.33 – Comparison of the tuning performance when the closed loop estimated GMS model is used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.34 – Comparison of the tuning performance when the closed loop estimated Kano model is used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

(a) Comparison of the iae_Q . (b) Comparison of the $std(OP)$.

Figure 6.35 – Comparison of the tuning performance when the closed loop estimated Karnopp model is used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

To study whether there are differences among the estimated valve models used in the AIC framework, a performance comparison, grouping the results by controller structure, is presented in Figures 6.36 and 6.37. Regarding the PID with CF and CR control structure, the best performance in each experiment is given by tuning the controller using the GMS model in the AIC framework, independently whether the model is estimated in open or closed loop. With respect to the FFPID control structure, except for the servo experiment using open loop estimated models in the AIC framework, the best results are obtained when the controller is tuned using the Karnopp model in the AIC framework. As for when the ISMC control structure is used, the best performance occurs when the open loop estimated Kano model or the closed loop estimated GMS model is used. In summary, when the GMS, Kano and Karnopp models are used in the AIC framework, it results in 10, 3 and 5 best performance indexes, when comparing the results by experiment type.

Figure 6.36 – Comparison of the controller tuning performance when different open loop estimated friction models are used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.37 – Comparison of the controller tuning performance when different closed loop estimated friction models are used in the AIC framework.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

As an example of how the controllers perform in the time domain, an extract of the servo experiment is presented in Figures 6.38 to 6.43. Note that the ISMC has an aggressive tuning, as it tries to compensate even minor deviations from the set point. This characteristic tends to be minimized when using a lower sampling time for the ISMC, which is not possible with the current available FPP hardware.

Figure 6.38 – Extract of the servo experiment using the PID with CF and CR, tuned using the open loop estimated GMS and Kano models in the AIC framework.

Source: from Author.

Figure 6.39 – Extract of the servo experiment using the PID with CF and CR, tuned using the open loop estimated Kano and Karnopp models in the AIC framework.

Source: from Author.

Figure 6.40 – Extract of the servo experiment using the FFPID, tuned using the open loop estimated GMS and Kano models in the AIC framework.

Source: from Author.

Figure 6.41 – Extract of the servo experiment using the FFPID, tuned using the open loop estimated Kano and Karnopp models in the AIC framework.

Source: from Author.

Figure 6.42 – Extract of the servo experiment using the ISMC, tuned using the open loop estimated GMS and Kano models in the AIC framework.

Source: from Author.

Figure 6.43 – Extract of the servo experiment using the ISMC, tuned using the open loop estimated Kano and Karnopp models in the AIC framework.

Source: from Author.

6.5 Test with the Teflon Gasket Valve

As the teflon gasket valve has a low friction index, it is very simple to control, therefore only a few tests are carried out, to test the AIC framework performance when the valve model is simpler. First a PID and a PID with CF and CR are tuned using the DS method and to do so, a first order plus dead time model of the valve is estimated using a step excitation signal. The first order plus dead time model of the teflon gasket valve is (in the Laplace domain):

$$\frac{OP_t(s)}{x_t(s)} = \frac{0.68914}{0.8305 s + 1} e^{-0.16 s}. \quad (6.24)$$

Applying the DS method to obtain a closed loop time constant 50% faster than the model time constant, a PI controller is calculated as $K_p = 2.10$ and $K_i = 2.55$. The PID with CF and CR has the same PID parameters, the CF algorithm is tuned with $e_l = e_h = 1$, $t_{e_l} = 10$ s and $t_{e_h} = 2$ s, and the CR with $a_{CR} = 0.26$.

The control structures tested in the AIC framework are the PID with CR and CF, the ISMC and the FFPID. Only the Kano model is used in the AIC framework, for simplicity purposes, and the open loop I/P valve model uses the time constant estimated with ramps input signal ($\hat{\tau}_{I/P_r}$). The resulting tunings are presented in Tables 6.16 to 6.18. When the open loop estimated Kano model is used in the AIC framework, to tune the PID with CF and CR, the CF algorithm is practically disabled (negative value of e_h). The AIC delivers a CR constant that is somewhat close to what is suggested in the literature. The ISMC tunings vary greatly when using different estimated valve models in the AIC framework and the FFPID tunings are pretty consistent among the open and closed loop estimated models used in the AIC framework.

Table 6.16 – PID with CF and CR friction compensation tunings in the teflon gasket valve test.

Model	K_p	K_i	K_d	τ_{df}	e_l	e_h	t_{e_l}	t_{e_h}	a_{CR}
Kano OL	1.97	6.98	4.38	8.87	0.88	-0.50	0.004	0.23	0.36
Kano CL	1.86	7.97	3.85	7.48	9.65	0.23	1.94	0.05	0.19

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

Table 6.17 – ISMC tunings in the teflon gasket valve test.

Model	k_{ismc}	λ_{ismc}	Φ_{ismc}	τ_{ismc}
Kano OL	25.00	1975.35	0.75	0.18
Kano CL	776.84	9.48	1.00	0.11

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

Table 6.18 – FFPID tunings in the teflon gasket valve test.

Model	K_p	K_i	K_d	τ_{df}	$e_{I_{th}}$	k_{ff}
Kano OL	3.20	1.18	0.41	0.08	0.09	0.77
Kano CL	2.31	1.84	0.16	0.06	0.001	0.64

Source: from Author.

OL: model with open loop estimated parameters and CL: model with closed loop estimated parameters.

The performed tests are the same presented in Section 6.2 and the performance comparison among the different tunings is presented in Figures 6.44 to 6.46. The best performances are achieved when using the ISMC controller, followed by the PID with CF and CR controller, both tuned using the AIC framework. The drawback regarding the ISMC controller is its high control effort, that is at least one order of magnitude higher than the PID with CF and CR. In general, using an open or closed loop estimated model in the AIC framework does not affect greatly the controller tuning performance. Yet, the DS method presents lower performances than the AIC framework, which is not surprising, as the former utilizes a simplified plant model.

Figure 6.44 – Comparison of the iae_Q index, in the teflon gasket valve test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.45 – Comparison of the std(OP) index, in the teflon gasket valve test.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

Figure 6.46 – Comparison of the std(OP) index, excluding the ISMC controller.

Legend: regulatory (white), servo (black) and aleatory (gray) experiments.

Source: from Author.

For a time domain performance comparison between the controllers, an extract from the servo experiment is presented in Figures 6.47 to 6.50.

Figure 6.47 – Extract of the servo experiment using the PID and PID with CF and CR, tuned using the DS method.

Source: from Author.

Figure 6.48 – Extract of the servo experiment using the PID with CF and CR, tuned using the DS method and the AIC with the open loop estimated Kano model.

Source: from Author.

Figure 6.49 – Extract of the servo experiment using the PID with CF and CR and FFPID, tuned using the the AIC with the open loop estimated Kano model.

Source: from Author.

Figure 6.50 – Extract of the servo experiment using the FFPID and ISMC, tuned using the the AIC with the open loop estimated Kano model.

Source: from Author.

6.6 Concluding Remarks

In this chapter, the automatic friction compensation using the AIC framework was designed. If the developments of Chapters 4, 5 and 6 are combined, then it is possible to monitor the valve behavior during normal operation and if a deviation occurs, for example due to an increase in a friction parameter, then it is possible to estimate a new valve model and then automatically tune a given controller structure to compensate for the changes in the valve dynamics.

Choosing a friction model to use in the AIC framework is not an easy task, as using a more complex friction model does not deterministically result in better tuning performances. By viewing the experiments individually, grouped by the type of estimated model that is used (e.g. closed or open loop estimated models) and by experiment type, then the GMS, Kano and Karnopp tuned controllers presented the best results in 21, 9 and 12 experiments, respectively, accounting for all performed tests. Except for when using the $\hat{\tau}_{I/P_s}$ as the I/P model time constant, if the GMS model is used in the AIC framework, the tuning performance is very consistent, with little impact whether the model is estimated in open or closed loop. When the Kano and Karnopp models are used in the AIC framework instead, the performance tend to vary if the valve model is estimated in open or closed loop. The GMS model is specially effective to tune the CF method, as shown in Section 6.3. If performance and consistency is the controller first objective and there is a computationally powerful processor available, then it is preferable to use the GMS model. If the processing power has to be minimized, then the Karnopp and Kano models can be used. Still, even if the GMS or Karnopp model is used, as they tend to be much slower than the Kano model, the latter can be used for a fast valve model estimation and controller tuning, until the more complex model is being calculated.

With regard to the controller structure, even though the FFPID and ISMC are more efficient in some test cases, the PID with CF and CR is very consistent, has a simpler control structure and presents lower control effort. Therefore, the tests show that the PID with CF and CR is the preferable controller structure for diaphragm control valves with digital positioners.

In general, using the AIC framework is more effective for tuning the controllers than using the DS method with friction compensation algorithms, configured as suggested in the literature.

7 Conclusions

The algorithms and guidelines for estimating the valve with friction model in open or closed loop systems was derived for the Kano, Karnopp, LuGre and GMS friction models. From simulated tests, only the Karnopp model is estimated perfectly when measurement noise is simulated. In experimental tests, however, the GMS model tends to have a more precise stem velocity prediction precision. Even though the Karnopp performs quite well also, but may present undesired stick–slip behavior in some particular cases. The LuGre model simulation may fail if the diaphragm pressure has measurement noise and therefore was eliminated from the controller tests. The Kano model, despite being very computationally efficient, has inaccurate predictions, specially when its input signal has noise. In this work, the GMS model has 14 parameters, which makes the estimation process very time consuming, therefore one may consider if the added complexity is worth to obtain slightly better model prediction precisions, when compared to the Karnopp model.

To achieve the automatic friction compensation, the AIC framework was designed to tune some usually employed controller structures that are used to compensate diaphragm valve friction. In general, when the estimated GMS model is used in the AIC framework, the controller tuning performance is more likely to be optimal, however as this is not a deterministic phenomena, in some tests the Karnopp or Kano models provided better tunings.

From the performed modeling and control experiments, it is possible to conclude that the GMS model is more likely to deliver better results over the other models, as it has the most consistent performance. However, the Karnopp model can also produce good results, and may substitute the GMS model without great losses. The Kano model is negatively affected by measurement noise and should not be used to model diaphragm valves, unless the valve has no stem position sensor. Also, the Kano model is more likely to produce poorer controller tunings, when compared to the other models. The LuGre model should be avoided, as it may fail completely if the valve input (P) has noise.

Future Work

The GMS model used in this work has a high number of parameters, which mainly improve the presliding prediction precision. As this phenomenon is not of interest when modeling diaphragm valves, since the available sensors that are frequently used in the industry to measure the valve stem position do not have micrometric resolution, a simplified version of the GMS model, with only one Maxwell element (resulting in 7 parameters), can be tested to verify whether this simplified GMS model still outperforms the other models.

In this work, the valve model integration algorithm has a fixed time step. The computational efficiency of the Karnopp, LuGre and GMS models can be greatly improved if an adaptive integration time step algorithm can be developed. The smaller time steps are necessary mainly when the system is in presliding state.

A more precise position sensor can be installed on the valve, to check whether there is a bigger difference between the prediction precision of the friction models. The position sensor can be a linear magnetic encoder, which has micrometric resolution, minimal measurement noise and may be applicable to industrial applications.

The controller structures tested in this work do not use all the available information regarding the estimated friction models, as the FFPID and ISMC controllers use a simplified friction model, since estimating the internal states of the friction models is a difficult task. A more precise test, that has the potential to use all information regarding the estimated models, is to design a Moving Horizon Estimation and a Model Predictive Control for the valve position controller.

The ISMC and the FFPID controllers are sensitive to the sampling time, therefore a hardware that allows lower sampling times can be designed, to test whether the performance of such controllers improves.

The AIC framework can be extended to ensure that the controller tuning is robust with respect to valve model parametric uncertainties.

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Appendices

APPENDIX A – Optimization Algorithms

This appendix groups the optimization algorithms used in this thesis, namely: the genetic algorithm, differential evolution, Monte Carlo with simplex, successive nonlinear linear regression and the grid search with differential evolution and simplex optimization.

Algorithm A.1 – The genetic algorithm scheme, based on Ferragud (1999).

Input: Residual function, N : number of population, Pop , individuals ($N = 10 \cdot d_f$), $minres$: residual to stop optimization, Cp : crossover probability (0.5), Mp : mutation probability (0.5), lb : lower bound vector and ub : upper bound vector.

```

1: Initialize  $Pop$  with aleatory points inside search space
2: for  $it = 1 : 1000$  do
3:    $r \leftarrow$  Calculate the residual of each individual in population
4:   if best residual of  $Pop$  did not decrease after 100 iterations then
5:     end optimization
6:   else
7:      $Pop \leftarrow$  SELECTION( $Pop, r$ )
8:      $Pop \leftarrow$  CROSSOVER( $Pop, Cp$ )
9:      $Pop \leftarrow$  MUTATION( $Pop, Mp, lb, ub$ )
10:  end if
11: end for
12: function SELECTION( $Pop, residuals$ )
13:    $Pop \leftarrow$  Select  $N$  individuals aleatory from  $Pop$ , with reposition, such that the lower
    the individual residual value, the higher is its likely to be selected
14:   return  $Pop$ 
15: end function
16: function CROSSOVER( $Pop, Cp, search\ space\ bounds$ )
17:   for  $in : 1 : 2 : N - 1$  do
18:     if uniform random number  $< Cp$  then  $\triangleright$  Selection of individual  $in$  from  $Pop$ 
19:        $Pop(in) \leftarrow$  random linear combination of  $Pop(in)$  and  $Pop(in + 1)$ 
20:        $Pop(in + 1) \leftarrow$  random linear combination of  $Pop(in)$  and  $Pop(in + 1)$ 
21:     end if
22:   end for
23:   return  $Pop$ 
24: end function
25: function MUTATION( $Pop, Mp,$ )
26:   for  $in : 1 : N$  do
27:     if uniform random number  $< Mp$  then  $\triangleright$  Selection of individual  $in$  from  $Pop$ 
28:        $Pop(in) \leftarrow$  Perturb each entry of  $Pop(in)$ , with probability  $Mp$ , using a
        random variable and search space parameter range
29:     end if
30:   end for
31:   return  $Pop$ 
32: end function

```

Algorithm A.2 – The differential evolution scheme, based on Storn and Price (1997).

Input: Residual function, N : Number of population, Pop , individuals ($N = 10 \cdot d_f$), Cr : Crossover probability (0.7), W : Crossover weight (0.8), lb : lower bounds vector and ub : upper bounds vector

```

1: Generate  $N$  aleatory parameters vectors inside search space
2: Evaluate the residuals
3: for  $it = 1 : 1000$  do
4:   if best residual of  $Pop$  did not decrease after 100 iterations then
5:     end optimization
6:   end if
7:   for each individual in  $Pop$  ( $I$ ) do
8:     for each parameter of individual ( $Ip$ ) do
9:       if uniform random number  $< Cr$  then
10:        Select two aleatory individuals in population ( $I_1$  and  $I_2$ )
11:         $Ip^* \leftarrow Ip + W \cdot (Ip_1 - Ip_2)$   $\triangleright$  Creation of crossed individual ( $I^*$ )
12:      end if
13:    end for
14:    Evaluate  $I^*$  residual
15:    if residual decreased then
16:       $I \leftarrow I^*$ 
17:    end if
18:  end for
19:  Save the best overall residual and parameters vector
20: end for

```

Algorithm A.3 – The Monte Carlo with Simplex optimization algorithm.

Input: Residual function, search space bounds

```

1:  $Pop \leftarrow$  Select a population of  $\min(40 \cdot 2^{d_f}, 60000)$  aleatory parameters vector from the search space
2: Calculate the residuals of each element in  $Pop$ 
3: Select the best 3% residuals from  $Pop$  and use its corresponding parameters vector as the initial point for a Simplex optimization with 200 iterations
4: The parameters vector that resulted in the best residual from previous step is used in a Simplex optimization with 1500 iterations

```

Algorithm A.4 – The Simplex scheme, based on the work of Nelder and Mead (1965) and the MATLAB[®] implementation, modified to run in parallel.

Input: Residual function, initial parameters vector (θ) with dimension D, *maxres*: maximum accepted distance between residuals, *maxdist*: maximum accepted distance between parameters vectors values.

```

1: Generate D new parameters vectors by perturbing  $\theta$  with 5% magnitude
2: Evaluate the residuals at each D + 1 points
3: for  $it = 1 : 1000$  do
4:    $\theta_r \leftarrow$  Calculate the average of the best D residuals ( $\theta_{av}$ ) and reflect the parameter
      that resulted in the worst residual ( $\theta_{worst}$ ) with respect to the average
5:    $\theta_e \leftarrow$  Double the distance between  $\theta_r$  and  $\theta_{av}$ 
6:    $\theta_c \leftarrow$  Halve the distance between  $\theta_r$  and  $\theta_{av}$ 
7:    $\theta_{ic} \leftarrow$  Halve the distance between  $\theta_{worst}$  and  $\theta_{av}$ 
8:   Evaluate the residuals with  $\theta_r$ ,  $\theta_e$ ,  $\theta_c$  and  $\theta_{ic}$ 
9:   if  $\theta_r$  has the best residual then
10:    if  $\theta_e$  has the best residual then
11:       $\theta_{worst} \leftarrow \theta_e$ 
12:    else
13:       $\theta_{worst} \leftarrow \theta_r$ 
14:    end if
15:  else
16:    if  $\theta_r$  residual is lower than the second worst residual then
17:       $\theta_{worst} \leftarrow \theta_r$ 
18:    else
19:      if  $\theta_r$  residual is lower than  $\theta_{worst}$  then
20:        if  $\theta_c$  residual is lower than with  $\theta_r$  then
21:           $\theta_{worst} \leftarrow \theta_r$ 
22:        else
23:          SHRINK(parameters vectors)
24:        end if
25:      else
26:        if  $\theta_{ic}$  residual is lower than with  $\theta_{worst}$  then
27:           $\theta_{worst} \leftarrow \theta_{ic}$ 
28:        else
29:          SHRINK(parameters vectors)
30:        end if
31:      end if
32:    end if
33:  end if
34:  if no decrease in best residual after 100 iterations then
35:    end optimization
36:  end if
37:  if distance between best residual and other residuals  $< maxres$  and distance
      between parameters vectors  $< maxdist$  then
38:    end optimization
39:  end if
40: end for

```

```

41: function SHRINK(parameters vectors)
42:   Halve the distance between the parameters vectors with D worst residuals and the
      parameters vector with best residual
43:   Evaluate the new residuals
44: end function

```

Algorithm A.5 – The successive nonlinear linear regression scheme, based on Rizos and Fassois (2009).

Input: Residual function, search space bounds, lin_n : number of linear parameters, $nlin_n$: number of nonlinear parameters, lb : lower bounds vector and ub : upper bounds vector.

```

1: Pop  $\leftarrow$  Select a population of  $500 \cdot nlin_n$  aleatory parameters vector inside the search
   space
2: Calculate the residuals of each element in Pop
3: lin parameters  $\leftarrow$  Select the parameters vector with best residual from Pop
4: Calculate the experimental data  $F_f$ 
5: PopGA  $\leftarrow$  select the best  $10 \cdot nlin_n$  residuals nonlinear parameters from Pop
6: Start the initial population of the GA algorithm with PopGA
7: for  $it = 1 : 1000$  do
8:   if  $it > 1$  then
9:     Update the PopGA using previous  $it$   $nlin$  parameters
10:  end if
11:   $nlin$  parameters  $\leftarrow$  Run GA with 20 iterations, using PopGA and fixed  $lin$ 
     parameters
12:  Simulate the valve model using  $nlin$  parameters and  $lin$  parameters
13:   $lin$  parameters  $\leftarrow$  solve LSE using valve simulated data and  $F_f$ 
14:  if no decrease in best residual after 100 iterations then
15:    end optimization
16:  end if
17: end for

```

Algorithm A.6 – Grid Search with Differential Evolution and Simplex Optimization (GDES).

Input: Residual function, search space bounds.

```

1: From the search space, select points for each parameters and evaluate the residual for
   all possible combination of parameter points
2: Pop  $\leftarrow$  Select the best  $10 \cdot d_f$  residuals and create an initial population for the DE
   optimization
3: Pop  $\leftarrow$  Perturb the 11th best residual onwards, by adding a normal random variable
   with standard deviation equal to a hundredth of the parameters bounds
4: Pop  $\leftarrow$  Replace the worst 10 parameters with random points inside search space
5: parametersDE  $\leftarrow$  Perform a DE optimization with Pop
6: parameters  $\leftarrow$  Perform a Simplex optimization using parametersDE as the initial
   parameters vector

```