MODELING AND CONTROL OF MCKIBBEN ARTIFICIAL MUSCLE – APPLICATION OF MODEL PREDICTIVE CONTROL AND GENETIC ALGORITHMS

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January 2019

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ACKNOWLEDGEMENTS

Put your acknowledgements here.

Many thanks to everybody who already sent me a postcard!

Regarding the typography and other help, many thanks go to Marco Kuhlmann, Philipp Lehman, Lothar Schlesier, Jim Young, Lorenzo Pantieri and Enrico Gregorio[1], Jörg Sommer, Joachim Köstler, Daniel Gottschlag, Denis Aydin, Paride Legovini, Steffen Prochnow, Nicolas Repp, Hinrich Harms, Roland Winkler, and the whole LaTeX-community for support, ideas and some great software.

Regarding LyX: The LyX port was initially done by *Nicholas Mariette* in March 2009 and continued by *Ivo Pletikosić* in 2011. Thank you very much for your work and the contributions to the original style.

1 Members of GuIT (Gruppo Italiano Utilizzatori di TeX e LaTeX)

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ACRONYMS

PAM Pneumatic Artificial Muscle

PID Proportional-Integrative-Derivative

MPC Model Predictive Control

EA Evolutionary Algorithm

GA Genetic Algorithm

FA Firefly Algorithm

MFA Modified Firefly Algorithm

PSO Particle Swarm Optimization

Part I

THESIS

1 INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The current state of the art in hydraulic actuators consists almost entirely of oil driven valves, pistons and motors. However, this kind of actuator cannot be used in some particular applications, such as power assist systems and rehabilitation: they have significant heaviness and rigidity, because of their mechanical structure and motorization [1]. In this context, it is problematic to share a robot working space with humans around it, and so this kind of actuator cannot be used to actuate, for example, orthotics.

McKibben muscles were invented by Joseph L. McKibben to motorize pneumatic art orthotics. They in general consist of an inner rubber tube enclosed in a braided outer nylon sleeve. These muscles can be used as actuators of rehabilitation systems due to the following advantages:

- Light weight
- High power to weight ratio
- High flexibility
- Low cost
- Low environmental impact

However, there are drawbacks: it is well known that the muscle has poor control performance due to the existence of strong nonlinearities, such as hysteresis and saturation characteristics. Furthermore, the wear of the materials (nylon sleeve and rubber tube) may cause a shorter lifetime with respect to other actuators.

1.2 MODELING OF MCKIBBEN ARTIFICIAL MUSCLE

As already mentioned, the control of McKibben muscles is not easy to achieve. A PID control solution may be developed, but it has flaws: the parameters of the controller will have to be tuned different types of muscles and for various loads. This is generally not an acceptable solution for this kind of application.

Thus, model-based control techniques are better suitable for this job. The plant model needs to be very precise for the control to be effective, and to do so identification techniques are used to get a first linear approximation of the model. Later, a hysteresis component is added to this linear model, to keep track of the nonlinearities added by the hysteretic behaviour of the muscle. Adding a hysteresis component to a linear model makes it more complex, so the choice of an appropriate hysteresis modeling technique is crucial to achieve good control performance.

This allows to get a model having good fit with respect to the real one and apply a model-based control approach, namely the **Model Predictive Control** (MPC). Further details about the developed controller are in Chapter 6, and the theory behind MPC can be found in Appendix **??**.

1.3 AIM OF THE STUDY

The aim of this dissertation is to get precise control of the displacement for a tap water-driven McKibben artificial muscle. To do so, a list of steps will be followed:

1. *Derivation of a Simple Linear Model*

   Using linear identification techniques, it is possible to map the input pressure to the output displacement, and get a precise yet simple linear model of the muscle. While in pneumatic artificial muscles it is required to take into account the temperature dynamics and the compressibility of air, using water as the muscle allows to disregard them. This grants a simpler model of the muscle.

2. *Introduction of a Hysteresis Component*

   The linear identification method grants a very simple yet linear model that does not take nonlinearities into account. The biggest source of nonlinearity for the McKibben muscle is hysteresis. A hysteresis component is added to the linear model, so that it will better follow the actual behaviour of the muscle. This step is essential to get good control performance.

3. *Controller Design*

   The application of Model Predictive Control and Adaptive Control techniques are proposed, using the muscle model obtained from linear system identification and modified with the introduction of the hysteresis component. these results are confronted with PI and PID control.

4. *Adaptive Parameter Estimation*

   Model's parameters change according to the load of the muscle and its working conditions. To retain good control performance, an adaptive estimation is needed to update the controller, and achieve perpetual stable results. To do so, a {Genetic Algorithm}/{LS} approach is proposed.

2 COMPOSITION OF THE THESIS

3 TAP WATER-DRIVEN MCKIBBEN ARTIFICIAL MUSCLE

4 MODELLING OF MCKIBBEN ARTIFICIAL MUSCLES

In this Chapter, the muscle models used as nominal models for model-based control are derived.

4.1 INTRODUCTION

McKibben muscles are actuators used mainly for medical purposes in rehabilitation and welfare. The reason is their high flexibility, light weight, low cost, human and environmental friendliness and ease of use. As mentioned in Chapter 1, the control of this kind of actuators is often problematic, due to their inherent high nonlinearity.

Many muscle models have been proposed, both static and dynamic. One of the most known static models is derived by Chou [2], which is based on the equilibrium between the input pressure and the release of energy. Although the main interest is to obtain the dynamic model to use in control, the static one is also reviewed and evaluated because they are used with feed-forward control applied to rehabilitation devices using the McKibben muscle.

Dynamic muscle models can be categorized in analysis oriented and control oriented. Analysis oriented models provide very high accuracy, but they are also very complex. For this reason they are not much suitable for control purposes.

Control oriented models provide lower accuracy than analysis oriented ones, but their lower complexity allows them to be used more efficiently for control.

Since tap water driven muscles are simpler than pneumatic ones, the idea is to use linear system identification and obtain a simple model of the muscle's dynamics. Being this only a linear model, it does not take into account the presence of strong nonlinearities, such as the friction between the braids and the hysteretic behaviour of the muscle. However, the introduction of a hysteresis model can lead to achieving higher precision with the model derived from linear system identification.

Through history, several hysteresis models have been developed. Notable examples are the Maxwell-slip model [3], the Jiles-Atheron model [4] and the Preisach model [5]. Common interest points of these models are friction of the braided sleeve, and the hysteresis caused by it, which both add nonlinearities to the model.

These hysteresis models are precise, yet complex in structure. To overcome this problem, the Bouc-Wen [6] [7] hysteretic model is combined with the identified muscle model. Including the hysteretic model raises the number of parameters that have to be identified for the system, but this is easily achieved, at first, by trial and error. Later, an adaptive algorithm is developed to get the best parameters for the muscle, and thus the updated model can be use as a nominal model for model-based control techniques.

The accuracy of the proposed model is compared to experimental results by analysing the pressure–displacement characteristics and the hysteresis characteristics. Moreover, the effects of changing the load of the muscle are studied, because they may have a great impact upon control performances.

4.2 STATIC MODEL

4.2.1 *Introduction*

The relationship between the axial contraction force and the pressure difference amid supply and atmospheric pressure has been reported in different papers [8] [9].

The association is based on the equilibrium between the input work in the McKibben muscle (i. e. when the fluid is supplied to the inner rubber tube) and the output work (i. e. when the actuator shortens or elongates because of the volumetric change associated with the pressure difference).

Figure 1 shows the geometric structure, which follows the geometric relationships in Equation 1.

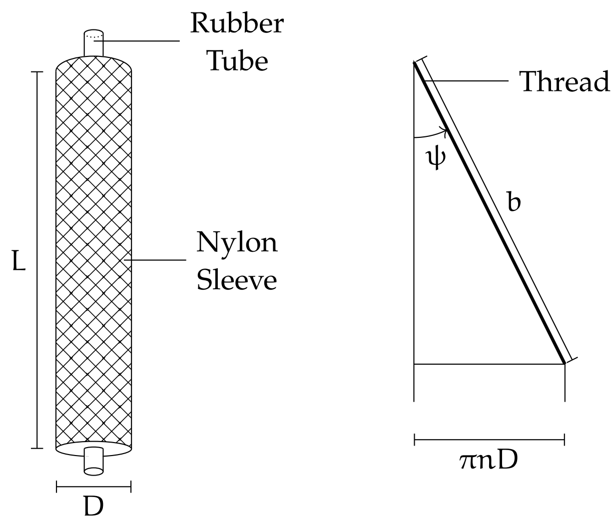

Figure 1: Geometric structure of a McKibben artificial muscle

$$L = b\cos(\psi), \quad D = \frac{b\sin(\psi)}{n\pi} \tag{1}$$

where L is the length of the muscle, D is the outer diameter of the muscle, b is the thread length, n is the number of turns of a thread, and ψ is the angle formed by the sleeve's threads and its vertical axis.

4.2.2 *Static Model of the Muscle*

The input work W_{in} is applied to the muscle when the fluid (liquid or air) pushes the internal surface of the rubber tube. This can be expressed as the product of the supply pressure and the change in volume.

$$dW_{in} = (P - P_0)\, dV = P' dV \tag{2}$$

Where P is the supply pressure, P_0 is the atmospheric pressure, P' is the pressure difference and dV is the volumetric change.

Equation 3 shows the volume of the muscle, with the assumption that it has cylindrical shape.

$$V = \frac{1}{4}\pi L D^2 \tag{3}$$

Then, from Equation 1,

$$V = \frac{1}{4}\pi L D^2 = \frac{b^3}{4\pi n^2} \sin(\psi)^2 \cos(\psi) \tag{4}$$

When the actuator contracts, the output work of the system W_{out} is given by Equation 5.

$$dW_{out} = F \times (-dL) \tag{5}$$

Where F is the axial tension, and dL is the axial displacement change.

From Equation 1 we can express $dL/d\psi$ as follows.

$$\frac{dL}{d\psi} = -b \sin(\psi) \tag{6}$$

With the assumption that the input work and the output work should be equal if the system is lossless and without energy storage, as for Equations 2, 4, 5 and 6, then the relation shown in Equation 7 can be obtained.

$$F = -P' \frac{dV/d\psi}{dL/d\psi} = \frac{\pi P'}{4} \left(\frac{b}{\pi n}\right)^2 \left(3\cos^2(\psi) - 1\right) \tag{7}$$

From this, it can be observed that the tension F is linearly proportional to the pressure difference P', and it is a monotonic function of the angle ψ $(0° < \psi < 90°)$.

4.2.3 *Modified Static Model*

The static model of a McKibben muscle can be expressed as Equation 7. However, that model does not take into account the thickness t_k of both the nylon sleeve and the internal rubber tube. If this is considered, then the volume calculated in Equation 3 becomes the following.

$$\begin{aligned} V &= \frac{1}{4}\pi L\left(D - 2t_k\right)^2 \\ &= \frac{b^3}{4\pi n^2}\sin\left(\psi\right)\left(3\cos^2(\psi) - 1\right) - b\cos\left(\psi\right)t_k\left(\frac{b}{n}\sin\left(\psi\right) - \pi t_k\right) \end{aligned} \tag{8}$$

From Equation 8 then it is possible to obtain the equivalent of Equation 7 with thickness included. The result is shown in Equation 9.

$$F = \frac{b^2P'}{4\pi n^2}\left(3\cos^2\left(\psi\right)\right) + \pi t_k P'\left[\frac{b}{\pi n}\left(2\sin(\psi) - \frac{1}{\sin(\psi)}\right) - t_k\right] \tag{9}$$

4.2.4 *Static Model Validation*

It is possible to validate the static model obtained. Stepwise voltage is applied to the input and output proportional valves, to study the behaviour of the muscle under quasi static conditions.

(Aggiungere validazione del modello con enfasi sull'errore derivante attriti e approssimazioni)

4.3 Muscle Model Based on System Identification

If all sources of non linearity could be taken into account, then theoretical models may agree with experimental results. However, by taking into consideration these elements, the models would become very complex and they would be difficult to control. Moreover, the models would lack in versatility, meaning that these parameters would have to be changed for different muscles and weights.

The model of the muscle is thus obtained through linear system identification techniques and tools such as MATLAB and Simulink. In this section the derivation of the muscle model based on system identification is described, as well as the improvement of the identified model by using the Bouc-Wen model of hysteresis.

4.3.1 *Identification Experiments*

For the identification step, a stepwise signal has been generated and given to the input and output proportional valves. The two signals are symmetric one another, due to the nature of the valves. They range from 0 to 10 Volts, and are shown in figure 2. The algorithm for generating the signals is in Appendix A (Algorithm A.1.1).

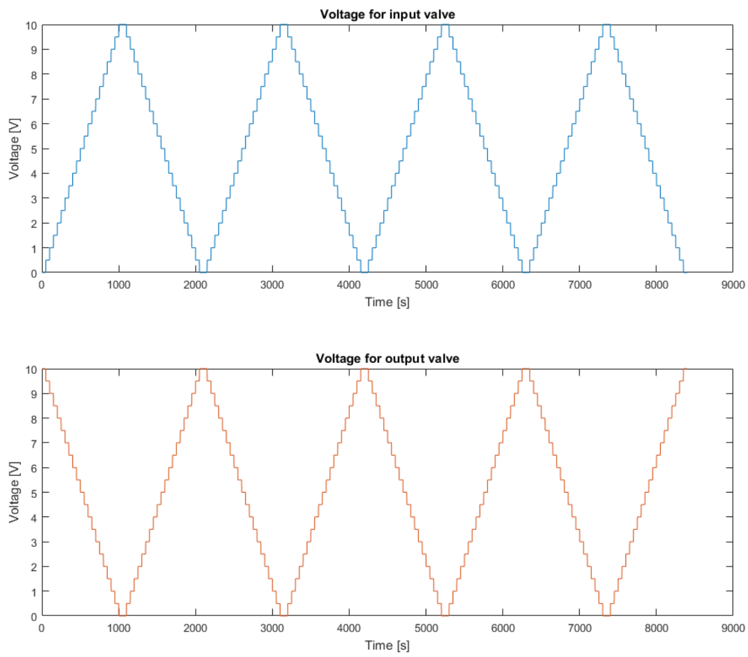

Figure 2: Input waves for proportional valves

Figure 3 shows the pressure and displacement characteristics of the muscle with the input just introduced.

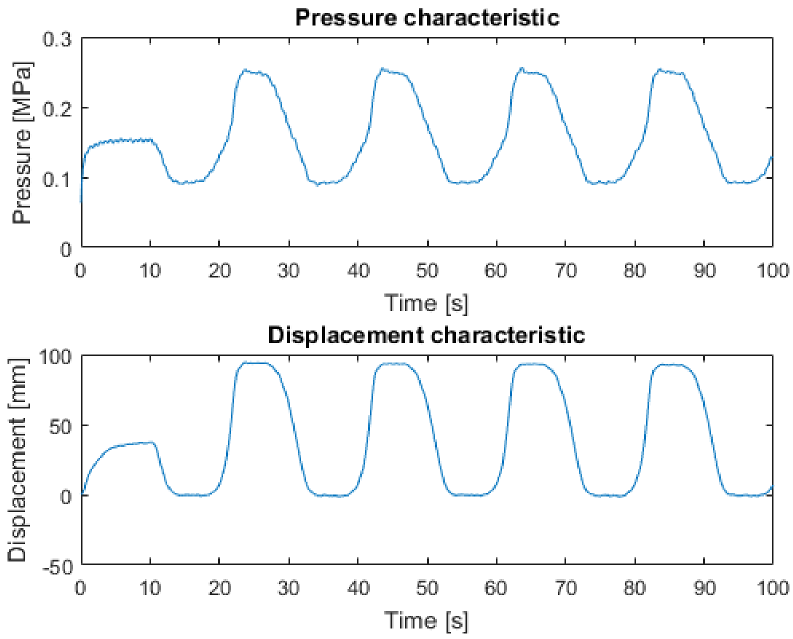

Figure 3: Pressure and displacement characteristic

By plotting this data with pressure on the x-axis and displacement on the y-axis, it is possible to notice the hysteretic behaviour of the muscle, as shown in Figure 4.

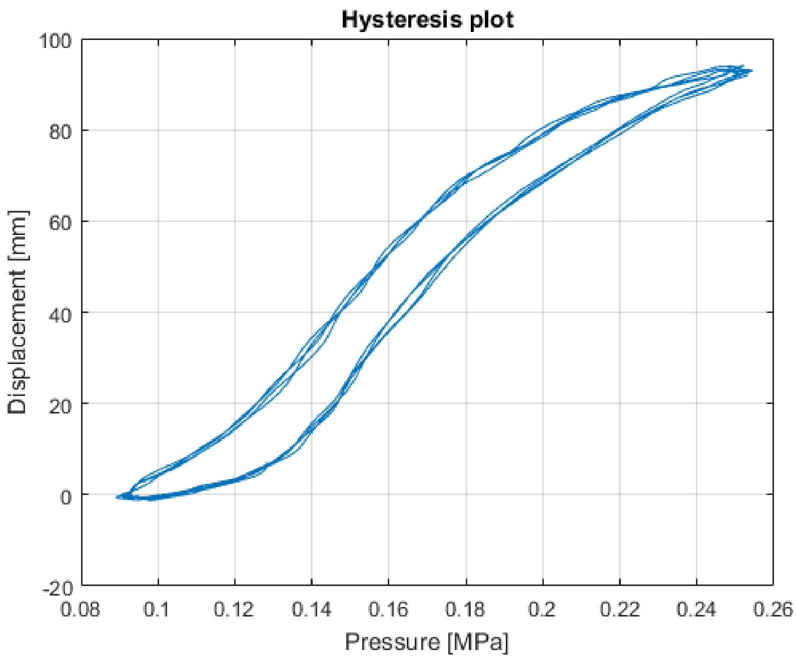

Figure 4: Pressure and displacement characteristic - Hysteresis plot

Using the MATLAB System Identification Toolbox [10], we can get a discrete transfer function from input and output values. The description on how to use the toolbox is provided in Appendix **??**.

The input and output data are given to the toolbox. After that, input and output data are treated in the following way:

- their mean is put to 0
- the data is split in half and used in the following way:
  - the first half is used for the *estimation process*, by which the toolbox attempts to find a discrete function that correctly approximates the input-output characteristic of the system.
  - the second half is used for the *validation process*, by means of which the toolbox computes the fit of the identified transfer function.

The toolbox permits to select the number of zeros and poles that the transfer function must present. A number of 1 poles and 1 zeros has been chosen for this step.

The identification step then provides the discrete transfer function in Equation 10, where L(z) and P(z) represent respectively the z transform of displacement and pressure.

$$G(z) = \frac{L(z)}{P(z)} = \frac{24.9366\ z^{-1}}{1 - 0.9618\ z^{-1}} \tag{10}$$

Se necessario, è possibile usare una funzione di trasferimento con due poli e due zeri invece di una con un polo ed uno zero

The fit of this transfer function with respect to experimental data is shown in Figure 5.

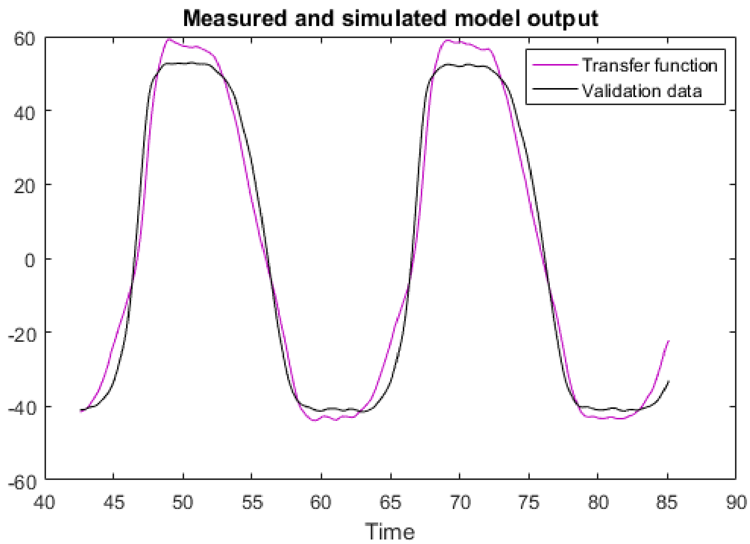

Figure 5: Transfer function fit

It is possible to raise the number of poles and zeros of the transfer function in order to improve its fit with respect to experimental data. The trade-off is that the resulting transfer function will be more complex.

Aggiungere diagramma pressione-displacement sperimentale e il corrispettivo diagramma derivante dalla funzione di trasferimento identificata

The transfer function in Equation 10 can be written rewritten as follows

$$L(z) - 0.9618L(z)z^{-1} = 24.9366P(z)z^{-1} \tag{11}$$

This implies

$$\begin{aligned} l(k) &= 0.9618l(k-1) + 24.9366p(k-1) \\ &= al(k-1) + bp(k-1) \\ a &= 0.9618, \quad b = 24.9366 \end{aligned} \tag{12}$$

So the displacement at step k depends on the displacement and pressure at the previous step.

4.4 HYSTERESIS MODELING

Hysteresis represents a property of systems that show the dependence of their state from their history. It is a nonlinear phenomenon exhibited by systems stemming from various science and engineering areas: under a low-frequency periodic excitation, the relationship between the system's input and output is not the same for loading and unloading This means that the same input applied at different times can yield different output with respect to the history of the system.

The etymology of the term "hysteresis" is derived from the ancient Greek, and it means "delay" or "lagging behind".

A fundamental theory that allows a general framework for modeling hysteresis has not been developed yet.

For specific problems, models derived from a general understand of physics are normally used. This kind of models are, however, hard to derive and difficult to use in practical application due to their complexity. For this reason, alternative models of these complex systems have been proposed. Phenomenological (or semi-physical) models are simpler models that, although not giving the best description of the behaviour of a system, combine some physical understanding of the system along with some kind of black-box modeling, keeping relevant input-output information that is useful for characterization, design and control purposes.

Aggiungere descrizione dettagliata isteresi e introdurre cosa si leggerà in seguito

4.5 MODELS OF HYSTERESIS

There is a large variety of hysteresis models available in literature, such as:

- the Preisach model [11], used to model electromagnetic hysteresis
- the Maxwell-Slip model [12], used for friction simulation and compensation,
- the Bouc-Wen model, extensively used in the areas of smart structures and civil engineering [7]

The latter consists of a first-order nonlinear differential equation that relates the input displacement to the output restoring force in a rate-independent hysteretic way [13].

4.6 THE BOUC-WEN MODEL OF HYSTERESIS

Proposed by Bouc [6] in 1971 and later modified by Wen [7] in 1976, the Bouc-Wen model has been vastly used to mathematically describe components and devices that present hysteretic behaviours, particularly within the areas of civil and mechanical engineering.

The differential equation consists of several parameters. By choosing them appropriately, it is possible to accommodate the response of the model to the real hysteresis loop [14]. The derivation of the model is available in Appendix B.

Equation 12 can be modified by adding a virtual hysteresis component. This should allow the hysteresis loop to adapt to the experimental values by changing the model's parameters.

$$l(k) = a\left[\alpha l(k-1) + (1-\alpha)w(k-1)\right] + bp(k-1) \tag{13}$$
$$\alpha \in [0,1], \quad a = 0.9618, \quad b = 24.9366$$

Here w is a virtual hysteresis variable introduced by the use of Bouc-Wen model. It is possible to implement two different versions of the hysteresis model:

- the one proposed by Bouc and modified by Wen, that will be henceforth called *classic* version
- a more recent and flexible version proposed by Song and Der Kiureghian, that will be called *generalized* version

4.6.1 *Classic Bouc-Wen Hysteresis Model*

The classic Bouc-Wen model's virtual hysteresis variable w is described by Equation 14.

$$\dot{w} = A\dot{l} - \beta\left|\dot{l}\right||w|^{n-1} - \gamma\dot{l}|w|^{n} \tag{14}$$

A, β, γ and n are Bouc-Wen model's parameters. They control the shape and the slope of the hysteretic loop. Further details are described in Appendix B.

4.6.2 *Generalized Bouc-Wen Hysteresis Model*

Song and Der Kiureghian [15] proposed a generalized Bouc-Wen model for highly asymmetric hysteresis that in certain cases shown higher flexibility and resiliency than the classic Bouc-Wen model.

The generalized Bouc-Wen model's virtual hysteresis variable w is described by Equations 15 and 16.

$$\dot{w} = \dot{l}\left[A - |w|\Psi(l, \dot{l}, w)\right] \tag{15}$$

$$\begin{aligned}\Psi(l, \dot{l}, w) &= \beta_1 \operatorname{sgn}(\dot{l}w) + \beta_2 \operatorname{sgn}(l\dot{l}) + \beta_3 \operatorname{sgn}(lw) \\ &\quad + \beta_4 \operatorname{sgn}(\dot{l}) + \beta_5 \operatorname{sgn}(w) + \beta_5 \operatorname{sgn}(l)\end{aligned} \tag{16}$$

where $\beta_1, \ldots, \beta_6$ are fixed parameters.

4.7 HYSTERESIS VARIABLE APPROXIMATION

Equations 14 and 15 should be approximated to a discrete time equation, as Equation 13 is in discrete time. To do so, it is possible to use forward difference approximation method, as shown in Equations 17 and 18. T_s represents the sampling time for the approximation.

$$\frac{dx}{dt} \approx \frac{x(t+T_s) - x(t)}{T_s} = \frac{x(k+1) - x(k)}{T_s} \tag{17}$$

$$\frac{d^2x}{dt^2} \approx \frac{x(t+2T_s) - 2x(t+T_s) + x(t)}{T_s^2} = \frac{x(k+2) - 2x(k+1) + x(k)}{T_s^2} \tag{18}$$

4.7.1 *Classic Bouc-Wen Model*

In the classic version of the Bouc-Wen model, the virtual hysteresis variable w can be discretized as follows.

$$\begin{aligned}\frac{w(k+1) - w(k)}{T_s} &= A\frac{l(k+1) - l(k)}{T_s} - \beta\left|\frac{l(k+1) - l(k)}{T_s}\right||w(k)|^{n-1} \\ &\quad - \gamma\frac{l(k+1) - l(k)}{T_s}|w(k)|^n\end{aligned} \tag{19}$$

Solving for $w(k)$ gives the result in Equation 20.

$$\begin{aligned}w(k) &= A\left[l(k) - l(k-1)\right] - \beta|l(k) - l(k-1)||w(k-1)|^{n-1} \\ &\quad - \gamma\left[l(k) - l(k-1)\right]|w(k-1)|^n + w(k-1)\end{aligned} \tag{20}$$

4.7.2 *Generalized Bouc-Wen Model*

In the generalized version of the Bouc-Wen model, the virtual hysteresis variable w can be discretized as follows.

$$\frac{w(k+1) - w(k)}{T_s} = \frac{l(k+1) - l(k)}{T_s}\left[A - |w(k)|\Psi(l, w, k)\right] \tag{21}$$

$$\begin{aligned}\Psi(l, w, k) &= \beta_1 \operatorname{sgn}\left(\left[\frac{l(k+1) - l(k)}{T_s}\right] w(k)\right) \\ &\quad + \beta_2 \operatorname{sgn}\left(\left[\frac{l(k+1) - l(k)}{T_s}\right] l(k)\right) \\ &\quad + \beta_3 \operatorname{sgn}\left(l(k)w(k)\right) + \beta_4 \operatorname{sgn}\left(\frac{l(k+1) - l(k)}{T_s}\right) \\ &\quad + \beta_5 \operatorname{sgn}\left(w(k)\right) + \beta_6 \operatorname{sgn}\left(l(k)\right)\end{aligned} \tag{22}$$

Solving Equation 21 for w(k) gives the result in Equation 23.

$$\begin{aligned} w(k) &= [l(k) - l(k-1)]\,[A - |w(k)|\Psi(l,w,k)] + w(k-1) \\ \Psi(l,w,k) &= \beta_1 \operatorname{sgn}([l(k) - l(k-1)]\,w(k)) \\ &\quad + \beta_2 \operatorname{sgn}([l(k) - l(k-1)]\,l(k)) \\ &\quad + \beta_3 \operatorname{sgn}(l(k)w(k)) + \beta_4 \operatorname{sgn}(l(k) - l(k-1)) \\ &\quad + \beta_5 \operatorname{sgn}(w(k)) + \beta_6 \operatorname{sgn}(l(k)) \end{aligned} \tag{23}$$

4.8 IDENTIFIED MODEL SUMMATION

The previous sections can be summarized with Equations 24 and 25.

4.8.1 *Classic Bouc-Wen Model*

$$\begin{cases} l(k) = a\,[\alpha l(k-1) + (1-\alpha)w(k-1)] + bp(k-1) \\ w(k) = A\,[l(k) - l(k-1)] - \beta|l(k) - l(k-1)||w(k-1)|^{n-1} \\ \qquad -\gamma\,[l(k) - l(k-1)]\,|w(k-1)|^{n} + w(k-1) \\ \qquad \alpha \in [0,1]\,, \quad a = 0.9618, \quad b = 24.9366 \end{cases} \tag{24}$$

4.8.2 *Generalized Bouc-Wen Model*

$$\begin{cases} l(k) = a\,[\alpha l(k-1) + (1-\alpha)w(k-1)] + bp(k-1) \\ w(k) = [l(k) - l(k-1)]\,[A - |w(k)|\Psi(l,w,k)] + w(k-1) \\ \Psi(l,w,k) = \beta_1 \operatorname{sgn}([l(k) - l(k-1)]\,w(k)) \\ \qquad +\beta_2 \operatorname{sgn}([l(k) - l(k-1)]\,l(k)) \\ \qquad +\beta_3 \operatorname{sgn}(l(k)w(k)) + \beta_4 \operatorname{sgn}(l(k) - l(k-1)) \\ \qquad +\beta_5 \operatorname{sgn}(w(k)) + \beta_6 \operatorname{sgn}(l(k)) \\ \qquad \alpha \in [0,1]\,, \quad a = 0.9618, \quad b = 24.9366 \end{cases} \tag{25}$$

4.9 EVALUATION OF PROPOSED MODELS

The models previously proposed are tested and evaluated to estimate the error with respect to experimental data.

Without taking the Bouc-Wen model into consideration, given experimental input values p, using equation 10 the simulated output $\hat{l}$ with respect the experimental values l is shown in Figure 6.

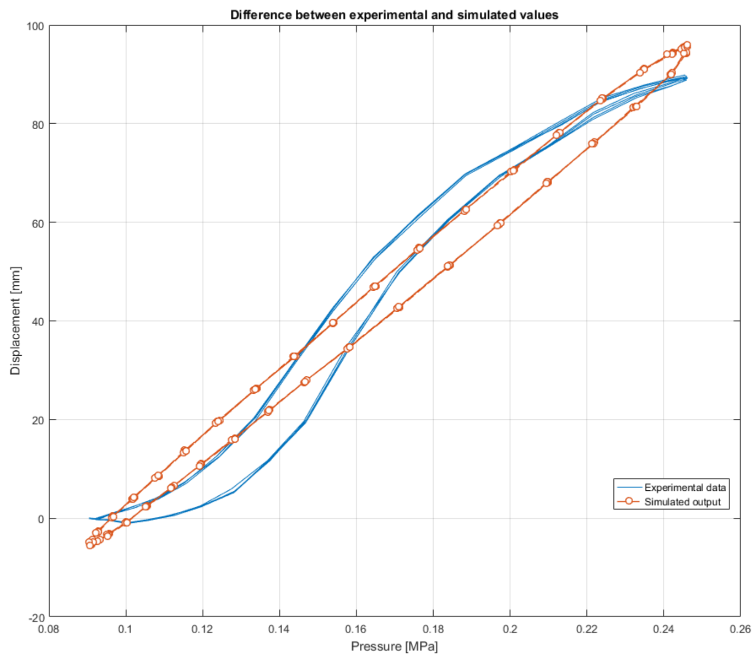

Figure 6: Comparison between experimental data and simulated output

If the Bouc-Wen model is taken into consideration, then the parameters must be fixed appropriately. To get a fairly good fit it is possible to tune these parameters by trial and error. Further methods for finding the best sets of parameters for the hysteresis model are discussed in Chapter 5.

4.9.1 *Classic Bouc-Wen Model Parameters*

The parameters to be chosen for the classic version of the Bouc-Wen model are α, A, β, γ and n. For this work, n will be fixed at 1 for both the classic and generalized version of the hysteresis model. Details about how each parameters alters the shape of the hysteretic loop are in Appendix B.
The parameters in Table 1 have been fixed by trial and error. All parameters are adimensional.

Parameter	Value
α	0.5
A	0.9
β	0.002
γ	-0.001
n	1

Table 1: Parameters for the Classic Bouc-Wen Model

Given experimental input p, the simulated output of the system taking into consideration the classic Bouc-Wen model of hysteresis is shown in Figure 7.

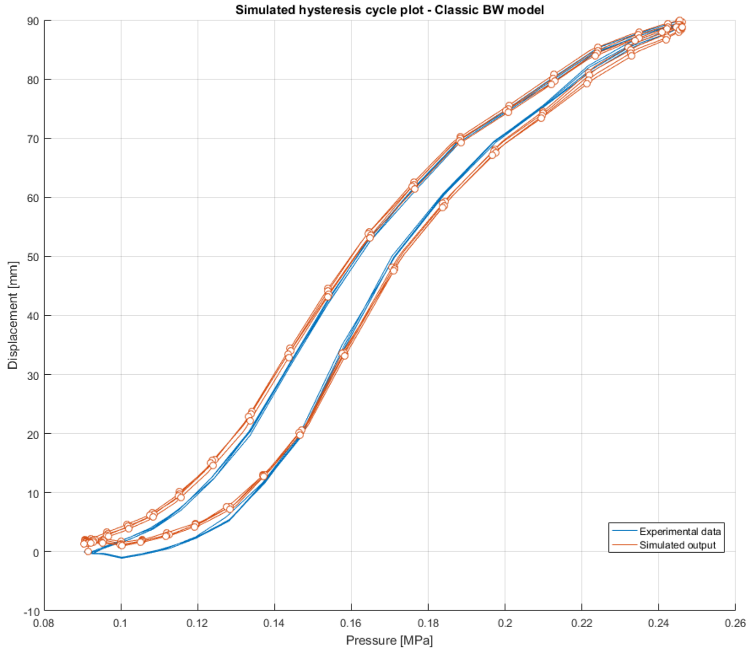

Figure 7: Comparison between experimental data and simulated output with classic Bouc-Wen model

4.9.2 *Generalized Bouc-Wen Model Parameters*

The parameters to be chosen for the generalized version of the Bouc-Wen model are α, A, n, β_1, $\ldots$, β_6. As previously stated, the value of n is fixed to 1.

As for the classic version of the hysteresis model, the parameters in Table 2 have been selected by trial and error. All parameters are adimensional.

Given experimental input p, the simulated output of the system after taking into consideration the generalized Bouc-Wen model of hysteresis is shown in Figure 8.

Parameter	**Value**
α	0.9
A	1
n	1
β_1	0.01
β_2	0.005
β_3	0.1
β_4	-0.01
β_5	-0.1
β_6	0.001

Table 2: Parameters for the Generalized Bouc-Wen Model

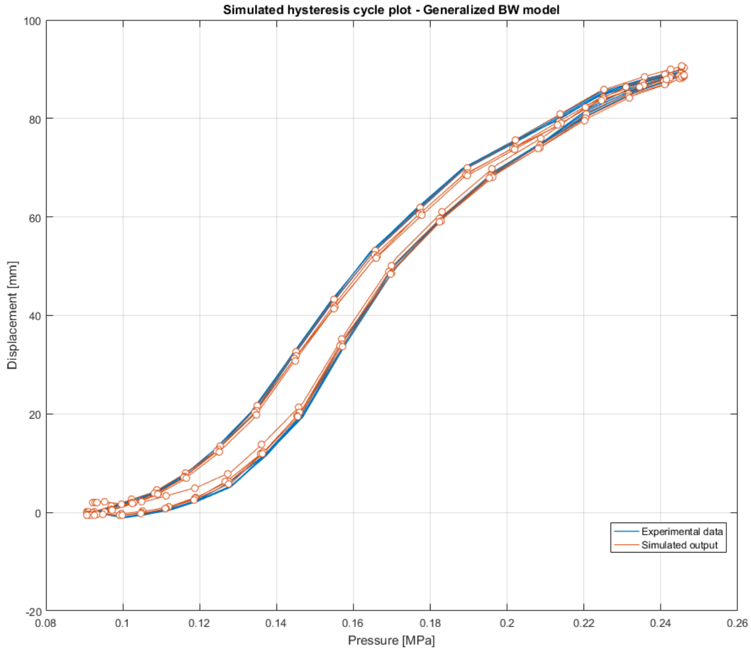

Figure 8: Comparison between experimental data and simulated output with generalized Bouc-Wen model

5 HYSTERESIS PARAMETER OPTIMIZATION

In this chapter, the methods to obtain the model's parameters are explained. Section 5.2 introduces the concept of *evolutionary algorithm*, with particular regard towards a simple genetic algorithm approach with the purpose of optimization.

After that, Section **??** introduces methods of *multi-variable optimization*, with the goal of transforming the search of parameters into an optimization problem.

Section **??** describes the implementation of said algorithms, and Section **??** shows the result for each of them.

5.1 INTRODUCTION

After having described how to get a discrete model of the McKibben artificial muscle, the Bouc-Wen model of hysteresis has been introduced. This model proves useful to describe a hysteretic behaviour in a simple manner, and can provide great advantages in terms of performance when it comes to control.

However, there are parameters that have to be tuned in order for the model to operate correctly. The tuning may be done by trial and error, or the whole process may be automated.

The parameter refinement process makes use of an algorithm to find the parameters of the Bouc-Wen model that give a best approximation of the real experimental data. Such algorithms include, but are not limited to, Recursive Least Squares (RLS), evolutionary algorithms and multi-variable optimization algorithms.

For this work, different approaches based on evolutionary algorithms and multi-variable optimization methods have been tested.

5.2 EVOLUTIONARY ALGORITHMS

An evolutionary algorithm is a population-based optimization algorithm that mimics the behaviour of biological evolution, simulating the steps of reproduction, mutation, recombination and selection.

Each individual is tested in an optimization problem, and the best characteristic of the population are passed through the generations. The evaluation of an individual is done by means of a fitness function. A fitness function is a operator that assigns a fitness value to each individual. Depending on the nature of the problem, individuals with lower (or higher) fitness values are judged "better" from the algorithm and have a higher probability of being chosen in the mating step to generate new, better individuals. Therefore, their characteristics have a higher chance to be passed onto next generations in order to iteratively refine the parameters and arrive at a acceptable solution.

Parameter	Description
pop_size	The population's size, i.e. the number of individuals (candidate solutions) that evolve to find a good approximation.
max_gen	The maximum generation. After reaching that stage of evolution, the algorithm stops.
d	The chromosome's dimension, i.e. the number of variables to be optimized by the algorithm.
L	A d-dimensional vector containing the lower bounds for each variable.
U	A d-dimensional vector containing the upper bounds for each variable.
p_{cross}	The crossover probability. It controls the chance of inheriting a chromosome from a specific parent with respect to the other.
p_{mut}	The mutation probability.
m_m	The mutation magnitude, i.e. how much a given chromosome changes in the event of a mutation.

Table 3: Parameters for the genetic algorithm

After a certain amount of generations, or after one individual reaches a fixed fit value, the algorithm stops and the best individual is chosen as the solution to the optimization problem.

5.2.1 *Genetic Algorithm*

A genetic algorithm (GA) [16] is a kind of evolutionary algorithm inspired by the concept of natural selection that permeates a biological evolutionary process.

Genetic algorithms are a class of stochastic global search algorithm operating on a set called *population* of current approximations, called *individuals*. Individuals are encoded as a set (*chromosome*) of parameters (*genes*).

Once a population has been created, each individual performance is assessed according to the objective function characterising the problem that has to be solved.

Algorithms belonging to this class are divided into the following steps: *initialization*, *evaluation*, *crossover* and *mutation*. The description and peculiarities of each step are discussed in Section 5.2.3. The genetic algorithm also makes use of several parameters, which are summarized in Table 3.

5.2.2 *Algorithm Overview*

5.2.3 *Algorithm Steps*

5.2.3.1 *Initialization Step*

For a genetic algorithm, the initialization step consists in the creation of the individuals, and by extension that of the population.

One of the most common initialization methods is random initialization: each gene of any individual is randomly chosen between a defined interval. This gives a higher chance of finding good results from the first generations, and refine the solution starting from them.

Another initialization method may be to create a population of equal individuals, and mainly rely on mutation for the first generations in order to find better approximations. This method, while it may better reflect the natural behaviour of a biological evolutionary process, takes also a much larger number of generations to return appreciable results.

For this reason, the GA developed for this work makes use of random initialization.

5.2.3.2 *Evaluation Step*

The evaluation step concerns assessing a fitness value to each individual in order to rank them according to their performance in solving the optimization problem. The fitness value is assigned to each individual by means of a *fitness function*.

Experimental input pressure and output displacement, respectively described in Equations 26 and 27, are taken from data acquired by the identification experiments described in Section 4.3.1.

$$u = [u_1, u_2, \ldots, u_k] \tag{26}$$

$$l = [l_1, l_2, \ldots, l_k] \tag{27}$$

with k representing the number of points for which the experimental data has been sampled.

Each individual is used to perform a specific simulation of the model with its genes set as Bouc-Wen hysteresis parameters, using u as input. The simulated output displacement $\hat{l}$ is then compared to the experimental displacement l.

The fitness function chosen for this step is described in Equation 28. This function returns the fitness value for the i-th individual of the population.

$$\mathrm{fit}(i) = -\frac{1}{\sum_{i=1}^{k} \left(l_i - \hat{l}_i\right)^2} \tag{28}$$

Judging from the nature of the fitness function, it is clear that individuals with a fitness value close to 0 are better than others, as it means that their simulated output is close to experimental data.

6 CONTROLLER DESIGN

Part II

APPENDICES

A

SCRIPTS AND ALGORITHMS

This Appendix contains all scripts and algorithms used for this work.

A.1 SCRIPTS

A.1.1 *Stair Input Generation*

This script generates the step wave that is to be given as input to the input and output proportional valves. Given that they have to be symmetric, the wave given to the output valve is defined as follows.

$$y' = 10 - y$$

Stair input generation

```
close all
clc
step = 1;        % Volts between two consecutive steps
y = zeros(1,50*10*(1/step));
for v = 0:step:10
        y((v*50)*(1/step)+1:(v+step)*(1/step)*50) = v;
end
y = [y fliplr(y)];
y = [y y y y]';
last = (length(y)-1)/10;
t = (0:0.1:last)';
y = [t y];
```

B

BOUC-WEN MODEL OF HYSTERESIS

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