Design of a hysteresis predictive control strategy with engineering application cases

Nubia Ilia Ponce de León Puig

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Design of a Hysteresis Predictive Control Strategy with Engineering Application Cases

Nubia Ilia Ponce de León Puig

Directors:
José Rodellar Benedé
Leonardo Acho Zuppa

September 2021
To my loved ones

To all students who are struggling to achieve their goals

A mis seres queridos

A todos los estudiantes que están luchando por alcanzar sus metas
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Abstract

This doctoral thesis exposes the development of a redesigned Predictive Control strategy that uses hysteresis to improve the performance of the controlled systems in different fields of application. The approach may use one of the three hysteresis models presented in this thesis. Moreover, the hysteresis may be used as a modulation stage or as a reference trajectory generator. The first step in the methodology of this research will be to validate the hysteresis dynamic model that will be used within the control scheme. Due to the three exposed hysteresis models have the same constitution, it is assumed that the test of one is enough to guarantee the validation of the other two hysteresis systems. This validation consists on implementing the hysteresis model in an experimental platform to confirm that the model is indeed feasible. Later, it will be seen that this application is within the scope of renewable energies.

Once the hysteresis model is validated, the proposed strategy is developed. This is, an Adaptive-Predictive control scheme with a modulation stage for the control signal. This stage employs hysteresis to improve the functioning of the adaptive phase and in general the entire closed-loop performance. It will be shown how the use of this modulation scenario solves the parametric drift problem commonly present in some adaptive based controlled systems. Additionally, a fault detection system within the Adaptive-Predictive control scheme is also proposed and validated through a numerical simulation. Furthermore, it will be seen how the hysteresis also can be used as a model to generate the reference trajectory needed to accomplish the control objective.

Finally, the proposed strategy is implemented in a varied set of control systems to validate it. These control systems are: a nonlinear Van der Pol oscillator, a nonlinear base-isolated system, a DC-DC buck converter, and a single-phase inverter.
Resumen

Esta tesis doctoral expone el desarrollo de una estrategia de Control Predictivo rediseñada que utiliza histéresis para mejorar el rendimiento de los sistemas controlados en diferentes campos de aplicación. Este esquema de control puede utilizar uno de los tres sistemas de histéresis presentados en esta tesis. Además, la histéresis se puede utilizar como etapa de modulación o como generador de trayectorias de referencia. El primer paso en la metodología de esta investigación será validar el modelo dinámico de histéresis que se utilizará dentro del esquema de control. Debido a que los tres modelos de histéresis expuestos tienen la misma constitución, se asume que la prueba de uno es suficiente para garantizar la validación de los otros dos modelos de histéresis. Esta validación consiste en implementar el modelo de histéresis en una plataforma experimental para confirmar que este es realmente factible. Posteriormente, se verá que esta aplicación está dentro del ámbito de las energías renovables.

Una vez validado el modelo de histéresis, se desarrolla la estrategia propuesta. Es decir, un esquema de control Adaptativo-Predictivo con una etapa de modulación para la señal de control. Esta etapa emplea histéresis para mejorar el funcionamiento de la fase adaptativa y, en general, de todo el rendimiento del sistema en lazo cerrado. Se mostrará cómo el uso de este etapa de modulación resuelve el problema de la deriva paramétrica la cual es muy común en algunos sistemas basados en control adaptativo. Adicionalmente, también se propone y valida un sistema de detección de fallos dentro del esquema de control Adaptativo-Predictivo mediante una simulación numérica. Además, se verá cómo la histéresis también se puede utilizar como modelo para generar la trayectoria de referencia necesaria para lograr el objetivo de control.

Finalmente, la estrategia propuesta se implementa en un conjunto variado de sistemas de control para validarla. Estos sistemas de control son: un oscilador Van der Pol no lineal, un sistema no lineal de base aisladora, un convertidor Buck DC-DC y un inversor monofásico.
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Nomenclature

A-P: Adaptive-Predictive
AC-DC: Alternating Current to Direct Current
AC: Adaptive Control
AM: Adaptive Mechanism
CoDAlab: Control, Dynamics and Applications laboratory
DB: Driver Block
DC-DC: Direct Current to Direct Current
DG: Distributed Generation
DMC: Dynamic Matrix Control
GPC: Generalized Predictive Control
HDM: Hysteresis Delta Modulator
MAC: Model Algorithm Control
MPC: Model Predictive Control
MPP: Maximum Power Point
MPPT: Maximum Power Point Tracking
MRAC: Model Reference Adaptive Control
NN: Neural Network
P&O: Perturb and Observer
NOMENCLATURE

PC: Predictive Control
PE: Persistent Excitation
PLL: Phase-Locked-Loop
PM: Predictive Model
PV: Photovoltaic
PWM: Pulse Width Modulation
SMC: Sliding Mode Control
THD: Total Harmonic Distribution
UPS: Uninterruptible Power System
Chapter 1
Introduction

Over times, the mankind has witnessed a great amount of natural and artificial processes that in sort of way can be classified as controlled feedback systems. For instance, the african termite nests that employ air ducts to maintain the constant temperature in 30° C [1], or the float regulator of the water clock in the ancient Greece [2]. Nowadays, the control systems are extremely common and a basic necessity in the industrial field. However, the control theory as it is known today, has had a long process of developing until became to an integral part of almost everything around us, such as, autonomous vehicles, robotics systems, manufacturing processes and any industrial operation that requires the regulation of temperature, pressure, humidity, flux, position, velocity, etc [3]. In the last century, the control theory raised as a novel research topic among scientists such as Nyquist, Bode, Evans and Ziegler. It emerged from the first velocity control machine by James Watt [4], until get to what is today the foundation of the classic control theory: the methods of frequency response and place of the roots [4].

During the decades of 1950s and 1960s, the industrial plants were more complex, mainly because multiple inputs and outputs were added to fulfil the needs of those times [3]. Thus, the classic control theory lost its capability to accomplish the control requirements due to it did not have the potentiality to deal with this kind of systems. Hence, the modern control theory came along, based on the time-domain analysis and state variables synthesis [4]. This control theory allowed to deal with more complex systems in every kind of applications, either aerospace, robotics or industrial. It is accurate to say that is from the modern control theory from where the nowadays more popular control techniques were born [4]. Currently, the ones that highlight the most are for instance, Optimal Control, Adaptive Control, Robust Control and Predictive Control. Furthermore, over the last decades, it has
been demonstrated that all these control techniques are efficient in their own manner. Moreover, these techniques are still developing today, and each has found its own outstanding field of application. However, in the same way, these techniques also have shown drawbacks, mostly related to the difficulty of treating with nonlinear systems, or in general, systems that are too complex to fix to the mathematical implementations or even more, to the complexity of the plant itself. For instance, optimal control is a technique that has had considerable success from both theoretical and practical application point of view. It basically consists of solving a cost function that optimizes the system performance, in this manner the designed control law guarantees the optimal response of the plant [5]. This strategy is successfully applied in both continuous-time and discrete-time systems. Nevertheless, the benefits of optimal control are overshadowed for the case of systems that present nonlinearities or when the systems are subjected to constrains at the input variables or model states [4]. In these cases it is not possible to obtain a mathematical expression for the optimal solution, thus, it is necessary to work with an approximation of the problem. However, this is mainly impracticable for the majority of realistic problems [4].

In the struggle to solve the drawbacks of optimal control and by taking advantage of the latest improvements of digital microprocessors, Predictive Control (PC) emerged. The first generation of PC algorithms can be traced to the decades of 1970s and 1980s [6]. Predictive Control refers to a class of computer control algorithms that utilize an explicit model of the plant to predict its future response [4], [6], [7]. At each control sampling, the controller attempts to optimize the performance of the plant by computing a sequence of future manipulated variable adjustments, although, only the first element of the control input sequence is implemented [7]. Then, the process is repeated at each sampling instant using new information from the current state of the process output and the variables involved in the system [4], [8]. Furthermore, the control strategies utilize a pre-programmed reference trajectory, which is the desired behavior that the process output should replicate [9]. The basic block diagram of Predictive Control is depicted in Figure 1.1 [10].

Predictive Control is with no doubt one of the most common techniques that is currently employed in a wide range of applications due to its feasibility and its simplicity [4], [7], [8]. This technique has shown its effectiveness in relevant applications such as petrochemical, power electronics, civil engineering, robotics, aerospace, among many others [8]. The popularity of this technique is because it allows to manage the constrains within the control design. Moreover, it is robust to the uncertainties caused by differences be-
tween the mathematical model of the plant and the real plant, or faults in the plant parameters caused by external perturbations. Nevertheless, the Predictive Control algorithms have some drawbacks, such as the complexity of designing and solving the optimization problem, mainly when the dynamics of the process changes over time [4]. Finally, another common disadvantage is that the stability cannot always be theoretically guaranteed [7].

This thesis is grounded on the basic principle of Predictive Control: Using a predictive model, the objective is to calculate the control that makes the predicted output be equal to a desired output in a future time instant [10]–[12]. The main motivating hypothesis of this thesis is that, by adding a hysteresis component in the control loop, some problems not covered by the basic Predictive Control principle could be solved without the need of extending the prediction over a finite long horizon along with an optimization performance. Therefore, this approach expects to solve, for instance, the problem of bursting and parameter drift behavior induced by mismatches in the mathematical model, or when the plant itself is unstable, nonlinear or non-minimum phase [13]. This also expects to help solving issues such as delays at the process output [13]. Furthermore, this control strategy simplifies the mathematical implementation to obtain a simple control design even if the process to be controlled is too complex [14]. Moreover, it is proposed to save on every aspect of the implementation, such as mathematical resource, economical expense, software and programming resource or hardware physical space.

It will be seen that the proposal uses hysteresis within the control structure. The concept of hysteresis has been notably studied in different fields of science [15], [16]. The approach of this thesis employs a hysteresis system as a modulator of the control signal [13]. This modulator block is used to provide

![Figure 1.1: Basic block diagram of Predictive Control](image-url)
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Figure 1.2: Block diagram of the Adaptive-Predictive control with Hysteresis Modulation.

the persistent excitation that helps to improve the estimation of the parameters and in general the dynamics of the entire closed-loop control scheme. Moreover, it is proposed that the hysteresis can be also used as the stage that generates the reference trajectories within the Driver Block. The Adaptive-Predictive control scheme used along this thesis is the one presented in Figure 1.2.

Another aim of this research is focused on validating the proposed control scheme. To do that, it is resorted to some typical engineering applications in current days. The implementation of the control proposal is divided in two parts: the numerical and the experimental cases. All numerical simulations are conceived by using the software Matlab/Simulink. Along the thesis it will be cited the models and libraries employed to achieve the numerical simulations. On the other hand, for the experimental cases all the specifications related to the implementation will be explained as well.

1.1 Thesis Objectives

The overall aim of this thesis is to redesign a Predictive Control strategy by appealing to the concept of dynamic hysteresis. The hysteresis may be invoked within a proposed Hysteresis Delta Modulator that is inserted between the control signal and the Adaptive Mechanism. Additionally, the hysteresis also might be employed within the Driver Block to generate the reference trajectory.

The specific objectives of this thesis are the following:

• To design a signal modulator by employing a hysteresis system within

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its structure. This modulator will improve the closed-loop dynamics of the Adaptive-Predictive control scheme.

• To employ a redesigned dynamic hysteresis system to generate dynamic reference trajectories within the Driver Block.

• To design and perform adequate numerical simulations of selected engineering systems to validate the control approach.

• To implement and validate the proposal in experimental setups.

1.2 Background and State of the Art

The concept of Predictive Control had its first origin in the industrial field [6]. Mainly, it was dedicated to fulfill the control needs of the chemical and petro-chemical industrial processes [9], [17]. However, with the years, this control strategy attracted the attention of researchers and scientists due to its innovative and notable advantages. The first approaches of Predictive Control can be tracked to the decade of 1970’s. For instance, its methodology was introduced in a doctoral thesis in 1974 [18]. Subsequently, the original basic principle was formally defined in a US patent in 1976 [12]. Parallel, a model predictive heuristic control also was presented in the same year [19]. Since then, Predictive Control has evolved from the theoretical point of view. Moreover, it has been validated in different fields of application, showing that it is one of the best options among all control techniques that currently exist.

Generally speaking, Predictive Control may be defined as the family of control algorithms that use an explicit model of the process to obtain a control signal by predicting its future behavior during a predefined prediction finite horizon [6], [14]. Within this generalized definition, different approaches were provided back in the beginning of the Predictive Control scheme. First of all can be mentioned the Model Algorithmic Control (MAC) [20], and the Dynamic Matrix Control (DMC) [21], that are algorithms that use an explicit dynamic model of the process to predict future control signals and are strongly tied to the optimal control problem [22]. These techniques were very popular in the chemical industrial processes due to the simplicity of the algorithm that requires less information to solve the identification problem.
During the decade of the 1980s, these algorithms were successfully applied in multi variable systems with restrictions, however, these formulations lacked of a theoretical base to provided stability or robustness [23]. On the other hand, also in the decade of 1980s other line of study was developed focused on the adaptive control approach. In this branch highlights the Predictor-based self-tuning control [24], the Adaptive Control with extended horizon [25], the Generalized Predictive Control, (GPC), [26], or the Adaptive-Predictive control strategy [9]. Despite the fact that the different predictive control algorithms were constantly evolving, at that time there were still no guarantees of stability from the mathematical point of view. Hence, to face this issue, during the decade of 1990s, the study line of stability emerged. For instance, methods that guarantee stability for the nominal case [27], or an study of the limits of stability, mainly related to the modelling errors and the incorporation of adaptation within the control scheme [9].

Overall, it is possible to say that, from its birth to nowadays, Predictive Control expects to be a strategy that may overcome the stability, robustness and constraints issues [4]. Furthermore, such as all the current control strategies, Predictive Control also expects to be of fast response, simple to conceive, low-cost in terms of mathematical and computational resources and applicable to different kinds of systems. Thus, in the current state of the art it is possible to find many works related to amend the issues above mentioned. To cite some instances, recent works provide results that accomplish stability for distributed systems by defining a global PC problem that defines a stabilizing control law, or by analyzing input-to-state stability concepts [28], [29]. Moreover, for robustness and constrains satisfactions, it has been proposed the use of a finite number of optimization algorithm iterations per sampling instant [29]. On the other hand, the guarantees of stability and robustness also have been proved for nominal data-driven PC schemes for the cases of measurement and no measurement of noise [30]. Meanwhile, in the experimentation field, the stability of PC has been proved via Lyapunov techniques by adding terminal state constraint and terminal cost to the controller formulation [31]. Also, by resorting to Lyapunov theory, it has been proposed a Lyapunov-based model predictive control that improves trajectory tracking performances while guarantying stability [32].

Honoring the origin of Predictive Control in the industrial application, the most recent works that stand out are related to the application of Predictive Control in different areas. The treatment of these applications has encouraged the development in PC theory, control design and algorithms. Firstly, in the automotive field, the PC based-model control approach is mainly em-
ployed in the areas of power-train control, chassis control, energy management and clutch control \[33\], \[34\]. In addition, within the vehicles field, the Predictive Control strategy has been implemented in different kinds of transportation devices such as helicopters \[35\], trains \[36\], autonomous underwater vehicles \[37\], \[38\], and drones \[39\]. Secondly, it is worth to mention the applications of PC algorithms in the health care area. These have growth exponentially due to Predictive Control can adequately manage important aspects in this area such as safety, background knowledge of clinical and biology practice and models in the health area \[8\]. Some examples where PC has been used in the health area are, for instance, ambulance scheduling, management of Type 1 Diabetes, automatic controller for giving anesthesia and the optimization for drug delivery in cancer treatments \[40\]. In other way, PC concepts have been highly invoked in power electronics and electrical drives, more specifically for applications that require conversion, regulation and storage of energy \[41\]. The applications that highlight the most are in the field of DC-DC converters and DC-AC inverters \[42\]–\[46\]. From here, it comes naturally that the predictive control methodologies have been strongly applied in the field of renewable energy sources. Many works combine the strategy of extracting the maximum power point along with a predictive control algorithm to extract the maximum regulated energy from photovoltaic systems \[44\], \[47\]. Besides, PC is employed to improve the performance and the power quality obtained from grid distributed systems \[48\]. Also, in the wind turbine speciality, PC approaches are used to manage and regulate the energy supplied by these devices \[49\]. To continue this survey of the current state of the art of Predictive Control applications it can not be missed the robotics area, since it is one of the most interesting branch in the engineering and research field. Besides, it is one speciality where Predictive Control has found growth in many aspects. Recent works are dedicated to the trajectory tracking and to reduce the complexity of the robotics applications \[50\], \[51\]. Meanwhile, in the field of civil engineering, many Predictive Control approaches has been suggested. For instance, to reduce vibration in structures, to optimize the performance of irrigation canals, and to regulate heating, ventilation and air conditioning in buildings \[52\]–\[54\]. Finally, other applications where the PC algorithms have found their way are, for instance, in the agriculture applications or finances \[55\], \[56\].

From the above, it is notorious that predictive control has an enormous range of applications, this, due to its simplicity and its adaptability to fit in a wide range of systems. However, another important key why predictive control algorithms are very popular is because they have been combined with different conventional and favorable control strategies. In this manner, researches
and engineers have achieved to contribute with novel and resourceful control strategies. For instance, Sliding Mode Control (SMC) has been paced together with the Predictive Control concept to solve the problem of non-linearities and dynamical variations [57]. On the other hand, the fuzzy logic methodology also has been combined with Predictive Control for discrete-time systems with time-varying delays, and applications, for instance, in train operation [36], [58]. Furthermore, other techniques that have been involved with Predictive Control are the ones based on artificial intelligence, for instance, the Neural Network (NN) approach and the popular machine learning approaches [59], [60]. Both of them are highly employed in nonlinear systems such as in the power electronics field [46]. Finally, this study of the state of the art would not be complete without mentioning the current works related to combine strategies of Predictive Control and hysteresis control, since this is the main topic of this thesis. Due to the characteristics of PC and hysteresis, the combined techniques have proved to be very effective, mainly in the field of power electronics, where control switching is required [61], [62]. In these cases, the hysteresis controllers are employed to define the bounds of the current or voltage trajectory, depending on the control objectives. Nevertheless, to the best knowledge of the author of this thesis, the hysteresis within Predictive Control schemes, as presented here, has not been proposed before.

1.3 Layout of the Thesis

This thesis is organized in seven chapters. This Introduction is the first one, where the motivation and scope of the thesis have been stated. Moreover, in this first chapter the objectives of the thesis and the study of the state-of-the-art have been also presented.

Chapter 2 presents the theoretical background of the thesis by exposing the Predictive Control strategy. Moreover, the chapter defines the Adaptive Mechanism and the Driver Block.

Chapter 3 introduces the concept of hysteresis and presents the hysteresis models that will be employed along this research work. Additionally, in order to validate these models, it is presented an experiment that was developed within the renewable energy scope. It is used to verify the feasibility of the hysteresis model to be implemented in an experimental platform. The publications derived from this chapter are:
Chapter 4 presents a new hysteresis signal modulator that is inserted within an Adaptive-Predictive control scheme. This modulator uses a hysteresis model within its structure with the aim of improving the performance of the closed-loop system. This proposal finds to solve issues in the control area such as parameter drift or bursting. Here it is exposed how the proposal solves the parameter drift in the well-known Rhor’s example. Moreover, an example of a parameter estimation of a non-minimum phase system by using the hysteresis modulator is also presented. The publications derived from this chapter are:


Chapter 5 presents the numerical simulation cases of the proposed control strategy. These are a nonlinear Van der Pol Oscillator and a nonlinear base-isolated system. In this chapter it is also presented a fault detection approach which is applied to the based-isolated system. The publications derived from this chapter are:

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Chapter 6 presents two experimental cases that validate the control proposal implemented in an experimental platform. These cases are a DC-DC buck converter and a single-phase inverter. The publications derived from this chapter were partially done during my research staying at Ghent University in Belgium:


Chapter 7 asserts a detailed discussion of results, provides the conclusions of the thesis and the future work to continue the research in this subject.
Chapter 2
Theoretical Framework

This chapter presents the theoretical background of this thesis. First, it will be explained the basic strategy of Predictive Control theory. Furthermore, it will be explained the different stages that compose a Predictive Control framework, including the Driver Block and the Adaptive Mechanism concepts.

2.1 The Basic Strategy of Predictive Control

The basic strategy of Predictive Control follows the principle of calculating a control action that manipulates the predicted process output in order to follow the desired dynamic output, based on a model of the process [9], [14]. The basic strategy consists on the direct application of this principle in just a single-step prediction, in contrast to the extended strategy, which employs a finite prediction horizon [4], [9], [10]. It means, and knowing that the Predictive Control is formulated in discrete-time domain, that the desired output is calculated at each sampling instant. Therefore, the basic strategy accomplishes the following condition [9]:

\[ \hat{y}(k + 1|k) = y_d(k + 1|k) \] (2.1)

where \( \hat{y}(k + 1|k) \) is the output predicted at instant \( k \) for the next instant \( k + 1 \), and \( y_d(k + 1|k) \) is the desired output for the next instant \( k + 1 \). Thus, the designed control law \( u(k) \) to be applied at the instant \( k \) is the one that completes the condition in (2.1). In this notation, \( k \) represents the \( kT \) instant, where \( T \) is the sampling time always required in digital control.

The above concept describes how Predictive Control was initially conceived [9]. Nevertheless, as the applications were more complex, it was necessary to
extend the strategy by considering a longer prediction horizon [10]. In this chapter, it is point out the basic strategy, since, as the reader will see later, the proposal here exposed is supported on this basic strategy.

2.1.1 The Predictive Model

The first step of Predictive Control is to define a mathematical model that describes the dynamics of the system to be controlled [4], [9]. With this model it is possible to obtain a prediction of the process output at each sampling instant. A model that describes the dynamic behavior of a generalized class of systems can be stated by a differential equation as follows [3]:

\[ a_{m} \frac{d^{m}y}{dt^{m}} + ... + a_{1} \frac{dy}{dt} + a_{0}y = b_{n} \frac{d^{n}u}{dt^{n}} + ... + b_{1} \frac{du}{dt} + b_{0}u \]  

(2.2)

And by taking the Laplace transform of equation (2.2), its transfer function is

\[ G(s) = \frac{Y(s)}{U(s)} = \frac{b_{0} + b_{1}s + ... + b_{n}s^{n}}{a_{0} + a_{1}s + ... + a_{m}s^{m}} \]  

(2.3)

where \(a_{0}, ..., a_{m}\) and \(b_{0}, ..., b_{n}\) are the parameters of the process to be controlled and \(m\) and \(n\) are the coefficients that determine the order of the model [9]. Once the model of the process has been stated it is possible to predict the dynamic of the process by using an estimation of it. Since the Predictive Control is a discrete-time based strategy, the predictive estimation may be written in terms of the prediction instant \(k\). This prediction obviously depends on the estimated parameters of the process that may be updated at each sampling instant by the Adaptive Mechanism, as will be seen later in this chapter. Hence, an estimation model can be stated in the following generalized form [9], [10]:

\[ \hat{y}(k + 1|k) = \sum_{i=1}^{\hat{n}} \hat{a}_{i}y(k + 1 - i) + \sum_{i=1}^{\hat{m}} \hat{b}_{1}u(k + 1 - i) \]  

(2.4)

where \(\hat{y}(k + 1|k)\) is the output predicted at instant \(k\) for the next instant \(k + 1\), with \(i = 1, ..., \hat{n}\), and \(i = 1, ..., \hat{m}\). This Predictive Model uses the information from the output \(y(\cdot)\) and the input \(u(\cdot)\) known at instant \(k\).

2.1.2 Driver Block: The Desired Reference Trajectory

Within the Predictive Control scenario it is necessary to conceive the concept of desired reference trajectory. This trajectory is generated by the Driver
Block, and it allows the system output reach the set-point in a smooth manner without abrupt control actions and overshoots, but rapidly at the same time [9]. From the implementation point of view, the Driver Block uses a mathematical model to build a signal that serves as the reference trajectory. This model may employ the actual values of the process output to project the trajectory to which the desired process output should belong. The reference trajectory, defined as \( y_d(k+1) \), is recalculated at each sampling instant \( k \) and with it, the control signal also is recalculated at each instant [10].

An standard manner to build this trajectory is by using a stable model that requires the set-point as its input, and the actual process output as its initial condition. This means, the initial condition will change at each instant as the output of the process changes at each sampling time. A typical example of a model to generate the reference trajectory is the following [10]:

\[
y_r(k+1) = \alpha_1 y_r(k) + \alpha_2 y_r(k-1) + \beta_1 y_{sp}(k) + \beta_2 y_{sp}(k-1)
\]

\[
y_r(0) = y_0, \quad y_r(-1) = y_1
\]

where \( y_r \) is the reference output and \( y_{sp} \) is the set-point. With this model it is possible to obtain the complete trajectory with the initial conditions and the given values of the set-point. Moreover, the parameters \( \alpha_1, \alpha_2, \beta_1 \) and \( \beta_2 \) are the ones selected to make the system stable, avoiding overshoots and with the time constant that determines the response speed [3]. By following the format in (2.4), the Driver Block function may be generalized as follows [9]:

\[
y_d(k+1|k) = \sum_{i=1}^{p} \alpha_i y_d(k+1-i|k) + \sum_{j=1}^{q} \beta_j y_{sp}(k+1-i|k)
\]

where \( i = 1, \ldots, p \), \( j = 1, \ldots, q \), and \( y_d(k+1-i|k) = y(k+1-i) \). The equation above selects the corresponding value of the desired trajectory as the desired output for \( k+1 \) at the instant \( k \).

The fact that the desired reference trajectory is redefined at each sampling instant \( k \) introduces a level of feedback of the process output. Hence, the Driver Block is an essential part in the Predictive Control, specially in this doctoral thesis since here it will be proposed a specific manner to build this reference trajectory within the Driver Block stage by using hysteresis as will be presented in Chapter 6. Figure 2.1 depicts the overall structure of Predictive Control by including the Driver Block, where \( T_s \) is the sampling time.
2.1.3 Control Law of the Basic Strategy

Previously it was defined the Predictive Model and the Driver Block by equations (2.4) and (2.6), respectively. Now, if it is imposed the condition in (2.1), the general form of the control law \( u(k) \) can be obtained after some basic algebraic operations as follows [9]:

\[
\begin{align*}
    u(k) &= y_d(k+1|k) - \sum_{i=1}^{\hat{n}} \hat{a}_i y(k + 1 - i) - \sum_{i=2}^{\hat{m}} \hat{b}_i u(k + 1 - i) \\
    & \quad - \hat{b}_1(k) - \hat{a}_1(k) \cdot \hat{a}_1(k)
\end{align*}
\]

(2.7)

with \( i = 1, ..., \hat{n}, \ i = 2, ..., \hat{m} \) and \( k = 1, 2, ... \).

Note that the equation (2.7) is just valid for the case called here the basic strategy, it means, for the case where just a single step prediction is done.

2.2 Adaptive System within the Predictive Control Structure

In this Section it is mainly explained the concept of the Adaptive Mechanism, which works in collaboration with the Predictive Control strategy. This mechanism is conceived within the framework of Adaptive Control. This framework was born due to most of the control techniques are based on a good modelling of the plant to be controlled [63]. However, sometimes the plant may be too complex, for instance, it may be non-linear or time-varying. Hence, the mathematical model results difficult and the physical process is not fully understood. In consequence, the designed control may be not the adequate to accomplish the objective. In these cases, an identification system is required in order to obtain a progressive knowledge of the process to
be controlled. Usually, this technique is used with some form of recursive system identification [63].

The motivation of adding an adaptive system within the Predictive Control strategy was conceived due to the necessity of having a mechanism that makes the process parameters vary according to the changes produced in the process dynamic [9]. In this manner, the PC in combination with an adaptive system can be a complete solution, since it is not necessary to worry about the external perturbations that change the dynamic of the plant or deviate the variable under control from its objective.

Summarizing, the Adaptive Mechanism adjusts the parameters based on the alterations in the dynamic process, while the Predictive Control corrects the mentioned alterations or deviations through the Predictive Model [10].

2.2.1 The Adaptive Mechanism

The Adaptive Mechanism may be interpreted as a learning process, thus, it needs information to do this task. Within the Predictive Control structure, this information is given by the output predictive control law and the output process as it is shown in Figure 2.2. Additionally, the prediction errors are also part of the information that helps the mechanism to do the learning process. These errors add an incremental knowledge to the previous knowledge of the process dynamics [63].

From a conclusive point of view, the Adaptive Mechanism should produce a change in the parameters of the model. This means that the value of each parameter at instant $k$ will be generated by the Adaptive Mechanism through a function that depends on the error prediction at instant $k$ [10].

Figure 2.2: Overall control block diagram highlighting the Adaptive Mechanism.
CHAPTER 2. THEORETICAL FRAMEWORK

2.2.2 The Gradient Algorithm

In this thesis the Adaptive Mechanism is designed by resorting to the well known Gradient Algorithm [63]. In order to apply it, it is necessary a linear expression of the model in continuous-time form. The gradient algorithm is expressed as follows:

\[ y(t) = \theta^T \phi(t) \quad (2.8) \]

where \( y(t) \) is the output signal, \( \theta^* \) is a vector of unknown parameters related to the original plant parameters \( a_i \) and \( b_i \). Finally, \( \phi \) is the regression vector obtained from the filtered input and output signals. Then, the identification algorithm is defined by the equation called the adaptive law [63]:

\[ \dot{\theta}(t) = -\gamma \phi(t) e(t) \quad (2.9) \]

where \( \gamma > 0 \) is a fixed and strictly positive gain called the adaptation gain, which allows to vary the adaptation rate of the parameters [63]. Moreover, \( e(t) \) is the output estimation error \( e(t) = \hat{y}(t) - y(t) \). Therefore, the adaptive law can be written as:

\[ \dot{\theta}(t) = -\gamma \phi(t)[\hat{y}(t) - y(t)] \quad (2.10) \]

Additionally, the regression matrix is obtained by filtering the input and output signals of the Adaptive Mechanism. To do this, adequate stable filters should be designed. The more conventional option is to select second order filters whose parameters make them stable and without overshoots [3]. Figure 2.3 shows how the Adaptive Mechanism is implemented with these filters. Later on, in this thesis, the mathematical procedure will be extended more precisely for the implementation cases.

Figure 2.3: Adaptive Mechanism scheme.
2.2.3 The Demand of Persistent Excitation

When talking about adaptive control and identification algorithms, two main keys are expected. Firstly, it is important to guarantee the stability of the identifiers and the stability on the convergence of the output error $e(t)$. This may be done by invoking the Lyapunov theory [63]. However, in this work, this key is not considered since it is assumed that the stability will be guaranteed by the whole closed-loop Adaptive-Predictive control scheme. Secondly, the issue that concerns this research is the requirement to ensure the convergence of the parameters to their nominal value. This second point is possible thanks to the Persistent Excitation condition (PE) [64]. If the PE condition is adequately induced in the adaptive system, it is possible to guarantee the convergence of the estimated parameters. The PE condition establishes that the input signal has to be sufficiently changed in order to the parameters converge to their nominal values [64]. Some authors have presented a full discussion of the intuition behind the PE concept, mainly regarding that the input should be rich enough to excite all of the modes of the estimated system [65]. Additionally, different approaches have been proposed to obtain the persistent excitation signal that accomplishes the requirements and improves the on-line and of-line parameter identification. For instance, a published work proposed to employ chaotic signals in an adaptive parameter identification process applied to servo controlled systems [66]. In this paper the chaotic signals were successfully generated to achieve the convergence of the parameters.

The PE demand issue has motivated one of the contributions of this thesis. In Chapter 4 it will be exposed a technique to obtain the persistent excitation signal that allows to guarantee the convergence of estimated parameters within the structure of Predictive Control. Furthermore, this proposal expects to solve the parameter drift problem, described in the following subsection, which is present in many controlled systems.

2.2.4 Parameter Drift Phenomenon in the Rohr’s Example

One of the main drawbacks in identification processes is that if the convergence of the parameters is not guaranteed, it may be expected a negative phenomenon known as parameter drift. This may be derived due to all physical actuators are subjected to delays or saturation effects, among others conditions that can change the process dynamics. These conditions may deteriorate the performance of the closed-loop system, induce limit cycles,
or even produce instability [67]. Therefore, it is important to design an adequate Adaptive Mechanism which is capable of following the process dynamics even when it is modified by external disturbances or modelling errors.

In this subsection, an adaptive control system is invoked to numerically show the parameter drift and its related bursting phenomenon. This is the well-known Rohr’s example, which here is just used as a benchmark for numerical experiments. For more details see [13], [63]. The bursting Rohr’s example comprises a Model Reference Adaptive Control (MRAC), which was designed by assuming a first order plant model from a third-order one, as shown in Figure 2.4. The system represented by the second-order transfer function is the unmodeled dynamics, which may be seen as a disturbance term for the designed closed-loop system. The equations that describe the MRAC are [63]:

\[
\begin{align*}
    u(t) &= c_0(t)r(t) + d_0(t)y_p(t) \\
    e_0(t) &= y_p(t) - y_m(t) \\
    \dot{c}_0(t) &= -ge_0(t)r(t) \\
    \dot{d}_0(t) &= -ge_0(t)y_p(t)
\end{align*}
\]  

(2.11)

where \( u(t) \) is the control signal, \( y_m(t) \) denotes the reference output, \( e_0(t) \) represents the error and \( n(t) \) is an additive external noise. In addition, \( y_p(t) \) is the output signal, \( g \) is a selected constant gain, \( c_0(t) \) and \( d_0(t) \) are the controller parameters and \( r(t) \) is the user reference command.

---

Figure 2.4: Block diagram for the Rohr’s example with the Model Reference Adaptive Control.
The response of the plant is obtained by modelling the control scheme in Matlab/Simulink with the following values, \( r(t) = 4.3, n(t) = 0, g = 1 \), and zero initial conditions. First of all, the output process is depicted in Figure 2.5 where is notable what it was expected to show in this subsection: the bursting effect. On the other hand, in Figure 2.6 also it is observable the bursting phenomenon in the error signal. This response, both in the output and in the error signals, is highly linked to the parameter drift. This can be then defined as the effect when the parameters growth exponentially without limit. As an instance, the parameters drift of the Rohr’s example are depicted in Figure 2.7.

![Figure 2.5: Output plant with bursting response.](image1)

![Figure 2.6: Error signal with bursting response.](image2)

Later on, it will be seen that the proposal here conceived will solve the above parameter drift issue, as well as the bursting effect.
2.3 Final Chapter Remarks

This chapter exposed the basic theoretical framework for the development of this doctoral thesis. It was shown that the Predictive Control strategy used in this thesis is characterized by using only one sampling-time step prediction horizon. Additionally, this basic strategy resorts to the concepts of the Driver Block and the Adaptive Mechanism. Both concepts are important to develop the contribution of this research. Finally, an example of a Model Reference Adaptive Control was invoked to show the concept of parameter drift and bursting effect. Thus, with the proposal made here it is expected to solve these typical issues. Later on this example will be again invoked to show how the proposal works in solving these problems.
Chapter 3

Hysteresis Systems

This Chapter introduces three hysteresis models that can be used to complete the control proposal of this thesis. The control approach uses the hysteresis in a modulation stage called the Hysteresis Delta Modulation or in the Driver Block, as will be later exposed.

The first hysteresis model is a simple relay that captures the memory effect with signum functions. The second one is a dynamic model that depends on the state of its internal variable and it also uses signum functions in its composition. Finally, the third one is a contribution that states a recent mathematical hysteresis model, which is conceived as an extension of the second hysteresis model. Therefore, the three hysteresis models in this chapter have a similar mathematical constitution which make them easy and practical.

With the aim to evidence the viability of these models in engineering applications, it will be presented the development of an experimental platform conceived for a renewable energy application. Due to the three hysteresis models have a similar composition, it is reasonably expected that the test of one is enough to guarantee the validation of the other two systems. The application will prove that the hysteresis model is easily programmable, simple to conceive and it does not require much computational effort. This is important since the hysteresis model will be part of the granted Predictive Control approach and thus it must be feasible, simple and practical. The execution of the mentioned hysteresis platform is within the scope of solar energy. More specifically, in this section it is invoked one of the hysteresis models to be employed as a Maximum Power Point Tracking (MPPT) algorithm. Then, this approach is tested in the designed platform which consists basically of a photovoltaic (PV) panel, an Arduino board and the stages of
electronic instrumentation for signals acquisition and processing. Finally, the proposed hysteresis algorithm generates the duty-cycle that is manipulated to be the control signal for the conversion stage. This field of application was selected due to the current importance of the clean energies to improve the life on earth.

3.1 Introduction to the Hysteresis Concept

In recent years, the comprehension of hysteresis phenomenon and the development of adequate mathematical tools that describe it have attracted the attention of many researchers [15], [68], [69]. The main reason is that hysteresis is encountered in many different physical and mathematical applications. Examples include magnetic, mechanical and optical areas, among many others [69]–[71]. It is also well known that the phenomenon of hysteresis is a complex physical process that represents an important challenge, for instance, to control systems that contain in their nature some hysteresis behavior. Moreover, it is at the same time a source of strong technological progress for some crucial engineering systems [72], [73].

Talking about engineering applications, hysteresis can be described as a non-linear phenomenon that under zero-bias and low-frequency periodic excitation, its output has a periodic response with the same frequency of its input [72], [74]. Usually, hysteresis systems have an output versus input response that plots a closed-loop trajectory. Hence, it makes that hysteresis is linked with the formation of loops, which may take a variety of different forms depending on its input excitation and parameters that govern the hysteresis system [68], [69]. Besides, hysteresis can be described as a dependence of the state of a system on its time-history, thus providing a memory effect [75].

Through the years, different hysteresis models have been developed. For instance, in some magnetic applications, hysteresis is the main property used to produce permanent magnets and to manufacture magnetic recordings and energy conversion devices [69], [76]. Likewise, it has been shown that hysteresis considerably improves the performance of vibration control algorithms in civil engineering structures [74]. In these applications, the hysteresis Bouc-Wen model is traditionally employed in the stage of control design [71], [77], [78]. On the other hand, hysteresis models can be used in the design and characterization of novel actuators. In these cases, the hysteresis Preisach model results useful to design magnetic and piezoceramic actuators [79], [80]. Additionally, recent contributions resort to hysteresis to improve the performance
of controllers by introducing its behavior in the control scheme. This idea may solve usual control problems like saturation, parameter drift, bursting effect, and so on [13], [81]. Furthermore, there is a common control technique based exclusively in hysteresis behavior which is highly employed in power electronic systems, this is the hysteresis control technique [82].

In general, there are two ways to model hysteresis. One alternative is to create complex models that almost accurately reproduce the hysteresis phenomenon; however these kind of models are too arduous to be used in practical applications [16]. On the other hand, the other common alternative is to develop simple hysteresis models which, although not giving the best description of the physical hysteresis behavior of the system, do keep relevant input-output features useful for characterization, design and control purposes [16]. This second idea is the one followed in this thesis for the mathematical formulation of the hysteresis models.

3.2 Hysteresis Mathematical Models

The main objective of this section is to introduce the three hysteresis models that will be considered throughout this thesis. Firstly, the simplest case is the mathematical representation of hysteresis with signum functions to capture the memory effect. A mathematical representation of this model may be as follows [83]:

\[
zh(t) = ah \text{sgn}(xh(t) - bh \text{sgn}(\dot{x}h(t)))
\]  

(3.1)

where \( ah \) and \( bh \) are the parameters that govern the time rate and size of the loop, respectively. Additionally, \( xh(t) \) is the input to the hysteresis and \( zh(t) \) is the output. Note that the above equation (3.1) does not have internal dynamics. For simplicity hereinafter this hysteresis model will be provided by a Relay system, that can be found, for numerical experiment purposes, in Matlab/Simulink. An example of the hysteresis loop by using equation (3.1) with an input \( xh(t) = 10 \sin(2\pi t)e^{-0.1t} \), and parameters \( ah = 5 \) and \( bh = 1 \), is presented in Figure 3.1.

The second hysteresis model is the one that was originally conceived for chaotic generator purposes [84]. This is a dynamic model that captures the hysteresis behavior through the signum function as follows [81]:

\[
\dot{zhm}(t) = \alpha_{hm}[-zhm(t) + bhm \text{sgn}(xhm(t) + ahm \text{sgn}(zhm(t)))]
\]  

(3.2)
where $a_{hm}$ and $b_{hm} \in \mathbb{R}^+$ are the hysteresis loop parameters and $z_{hm}(t)$ is the internal variable of the model (see Figure 3.2). Additionally, the transition time-rate between $b_{hm}$ and $-b_{hm}$ is governed by the real positive parameter $\alpha_{hm}$, which is the transition rate. Finally, $x_{hm}(t)$ is the input signal. As an instance, a loop obtained from equation (3.2), with parameters $a_{hm} = 1$, $b_{hm} = 5$, $\alpha_{hm} = 50$ and input $x_{hm}(t) = 10 \sin(2\pi t)e^{-0.1t}$ is shown in Figure 3.3.

Finally, the third hysteresis model, developed during this research and which may be seen as an extension of the one in (3.2), is presented as follows:

$$\dot{z}_{nh} = -\alpha_{nh}[w_{nh} - b_{nh}\text{sgn}[x_{nh}(t)] - a_{nh}\text{sgn}(\dot{x}_{nh}(t))\text{sgn}(x_{nh}(t) + a_{nh}\text{sgn}(\dot{x}_{nh}(t)))]$$

(3.3)

where $a_{nh}$ and $b_{nh} \in \mathbb{R}^+$ are the parameters of the hysteresis loop, $\alpha_{nh} \in \mathbb{R}^+$.
is the transition time-rate, and \( z_{nh}(t) \) is the internal variable. Besides, \( x_{nh}(t) \) is the input signal. Figure 3.4 depicts the hysteresis loop obtained with the model in (3.3). The implemented parameters are \( \alpha_{nh} = 50 \), \( a_{nh} = 1 \) and \( b_{nh} = 5 \). Finally the input \( x_{nh}(t) \) is the same employed in the two previous cases.

Figure 3.4: Input versus output response of the proposed dynamic hysteresis model in (3.3).
CHAPTER 3. HYSTERESIS SYSTEMS

3.3 A First Application of a Hysteresis Model

The motivation of this doctoral research is to use hysteresis within Predictive Control schemes, under the hypothesis that it may improve their performance. Nevertheless, in order to integrate the hysteresis into the control structure, the first step is to understand and verify if the hysteresis model to be used meets the requirements to be inserted in a desired stage of the control scheme. A requirement is, for instance, that the hysteresis model should be easy to conceive, so it can be adjusted to the characteristics of the control application. Additionally, it should be easily programmable in any digital microprocessor and not requiring much programming code lines, thus making the whole control scheme does not spend much computational resources. By taking this into account, it was selected a specific first application to validate the hysteresis model given in (3.2). This application is in the field of renewable energies, more specifically in the solar energy area. It is a proposed new algorithm to extract the maximum energy from a photovoltaic (PV) system. The following section details the application and how the hysteresis model was successfully employed to accomplish the main objective.

3.3.1 Design and Experimental Implementation of a Hysteresis Algorithm to Optimize the Maximum Power Point Extracted from a Photovoltaic System

Nowadays, the energy extracted from renewable sources is considered one of the more studied issues among researchers, scientists and engineers [85], [86]. This is due to the current increasing need of fighting the negative impact in the environment that the conventional energies (petroleum or natural gas) have done in earth [87]. This is why solar energy is selected here as a benchmark application of the hysteresis model.

Essentially, a photovoltaic panel directly converts the sunlight into electric energy [87]. The principle of this kind of systems is that, ideally, under invariant radiation conditions and fixed temperature, there is a unique operating point where the PV panel supplies its maximum power [88]. This maximum peak is known as Maximum Power Point (MPP) and it is easily identified through the curve of PV voltage and PV power, as it is shown in Figure 3.5. The value of this point depends on the current irradiation and the cell temperature, however these factors never are constants in real applications.
Hence, it is necessary an algorithm to ensure that the PV system operates at its maximum power conversion efficiency even if the environmental conditions abruptly change from one value to another. Thus, an adequate Maximum Power Point Tracking (MPPT) algorithm must guarantee that the PV panel is always giving its maximum energy depending on the external conditions at the moment [86].

There are a great variety of algorithms that adequately work to accomplish the main objective, and all of them have been presented with their own advantages and disadvantages [86], [90]–[92]. Here, it is proposed a new algorithm based on a hysteresis model which is validated in an own experimental platform designed during this thesis [88]. The results obtained with the proposed algorithm are compared to the ones obtained with the most common MPPT algorithm, the Perturb and Observer (P&O) method [93], [94].

In order to achieve the maximum energy provided by a PV panel, the system requires an electronic conversion stage between the PV module and the load that will use the power produced by the PV panel. This stage is the one that employs the duty cycle generated by the MPPT algorithm. Thus, the aim is to manipulate the output of the conversion stage in accordance to the changes in irradiation and temperature. Usually, this conversion stage is done by a DC-DC converter [95]. The scheme shown in Figure 3.6(b) represents a proposed configuration of a conversion stage linked to a PV panel. Here, the converter is supplied by a DC motor linked to a variable resistance [96]. This scheme is an equivalence of the typical one that employs a DC-DC converter depicted in Figure 3.6(a). In both cases, the voltage ($V_{PV}$) and current ($I_{VP}$) information from the PV panel is used by the MPPT algorithm. However, in
CHAPTER 3. HYSTERESIS SYSTEMS

Figure 3.6: Two equivalent block diagrams of a PV system. (a) PV panel connected to a DC-DC converter. (b) PV panel connected to a variable load linked to a DC motor.

Figure 3.6(b), the DC motor linked to the load drives the current according to the MPPT algorithm due to the terminals of the variable resistance are connected to the PV panel [96]. Then, the DC motor receives the control signal obtained from the algorithm. In this way, the load, \(r_l\), seen by the PV panel is automatically actuated to track, as well as possible, the maximum power point.

As has already been indicated, the proposed MPPT algorithm in this doctoral research directly utilizes a hysteresis model [97]. This model is the one given in equation (3.2). Nevertheless, some modifications are done in order to adjust this model to fit within the performance of the PV panel. Thus, the hysteresis based MPPT algorithm is [88], [97]:

\[
\dot{d}(t) = \alpha_{PV} [ -d(t) + b_{PV} \text{sgn}(\Delta V_{PV}(t)) + a_{PV} \text{sgn}(\Delta P_{PV}(t)) ]
\]

(3.4)

where \(\alpha_{PV}\) is the transition time-rate, \(a_{PV}\) and \(b_{PV}\) are the parameters that govern the hysteresis loop. Additionally, \(\Delta V_{PV}\) is the variation in voltage of the PV panel and \(\Delta P_{PV}\) is the variation of the power from the PV panel. Finally, \(d(t)\) is the internal variable employed as the output of the hysteresis system.

To illustrate the performance of hysteresis in equation (3.4), it is considered the following scenario: \(\Delta P_{PV}(t) = \sin(0.1t)\), \(\Delta V_{PV}(t) = 5\sin(t)\), \(a_{PV} = 1\), \(b_{PV} = 5\) and \(\alpha_{PV} = 50\). Then, the obtained hysteresis loop \(d(t)\) vs \(\Delta P_{PV}(t)\) is shown in Figure 3.7(a). Note that the range from -5 to 5 in the loop \(d(t)\) vs \(\Delta P_{PV}(t)\) is given by the size parameter of the hysteresis loop \(b_{PV}\). In the implementation, this range it should be adjusted to be interpreted as

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usually is the duty cycle in digital applications, this is from 0 to 1. However, for numerical results it is possible to work with this range since what it is needed from the hysteresis system is the dynamic behavior that provides the persistent excitation condition. On the other hand, the hysteresis loop in three dimensions is depicted in Figure 3.7(c) and the time response of the variable $d(t)$ is reproduced in Figure 3.7(b). This last graphic represents a train of pulses that is adapted to be the MPPT reference command signal. In this result the $\Delta V_{PV}$ was programmed to be changing as evoking a shading condition. In this manner the duty-cycle of this train of pulses signal changes according the environmental conditions. Naturally, in the implementation, since the PV panel is sensitive to environment changes, the duty-cycle will change depending on the changes in voltage and current. Then, it is directly used as the MPPT reference command signal. Note that in equation (3.4) two inputs are required, voltage and power, both collaborate jointly to drive the hysteresis loop behavior. Hence, the proposed MPPT algorithm suitably works to accomplish the objective as the experimental results will be later evidenced.

An overview of the designed platform at CoDAlab (Control, Dynamics and Applications laboratory), where the experiments were carried out is depicted in Figure 3.8. To see the particularities of the electronic design, the programming code and a more detailed description of the experimental platform functioning, please consult the Appendix A.

Once the duty cycle is obtained from the MPPT algorithm expressed in equation (3.4), it is necessary to implement a control signal that interprets this duty cycles and becomes it an adequate signal for the DC motor linked to the potentiometer, which makes the function of the conversion stage. Additionally, the control law also should stabilize the DC motor. In this case, a Proportional-controller (P-controller) that stabilizes the position of the motor around a set point is employed. The $P$-controller is developed in terms of the position of the motor, $\theta$, captured by the potentiometer. Since the position of the motor is directly related to the resistance of the potentiometer, the $P$-controller is obtained from the voltage point of view [88]:

$$V_{PV} = R_l \cdot I_{PV}; \quad R_l := R_l(\theta)$$  \hspace{1cm} (3.5)

where $R_l$ is the resistance of the potentiometer. Therefore, the $P$-controller is expressed as: $u = k_p \cdot (V_{PV} - V_{sp})$, where $k_p$ is the proportional gain and $V_{sp}$ is the set point established by the user. Furthermore, the $P$-controller coupled to the reference command signal obtained from the MPPT algorithm, can
then be captured in the following control law:

\[ u_T = k_p \cdot (V_{PV} - V_{sp} + X) \]  

(3.6)

where \( X = d \) is the command signal. Moreover, for implementation purposes, it is required to adjust the control signal to an analog PWM format. Hence, the equation in (3.6) is rewritten as follows:

\[ u_{PWM} = k_p \cdot (V_{PV} - V_{sp} + X) + V_{offset} \]  

(3.7)

where \( V_{offset} \) is selected as the medium value of the PWM duty cycle range since the DC motor must turn both left and right side. On the other hand, \( u_{PWM} \) is the actual duty cycle that generates the PWM output signal and it is directly applied to the DC motor. For more details see the Appendix \[A\] and the paper in [88].
In order to corroborate the MPPT algorithm works as expected, two light intensity levels were programmed in a lamp to emulate the irradiance condition. The idea is that the MPPT algorithm should build the duty cycle according to the automatic light changes. In this manner, the DC motor adjusts the load seen by the PV panel to provide the corresponding maximum power. So, the Figure 3.9 depicts the PV voltage in open circuit under the effect of the automatic change of light. Here is notable a blinking result due to the half-wave rectifier implemented to obtain two different light levels. For more specifications of the implementation that provides the two light levels see the electronic circuit in Figure A.2 and the programming code in Appendix A.

One step previous to the experimentation is the characterization of the employed PV panel. This is necessary to observe the irradiation effect on the PV
panel and to obtain the characteristic curves for the two programmed light levels. The characterization stage consists on making variations in the load connected to the PV panel and obtaining the measurements from current and voltage at each programmed light level and each load variation. With this, the curves of Voltage-Current, Voltage-Power and Resistance-Power are obtained and shown in Figure 3.10(a), 3.10(b) and 3.10(c), respectively. The variation of the load is from 100 Ω to 4.7 kΩ. The measurements values are captured in Tables A.1 and A.2 presented in Appendix A. First, the graphic Voltage-Power in Figure 3.10(b) and the curve Resistance-Power in Figure 3.10(c) provide evidence that the maximum power point varies for each irradiation condition. In this maximum power point, it is supposed that the external load seen by the PV panel is similar to the internal resistance in the PV panel [96]. The experiment shows how the proposed algorithm achieves these maximum values of power according to the load and the irradiation variations. Additionally, as mentioned before, the proposed hysteresis algorithm is compared to the typical P&O method. This last one may be captured through the following discrete time dynamic model [95]:

\[ x(k + 1) = x(k) + (V_{PV}(k) - V_{PV}(k - 1)) \text{sgn}(P_{PV}(k) - P_{PV}(k - 1)) \]  

Both algorithms are implemented in the designed experimental platform shown in Figure 3.8. For more details of the platform functioning and its stages see Appendix A.

The first result of the carried out experiments by invoking the P&O algorithm is exposed in Figure 3.11. Here, the plots of the PV voltage (blue plot) and the PV current (red plot) signals are shown. The objective of this result is to emphasize that both voltage and current are affected by the light perturbation. Besides, a zoomed in version of these graphics is presented in Figure 3.12. Here, it is possible to observe the time response and the stabilization time of the PV voltage and PV current. Also, an overshoot at the signal responses is notable. On the other hand, the corresponding control signal \( u_{PWM} \) induced by the P&O algorithm is presented in Figure 3.13. This figure is representative since it shows the time evolution of the PWM signal produced by the control algorithm in response to the light intensity variation.

Additionally, and recalling that the control objective is to achieve, as close as possible, the maximum power point of the PV panel, the PV power plot obtained with the Perturb and Observer algorithm is exhibited in Figure 3.14. Note that the power value must be scaled with a factor of 0.057 due
to the electronic stage. From this result, the maximum power extracted in the lowest light level is approximately 0.0541 W and the maximum power extracted in the higher light level is approximately 0.0912 W. Both values are close to the maximum power values obtained from characterization and stated in Tables A.2 and A.1 respectively.

On the other hand, the experiments by using the hysteresis algorithm are next introduced. First results are depicted in Figure 3.15 where it is shown the PV voltage and PV current for the two light levels. A close-up of these signals is presented in Figure 3.16 where is notably that the overshoot seen in the results obtained with the P&O method was attenuated. In addition, the control signal obtained from the Hysteresis MPPT algorithm is shown in Figure 3.17. Finally, the experimental evaluation is concluded by showing the PV power graphic depicted in Figure 3.18. From here, the maximum power extracted with the proposed method in the lowest light level is approximately
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Figure 3.11: PV voltage and PV current time evolution by employing P&O method.

Figure 3.12: Zoom version of the PV voltage and PV current with P&O method.

Figure 3.13: Control signal (blue) by using the P&O algorithm and the PV voltage under the light change (red).
0.0556 W and the maximum power extracted in the higher irradiation level is approximately 0.0973 W. Both values are higher than those obtained with the P&O case (see Figure 3.14). Moreover, they are closer to the maximum power values in Tables A.2 and A.1 respectively.

### 3.4 Final Chapter Remarks

Several comments can be drawn from this chapter. First, it was seen that the dynamic hysteresis model in (3.2) was easily implementable in a low-cost digital microprocessor. This model is clear to program and it does not require much computational cost. Furthermore, it was feasible to adjust its parameters to this kind of application scenario. Due to the three hysteresis models are conceptualized under the same mathematical basis, that is, the three of them use signum function to capture the memory effect of the hysteresis, here it is assumed that the implementation of the model (3.2) gives us a general idea of how will be the implementation of the others.
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Figure 3.16: Zoom version of the PV voltage and PV current with the hysteresis method.

Figure 3.17: Control signal (blue) by using the Hysteresis algorithm and the PV voltage under the light change (red).

Figure 3.18: Power signal when the hysteresis algorithm is employed.
Here, the hysteresis worked to obtained a new algorithm to extract the maximum power from a photovoltaic panel. Thus, an innovative proposal was created by employing the hysteresis model that works better than the conventional strategies in the state-of-the-art on solar energy technology.

From now on, the hysteresis models will be invoked as an essential part of the proposed Predictive Control scheme as will be clearly described in the next chapter.
This chapter introduces the proposal of this doctoral research. This is an Adaptive-Predictive control scheme containing a hysteresis modulation stage. The main idea is that this stage may use one of the hysteresis models previously presented in Chapter 3. This control approach expects to face with some typical issues in control systems, such as the parameter drift and bursting effect, as will be seen in this chapter. In Chapter 2 it was evidenced the need for a condition of persistent excitation to improve the parameter identification within an adaptive control scheme. With this motivation, this chapter proposes a system that provides such persistent excitation with high frequency content along with the Adaptive-Predictive control structure. Simultaneously, this modulator improves the performance of the controlled closed-loop system.

The proposal is evaluated via two cases. First, the solution of the parameter drift phenomenon in the Rohr’s example illustrated in Section 2.2.4. In addition, a numerical experiment for the parameter estimation of a non-minimum phase system is presented. Finally, several practical cases are left for the following chapter, where different engineering systems are invoked to validate this proposal.

4.1 The Hysteresis Delta-Modulator

The proposal of the hysteresis modulation was inspired by the functioning of a digital Delta-Modulator, which is a 1-bit analog-to-digital signal conversion technique [98]. A Delta-Modulator is the simplest form of a differential
pulse-code modulation. Its main function is to transform a continuous-time signal into a train of pulses data stream \[99\]. This modulator is essentially used for data transmission, for instance, in transmission of voice information, and security of transmission communication \[98, 100, 101\]. The basic composition of a Delta Modulator is shown in Figure 4.1 where it is observable that it basically consists of a simple loop with a comparator in the forward path and an integrator at the feedback path \[98\].

Although the previous scheme is mainly designed for data transmission and applications in the telecommunication area, the idea is to use it as a modulator with hysteresis to improve the performance of controlled systems and parameter estimation tasks. This proposed scheme is called \textit{Hysteresis Delta Modulator} (HDM), and basically consists on replacing the quantizer by a hysteresis model as it is shown in Figure 4.2 \[13\]. In this scheme, the modulated signal is a train of pulses that takes two values and is bounded. Furthermore, it is important to highlight that the input signal can be easily retrieved by using a low-pass filter at the modulator output \[13\]. By way of illustration, Figure 4.3 shows the expected functioning of the HDM with a sinusoidal signal as input. From this, it is observable that the modulated signal is a train of pulses. Then, after the low-pass filter, the input signal is recovered. Later on, it will be shown that the modulated signal is, in fact, a signal with frequency content, what will indeed improve the parameter estimation performance.
4.2 The Hysteresis-Modulator within the Adaptive-Predictive Control Scheme

Once the basic operation of the Hysteresis Delta Modulator is clear, it is necessary to understand how this block is inserted into the Adaptive-Predictive control scheme. To do this, the overall control structure is presented in Figure 4.4. Furthermore, the functioning of each block is described:

- **Process**: The system to be controlled.
• **Predictive Model:** Calculates the control signal by employing a Predictive Model of the process [9]. This control signal makes the predicted process output belong to a desired trajectory.

• **Driver Block:** Builds the desired output trajectory that guides the output process to the set-point in an optimal manner [10].

• **Adaptive Mechanism:** Adjusts the parameters of the Predictive Model from the error predictions. Besides, it informs the Driver Block about the deviations of the process output. This block requires the information from both the output of the modulator stage and the process output [9].

• **Hysteresis Delta Modulator:** This block modulates the control signal generated by the Predictive Model and gives it to the process and to the Adaptive Mechanism to provide it with the persistent excitation required for the parameters estimation.

4.3 A Solution of the Rohr’s Example

In previous Section 2.2.4, a well-known adaptive system was invoked to illustrate the concepts of parameter drift and bursting effect. This is the Rohr’s example. Now, in this section, it is resorting again to this example, but this time it will serve as a benchmark to prove and validate the technique of including the proposed hysteresis modulator into an adaptive scheme. Hence, it will be demonstrated how just by adding the HDM block, the undesired parameter drift and bursting effect are eliminated. Figure 4.5 shows the diagram block of the Rohr’s example now with the HDM block inserted between the control signal $u(t)$ and the process. As a remainder, $y_m(t)$ denotes the reference output, $e_0(t)$ represents the error and $n(t)$ is an additive external noise. In addition, $y_p(t)$ is the output signal, $g$ is a selected constant gain, $c_0(t)$ and $d_0(t)$ are the controller parameters and $r(t)$ is the user reference command. In this new scheme, the modulator with hysteresis provides a modulated control signal. However, the original one may be easily retrieved by the plant, since it can behave as a signal filter. In this manner, the process receives the adequate control signal while the entire closed-loop system is enriched with the persistent excitation characteristic required by the adaptive
The numerical simulation was carried out in Matlab/Simulink. The hysteresis model employed inside the HDM block is the simplest one exposed in Section 3.2, this is a Relay that is found in the library “Discontinuities” in Simulink. The used values are switch on/off = \{-1,1\} and output on/off = \{-100,100\}. Moreover, the filter programmed within the HDM block is \( G(s) = \frac{1}{s+1} \). These experiments show the expected results. First, Figure 4.6 depicts the process output, which is stabilized at the desired set-point. From this result it is conclusive that the error signal, shown in Figure 4.7 is addressed to zero, meaning that the bursting effect was totally suppressed. This is a consequence of the removal of the parameter drift, as it is shown in Figure 4.8, where it is notable that the parameters converge to
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4.4 Parameter Estimation of a Non-minimum Phase System

The aim of this section is to validate the functioning of the HDM block when it is inserted in an Adaptive Mechanism as the one that will be employed throughout this thesis. For this purpose, it is resorting to an example of parameter estimation of a non-minimum phase system. The main idea is to corroborate that the parameter estimation adequately works when the HDM block is used. Furthermore, it will be seen through a comparative study that
the case with dynamic hysteresis provides a better estimation since it has a more uniform frequency content. Thus, it will be demonstrated that the persistent excitation condition is indeed necessary in adaptive based systems.

Non-minimum phase systems are characterized for having an unstable inverse [3]. This unstable inverse property represents a notable control challenge [10]. Here, it is considered the following example case:

\[ G(s) = \frac{-s + 2.28}{s^2 + 0.57s + 5.14} = \frac{a_1s + a_2}{s^2 + b_1s + b_2} \]  

(4.1)

Figure 4.9 shows the response of system (4.1) under a unitary step input. This is a precise representation of non-minimum phase processes that present the characteristic of having an unstable inverse [10]. It means, a response that is initially negative [9].

The parameter estimation is done by using the algorithm exposed in Section 2.2.1. Firstly, the stable second order filters are selected as:

\[ G_{F1}(s) = \frac{s}{s^2 + \lambda_1s + \lambda_2}, \quad G_{F2}(s) = \frac{1}{s^2 + \lambda_1s + \lambda_2} \]  

(4.2)

where \( \lambda_1 \) and \( \lambda_2 \) are real positive gains properly chosen by the designer. Then, by doing some basic algebraic steps, the process output is stated as:
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\[ Y(s) = [a_1 \ a_2 \ B_1 \ B_2] \begin{pmatrix} u_{f2} \\ u_{f1} \\ y_{f2} \\ y_{f1} \end{pmatrix} = \theta^T \phi \]  

(4.3)

where \( \theta^T \) is the parameters vector and \( \phi \) is the regression matrix formed by the filtered signals: \( u_{f2} \) and \( u_{f1} \) for the input plant, and \( y_{f2} \) and \( y_{f1} \) for the output plant. Besides, \( B_1 = \lambda_1 - b_1 \) and \( B_2 = \lambda_2 - b_2 \). In the time-domain, from system (4.3), the following expression is obtained:

\[ \hat{y}(t) = [\hat{a}_1 \ \hat{a}_2 \ \hat{B}_1 \ \hat{B}_2] \begin{pmatrix} u_{f2} \\ u_{f1} \\ y_{f2} \\ y_{f1} \end{pmatrix} = \hat{\theta}^T(t)\phi(t) \]  

(4.4)

where \( \hat{a}_1(t), \hat{a}_2(t), \hat{B}_1(t) \) and \( \hat{B}_2(t) \) are estimated signals to \( a_1, a_2, B_1 \) and \( B_2 \) respectively. Finally, by following the Gradient Algorithm in equation (2.10), the parameter estimation system results in:

\[
\begin{align*}
\dot{\hat{a}}_1 &= -\gamma u_{f2}[\hat{a}_1 u_{f2} + \hat{a}_2 u_{f1} + \hat{B}_1 y_{f2} + \hat{B}_2 y_{f1} - y] \\
\dot{\hat{a}}_2 &= -\gamma u_{f1}[\hat{a}_1 u_{f2} + \hat{a}_2 u_{f1} + \hat{B}_1 y_{f2} + \hat{B}_2 y_{f1} - y] \\
\dot{\hat{B}}_1 &= -\gamma y_{f2}[\hat{a}_1 u_{f2} + \hat{a}_2 u_{f1} + \hat{B}_1 y_{f2} + \hat{B}_2 y_{f1} - y] \\
\dot{\hat{B}}_2 &= -\gamma y_{f1}[\hat{a}_1 u_{f2} + \hat{a}_2 u_{f1} + \hat{B}_1 y_{f2} + \hat{B}_2 y_{f1} - y]
\end{align*}
\]  

(4.5)

The block diagram that represents the Adaptive Mechanism previously developed and linked to the process is depicted in Figure 4.10. Besides, Figure 4.11 shows the block diagram when the HDM is inserted for this parameter estimation example. For numerical experimentation, four scenarios are implemented and analyzed to do the comparison study. First scenario corresponds to the standard Gradient Algorithm, this is, a parameter estimation method without using the HDM block in it, see Figure 4.10. The other remaining three scenarios use the improved parametric estimation method by using the HDM block as it is shown in Figure 4.11. These three scenarios are carried out by employing one of the hysteresis models commented in the previous Chapter 3. Hence, one scenario uses the Relay block, the second one uses the model in equation (3.2), and the third one uses the proposed...
Therefore, given the system in (4.1) as the process, then the parametric estimation system in (4.5) is done with selected values: \( \gamma = 100 \), \( \lambda_1 = 10 \) and \( \lambda_2 = 5 \); and initial conditions \( \hat{a}_1(0) = 1 \), \( \hat{a}_2(0) = -2.5 \), \( \hat{B}_1(0) = 0.8 \) and \( \hat{B}_2(0) = 5 \). Summarizing, each scenario of this study is described below:

- **Standard scenario:** Parameter estimation without the HDM block.
- **Case 1:** It uses the HDM block with the Relay system (3.1) as the hysteresis model. The values within the Relay block in Simulink are: \( \text{switch on/off} = \{10, -10\} \) and \( \text{output on/off} = \{25, -25\} \).
- **Case 2:** It uses the hysteresis model in equation (3.2) within the HDM stage. The programmed values are set as \( a_{hm} = 10 \), \( b_{hm} = 25 \) and \( \alpha_{hm} = 100 \).
- **Case 3:** It employs the proposed hysteresis model in equation (3.3) within the HDM block. The values in this case are set as \( a_{nh} = 10 \), \( b_{nh} = 25 \) and \( \alpha_{nh} = 100 \).

Finally, the integrator implemented in all the three cases that use the HDM block is \( G(s) = \frac{1}{s} \).

The numerical experiments evidence which method gives the best parameter estimation performance. First, Figure 4.12 illustrates the implemented input...
signal for all the experiments. This signal was specially conceived to resemble a classical control signal with overshooting and converging to zero as time goes on. It is then noted that this signal is not a persistent excitation signal on the whole time-horizon. Therefore, this scenario represents an important challenge to any parameter estimation algorithm.

To continue, Figure 4.13 shows the numerical experiment results for each scenario corresponding to the estimation of parameter $a_1(t)$. In this figure is clear that Case 3, the case with the new hysteresis model (5.24), does the best estimation of parameter $a_1$, since it converges to its nominal value. The same conclusion is also observed in Figure 4.14 and Figure 4.15 for the estimation of parameters $a_2(t)$ and $b_1(t)$, respectively. Finally, note that in Figure 4.16 the standard estimation also does an adequate estimation of the parameter $b_2$, as well as does the Case 3.
Figure 4.13: Estimation signals for parameter $\hat{a}_1(t)$.

Figure 4.14: Estimation signals for parameter $\hat{a}_2(t)$.

Figure 4.15: Estimation signals for parameter $\hat{b}_1(t)$.
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Figure 4.16: Estimation signals for parameter $\hat{b}_2(t)$.

Figure 4.17: Modulated signals from the HDM block. (a) Modulated signal for the Case 1. (b) Modulated signal for Case 2. (c) Modulated signal for Case 3.
Furthermore, recalling the basic Fourier theory, which says that any periodic function can be reproduced as a summation of a constant, and infinite sine and cosine time functions called harmonics. Then, it can be inferred that a kind of persistent excitation signal requires a frequency content uniformly distributed. Hence, the Fourier analysis is presented for the corresponding output signal coming from the HDM block for Case 1, Case 2 and Case 3, respectively. These output signals are shown in Figure 4.17. Then, the Fourier analysis is depicted in Figure 4.18. From these graphics, it is clearly evidenced that the processed signals corresponding to Case 1 and Case 2 have a high energy harmonic. This provokes non-homogeneous energy distribution on the frequency content, and, consequently, reducing the performance of the corresponding parameter estimation process. Meanwhile, the case with the proposed hysteresis model has a better harmonic distribution, which was useful to improve the performance of the estimation process.

4.5 Final Chapter Remarks

This chapter served the purpose of explaining the motivation from where the Hysteresis Delta Modulation was conceived. It was also explained how the modulator is linked to the Adaptive-Predictive control scheme, and particularly, how this modulator works along with the Adaptive Mechanism to improve the parameter estimation. First, it was demonstrated how the HDM block may be a solution for the RHors example to eliminate the parameter drift and the bursting effect. On the other hand, the presented experiment
with the non-minimum phase system showed that the proposed hysteresis model within the HDM block makes a better estimation of the parameters. However, it is important to highlight that the parameters of the hysteresis model were randomly selected and the three cases used the same values for comparison purposes. Besides, the Fourier analysis has proven that the three cases have a high frequency content. Therefore, it is possible to conclude that the three cases may have a good performance by adequately selecting the parameters of the hysteresis models. The following chapter will present several practical cases where the Adaptive-Predictive with the hysteresis modulator framework is implemented and validated.
This chapter presents some implementation cases at a numerical level where the Predictive Control approach stated in Chapter 4 is validated.

First, the control scheme is applied to stabilize the well-known Van der Pol oscillator system. Initially, a bursting phenomenon is observed when there is a delay at the process output. Then, it will be evidenced that the control proposal faces this issue while accomplishing the regulation control objective. Secondly, the Predictive Control technique is also implemented to achieve the regulation control objective on a base-isolated structural system seismically perturbed. Besides, here the proposal to insert dynamic hysteresis within the Driver Block is put to the test. Finally, a proposal of a statistic fault detection system within the control scheme is also conceived.

The above cases are presented in this chapter with their respective numerical simulation results. With this, it is demonstrated that the proposal successfully completes the corresponding control objectives.

5.1 The Van der Pol Oscillator

The Van der Pol oscillator is a well-known dynamical system that contains a nonlinear resistive element and includes a positive feedback [102], [103]. This model was originally proposed by the dutch physic and engineer Balthasar Van der Pol in 1920 and it was the precursor of the first commercial radios [102]. Since then, the Van der Pol system has been studied and used in many engineering fields [103]. For instance, in the control area, the Van der Pol oscillator has been invoked to validate novel control techniques due to its main characteristics such as its nonlinear behavior and the fact that its
unique equilibrium point is unstable \cite{104, 105}.

The Van der Pol oscillator is governed by the following second order differential equation \cite{13}:

$$\ddot{w}(t) - \epsilon (1 - w^2(t)) \dot{w}(t) + w(t) = u(t)$$  \hspace{1cm} (5.1)

where \(w\) is the dynamic variable and \(\epsilon \in \mathbb{R}\) is the damping coefficient \cite{103}. If \(\epsilon = 0\), then the system has an undamped linear behavior \cite{105}. As \(\epsilon\) grows, the nonlinear effect grows as well. If the oscillator is implemented as an electrical circuit, then \(\epsilon\) should be positive, due to the physical limitations \cite{105}. This last statement is the one considered in this thesis. Moreover, the damping may be positive for \(|w| > 1\) and negative for \(|w| < 1\). The Van der Pol equation produces a self-sustained oscillation where the energy is dissipated over a cycle that balances the acquired energy \cite{102}. Hence, the equation (5.1) has a unique stable limit cycle for any constant of \(\epsilon > 0\) \cite{105}. Finally, \(u(t)\) is the control signal input.

Figure 5.1 illustrates the influence of \(\epsilon\) on the oscillator performance. The graphics are obtained by charting the phase plane with \(\epsilon = 1\), giving first the result depicted in Figure 5.1(a). Additionally, the graphic in Figure 5.1(b) is obtained with \(\epsilon = 6\). Both graphics were generated by using three different initial conditions: \(x_2(0) = \{1.5, 2.5, 3.5\}\) and \(x_1(0) = 0\).

By defining the state variables, \(x_1(t) = w(t)\) and \(x_2(t) = \dot{w}(t)\), the equation in (5.1) yields:

\[
\begin{align*}
\dot{x}_1(t) &= x_2(t) \\
\dot{x}_2(t) &= \epsilon(1 - x_1(t)^2)x_2 - x_1(t) + u(t)
\end{align*}
\hspace{1cm} (5.2)
\]

Furthermore, Figure 5.2(a) shows the state variable \(x_2(t)\) with \(\epsilon = 1\) and for initial conditions \(x_1(0) = 0.5\) and \(x_2(0) = 0\). Additionally, Figure 5.2(b) depicts the behavior of the state variable \(x_1(t)\) under the same initial conditions.

From the above exposition, it is observed that the Van der Pol dynamic is sensitive to the value of its main parameter, which makes it an interesting challenge in the control area. In this section it will be exhibited that this system is a typical candidate to present the bursting effect, thus parameter drift. For instance, when there is a small time-delay at the defined output equation
Moreover, it will be shown how the control proposal of this thesis solves this issue while the main stated control objective is accomplished. This is, to find the control law such the output $x_2(t)$ goes to zero while the variable $x_1(t)$ stays bounded as time goes on.

In accordance to the Adaptive-Predictive control technique exposed in Chapter 2, the first control design step consists of obtaining the linear system model of the Van der Pol plant. Then, since this technique is based on a discrete-time realization, it is required to write the discrete-time representation of this linear scheme. Finally, it will be exposed the mathematical implementation of the control strategy. This mathematical development will be invoked for future references in the rest of this thesis.

### 5.1.1 Adaptive-Predictive Control Mathematical Development

By linearizing the equation \( (5.1) \) around its un-stable equilibrium point, it yields

\[
\begin{pmatrix}
\dot{x}_1(t) \\
\dot{x}_2(t)
\end{pmatrix} = \begin{pmatrix}
0 & 1 \\
-1 & \epsilon
\end{pmatrix} \begin{pmatrix}
x_1(t) \\
x_2(t)
\end{pmatrix} + \begin{pmatrix}
0 \\
1
\end{pmatrix} u(t)
\]

Moreover, the output system equation is defined as:

\[
y(t) = (0 \ 1) \begin{pmatrix}
x_1(t) \\
x_2(t)
\end{pmatrix}
\]

Figure 5.1: Phase plane graphic of the Van der Pol oscillator with $x_1(t) = w(t)$ and $x_2(t) = \dot{w}(t)$. (a) With $\epsilon = 1$. (b) With $\epsilon = 6$. 

\[13\]
Figure 5.2: (a) Response of the Van der Pol state variable $x_2(t)$. (b) Response of the Van der Pol state variable $x_1(t)$.

From equations (5.3) and (5.4), the transfer function is obtained as follows:

$$G(s) = \frac{s}{s^2 - \epsilon s + 1}$$  

(5.5)

and its corresponding parameterization yields:

$$G(s) = \frac{a_1 s}{s^2 + a_2 s + a_3}$$  

(5.6)

Finally, note that the system (5.5) is a non-minimum phase one [103].

As was mentioned before, Predictive Control requires a discrete-time realization, thus the Euler discretization approach is used:

$$\frac{dx(t)}{dt} \approx \frac{x(k + 1) - x(k)}{T}$$  

(5.7)

where $T$ is the sampling-time period also used as the integration step. Then, by transforming the equation (5.6) into the discrete-time domain through the expression in (5.7), the Predictive Model has the form

$$\hat{y}(k + 1) = \frac{y(k)[-\frac{2}{T^2} - \frac{\hat{a}_2}{T} + \hat{a}_3] + y(k - 1)\frac{1}{T^2} - \hat{a}_1 \left[\frac{u(k + 1) - u(k)}{T}\right]}{\frac{1}{T^2} + \frac{\hat{a}_2}{T}}$$  

(5.8)

The above equation is the fundamental income to the basic Predictive Control algorithm, which consists in a single-step prediction. See Section 2.1. This is, at each sampling instant $k$, the following conditions is applied:

$$\hat{y}(k + 1|k) = y_d(k + 1|k)$$  

(5.9)
where $y_d(k+1)$ is the output defined by the Driver Block, which is the desired trajectory that should be followed by the process output. Once the above condition has been applied, the following control law is obtained:

$$u(k) = y(k)[-\frac{2}{T^2} - \frac{a_2}{T} + \hat{a}_3] + y(k-1)\frac{1}{T^2} + u(k-1)\frac{a_3}{T} + (\frac{1}{T^2} + \frac{\hat{a}_2}{T}) y_d(k+1)$$

(5.10)

It is observable that this control law depends on the estimated parameters of the process at $k$: $\hat{a}_1 := \hat{a}_1(k)$, $\hat{a}_2 := \hat{a}_2(k)$, and $\hat{a}_3 := \hat{a}_3(k)$, the sampling period $T$, and the process output also at instant $k$. The estimation of the parameters is executed by the Adaptive Mechanism, which will be explained later on.

As was settled in Subsection 2.2.1, the Adaptive Mechanism calculates an estimation of the process parameters, and these may change due to faults or physical alteration in the system under control. In this way, the dynamic of the closed-loop system adapts itself to changes in the parameters process. The used mathematical tool to develop the Adaptive Mechanism is the well-known Gradient Algorithm [106]. Here, it is particularly applied to the Van der Pol oscillator. However, this method can be generalized for different systems.

Generally speaking, the main objective of an adaptive algorithm is to estimate the coefficients of a plant when it is represented by its transfer function, and just using the information from the input and output of the system. Hence, the requirement to obtain the parameter estimation within the Adaptive-Predictive control scheme is the predictive control law $u(k)$ and the process output $y(t)$. Then, the first step is to filter these available measurements. To do this, two stable second-order filters are selected as follows:

$$G_{F1}(s) = \frac{s}{s^2 + \lambda_1 s + \lambda_2}, \quad G_{F2}(s) = \frac{1}{s^2 + \lambda_1 s + \lambda_2}$$

(5.11)

After basic algebraic steps, it is arrived to an output expression in Laplace domain stated as [63]:

$$Y(s) = a_1 u_{f1} + A_2 y_{f1} + A_3 y_{f2} = [a_1 \quad A_2 \quad A_3] \begin{pmatrix} u_{f1} \\ y_{f1} \\ y_{f2} \end{pmatrix}$$

(5.12)

where $A_2 = \lambda_1 - a_2$ and $A_3 = \lambda_2 - a_3$. Then, the time-domain estimation yields:
where $\hat{\theta} := \hat{\theta}(t)$ is the estimated parameter vector and $\phi(t)$ is the regression matrix formed by the corresponding filtered signals $u(t)$ and $y(t)$.

By invoking the un-normalized Gradient algorithm (see [63], [107]), the obtained parametric estimation dynamics is:

$$\dot{\hat{\theta}} = -\gamma \left( \begin{array}{c} u_{f1} \\ y_{f1} \\ y_{f2} \end{array} \right) \left[ \hat{\theta}^T \phi(t) - y \right]$$

where $\gamma$ is a positive constant gain. Hence, the expanded dynamics of the parametric estimation process is:

$$\dot{\hat{a}}_1 = -\gamma u_{f1}[\hat{a}_1 u_{f1} + \hat{A}_2 y_{f1} + \hat{A}_3 y_{f2} - y]$$

$$\dot{\hat{A}}_2 = -\gamma y_{f1}[\hat{a}_1 u_{f1} + \hat{A}_2 y_{f1} + \hat{A}_3 y_{f2} - y]$$

$$\dot{\hat{A}}_3 = -\gamma y_{f2}[\hat{a}_1 u_{f1} + \hat{A}_2 y_{f1} + \hat{A}_3 y_{f2} - y]$$

Finally, to complete the control design, the Driver Block uses a simple reference model as follows [10]:

$$y_d(k + 1) = -0.8y(k)$$

5.1.2 Van der Pol Oscillator with an Output Delay

In order to show the sensitivity of the Van der Pol oscillator of being an unstable closed-loop system, a small time-delay is added to its output signal, producing $y(t - \tau)$ with $\tau = 0.01$ seconds. Actually, this is a realistic situation in many industrial control applications, normally due to the sensing stage [108]. Nevertheless, first, it is presented the numerical results when the Adaptive-Predictive is implemented without the hysteresis modulation block, and no time-delay, to evidence that the control algorithm works as expected. Afterwards, the time-delay is inserted to check the vulnerability of the system under this small change, leading to parameter drift phenomenon and the bursting effect. Figure 5.3 is depicted to clarify the control implementation through the corresponding block diagrams. Two cases are exposed...
Figure 5.3: (a) The Adaptive-Predictive block diagram for the Van der Pol Oscillator. (b) The AP block diagram with the HDM block.

Here, first, it is shown how the Adaptive-Predictive control with no HDM block (see Figure 5.3(a)) addresses the control objective of regulating to zero the output of the Van der Pol oscillator. Afterwards, it is inserted the time-delay by deteriorating the control performance. Hence, the HDM block is inserted within the control scheme (see Figure 5.3(b)) to accomplish the control objective and to solve the parameter drift due to the time-delay.

Figure 5.4(a) indicates that the control objective is accomplished when the control signal goes into action at 20 seconds but requiring a pretty big impulsive control action as shown in Figure 5.4(c). In addition, Figure 5.4(b) shows the estimation of the parameters which are stabilized as the output does.

On the other hand, when the time-delay is added at the output, the results are worse as it is shown in Figure 5.5. Initially, Figure 5.5(a) shows the output response under the time-delay perturbation. Here is notable that the performance is strongly affected by the appearing bursting phenomenon. Therefore, the parameter drift is also evidenced in Figure 5.5(b) and the
Figure 5.4: Simulation results for the scheme shown in Figure 5.3(a). (a) Van der Pol output response. (b) Estimated parameters from the Adaptive Mechanism. (c) Control signal.
Figure 5.5: Simulation results of the system in Figure 5.3(a) with a delay at the output system. (a) Response of the Van der Pol variable $x_2(t)$ under the time-delay perturbation. (b) Parameter drift behavior. (c) Control signal.
control signal grows abruptly as depicted in Figure 5.5(c).

5.1.3 The Solution with Hysteresis Modulation

This section shows the numerical results when introducing the proposed Predictive Control strategy with the HDM block. This is, the modulation with hysteresis within the Adaptive-Predictive control scheme (see Figure 5.3(b)). In order to face the parameter drift and bursting issues induced by the time-delay in the Van der Pol system, the HDM block is invoked. Two of the hysteresis models presented in Chapter 3 were used and compared within the modulation block. The first case employs the basic hysteresis block with a static relay block (on/off). The second case used the dynamic hysteresis in equation (3.2). The parameters of the static relay block are $\text{switch on/off} = \{-5, 5\}$ and $\text{output on/off} = \{-6, 6\}$. Furthermore, the integrator used in the first case is $G(s) = \frac{1}{s}$. On the other hand, for the second case we recall here the dynamic hysteresis model in equation (3.2):

$$\dot{z}_{hm}(t) = \alpha_{hm}[-z_{hm}(t) + b_{hm}\text{sgn}(x_{hm}(t)) + a_{hm}\text{sgn}(z_{hm}(t))]$$ (5.16)

where the parameters are: $\alpha_{hm} = 1$, $b_{hm} = 4$ and $a_{hm} = 10$. The integrator within the HDM block for this case is: $G(s) = \frac{1}{s+1}$.

Figure 5.6(a) depicts the response of the output variable $x_2(t)$ when the system is subject to the previously mentioned time-delay and by introducing the HDM block with a simple hysteresis relay block. From this figure two important conclusions can be drawn. First, the bursting effect was totally eliminated just by introducing the modulation with hysteresis. Secondly, the nature outcome of the hysteresis can be observed at the output signal in its curly behavior. Inherently, if the bursting effect is eliminated, so does the drift of the parameters, just as it is shown in Figure 5.6(b). Finally, Figure 5.6(c) shows the control signal, which is a kind of train of pulses as a result of the hysteresis modulation.

On the other hand, the results obtained with the dynamic hysteresis equation (3.2) within the HDM block are presented in Figure 5.7(a) and Figure 5.7(b). In the first result, the control objective is favorably accomplished and the bursting behavior is eliminated as expected. In the second figure, the estimated parameters no longer present the drift behavior as expected. Finally, Figure 5.7(c) depicts the control signal.
Figure 5.6: Simulation results of the system in Figure 5.3(b) with a delay at the output system. (a) Response of the Van der Pol variable $x_2(t)$. (b) Estimated parameters behavior with the time-delay and the HDM block with the static relay block. (c) Control signal.
Figure 5.7: Simulation results of the system in Figure 5.3(b) with a delay at the output system and the HDM block with the dynamic hysteresis model.
(a) Response of the Van der Pol variable $x_2(t)$ under the time-delay perturbation. (b) Estimated parameters. (c) Control signal.
5.1.4 Conclusions from the Experiments

This first example resorted to the well-known Van der pol oscillator to validate the proposed control technique. The fact that the system may be complex due to its characteristics of instability and non-linearity is worth to note. Moreover, it was a good example to present how the control system can deteriorate just by adding a delay which is very common in the real implementations. In this section it was possible to verify that the Predictive Control design adequately works in accomplishing the established control objective. Furthermore, it was exposed how the hysteresis modulation helps to solve the parameter drift problem provoked by the delay at the output process. Summarizing, it was proven that the results are the expected with the proposed approach of this thesis.

5.2 Adaptive-Predictive Control Applied to a Base-Isolated Hysteresis System

A controlled base-isolated structure is a nonlinear system that is highly employed in civil engineering [14], [109]. This is conceived to mitigate oscillations on a structure when the base is subjected to external ground perturbations, such as earthquakes [14], [110], [111]. Hence, the base-isolated system represents a control challenge since it contains a natural hysteresis behavior that make it a nonlinear complex system to be controlled. Recently, most of the controllers in the state-of-art designed for this kind of systems are based on nonlinear control techniques. For instance, some of these use the well-known Sliding Mode Control [112], or the Adaptive Control methodology [113].

In structural civil engineering, the hysteresis base-isolated mechanism is one of the most implemented and accepted seismic protection device against earthquakes [111], [114]. This kind of system is found in several instances to attenuate vibrations on structures such as buildings, bridges, sculptures, wind turbines, communication antennas, and so on [111], [115]. In the context of the controllers that works to mitigate the negative impact of earthquakes by using the base-isolated system, several hysteresis mathematical models have been previously proposed. One of the most popular models, and the one invoked in this thesis is the well-known Bouc-Wen model [74], [116], [117].

In this section, it is resorting to a base-isolated structure described by the Bouc-Wen model, to implement an Adaptive-Predictive control technique as
was proposed in Chapter 4, with the difference that this time the HDM block is inserted at the output of an estimation parameter to avoid the zero-crossing that appears dividing in the obtained control law. The principle of adding persistent excitation to the closed-loop system is kept since the HDM block is placed at the feedback path. Besides, this case also worked to test the proposal of using hysteresis to generate the reference trajectory within the Driver Block. In addition, in this section it is also presented a fault detection algorithm for the base-isolated system, based on statistic concepts. Finally, numerical simulations show that the proposal works as expected.

For this validation case, it is considered the actuated base-isolated scheme illustrated in Figure 5.8. First, Figure 5.8(a) represents one of the many applications that the base-isolated system may have. This is a building over the base-isolation. Nevertheless, hereinafter it is used the simplified version of the base-isolated device which considers a single degree of freedom mass to emulate the building connected to the base. This simplified configuration is shown in Figure 5.8(b). Finally, Figure 5.8(c) represents the physical model. The equation that represents the system to be controlled is given by [14], [74]:

\[ m\ddot{y}(t) + c\dot{y}(t) + \Phi(y)(t) = f(t) + u(t) \]  

(5.17)

where \( m \) is the mass of the base, \( c \) is the viscous damping, and \( \Phi \) is the hysteresis restoring force of the isolated material. Besides, \( u(t) \) is the control force, and \( f(t) \) is the external perturbation force given by \(-ma(t)\) where \( a(t) \) is the earthquake ground acceleration. On the other hand, the hysteresis restoring force is described by the Bouc-Wen model as follows [14], [74]:
\[ \Phi(y)(t) = \alpha_i k_i y(t) + (1 - \alpha_i) D_i k_i z(t) \]
\[ \dot{z}(t) = D_i^{−1}(A_i \dot{y}(t) - \beta_i |\dot{y}(t)|z(t)|^{n-1}z(t) - \gamma_i |\dot{y}(t)|z(t)) \]  
(5.18)

where \( \alpha_i k_i y(t) \) is the elastic component and \( (1 - \alpha_i) D_i k_i z(t) \) is the hysteresis component; \( D_i > 0 \) is the yield constant displacement, and \( 0 < \alpha_i < 1 \) is the post-to pre-yielding stiffness ratio; \( A_i, \beta_i, \) and \( \gamma_i \) are non-dimensional parameters that control the shape and size of the transition from the elastic response \([118]\). It is assumed that \( n > 1, k_i > 0, \) and \( \beta_i + \gamma_i < 0 \) \([74]\, [119]\). Finally, the hysteresis component involves a non-dimensional auxiliary internal variable \( z(t) \). This is the solution of the nonlinear differential equation (5.18) and it is a non-measurable variable \([14], [74], [77], [113]\). With the above mathematical models, it is possible to design the control law that should accomplish the objective of attenuating the displacement of the base when it is subjected to the external perturbation.

### 5.2.1 Adaptive-Predictive Control Mathematical Development

The mathematical realization of the Adaptive-Predictive control scheme applied to the previously described base-isolated system follows the same procedure presented for the Van der Pol oscillator case. The first step is to obtain a linear model of the process. Note that the system to be controlled keeps being the nonlinear one, as was stated in equation (5.17), tough the control design is based on a linear implementation. This is an important characteristic of the proposed control, since it is simple to conceive and the control objective is accomplished as expected. Hence, the proposed linear model is as follows:

\[ m\ddot{y}(t) + c\dot{y}(t) + \alpha_i k_i y(t) = \dot{v}(t) \]  
(5.19)

Note that it is considered \( u(t) = \dot{v}(t) \) because it gives information about the past state of the control law, specially when it is implemented in discrete-time domain \([14]\). The parametrization of the equation above is:

\[ \dot{y}(t) + a_1 \dot{y}(t) + a_2 y(t) = a_3 \dot{v}(t) \]  
(5.20)

Then, by following the basic strategy of Predictive Control, it means making the prediction one-step in the future, the predictive control law is \([14]\):

\[ v(k) = \frac{y(k)[\frac{1}{T^2} - \frac{\dot{a}_1}{T} + \dot{a}_2] + \frac{u(k-1)}{T^2} + \frac{\dot{a}_2}{T} v(k-1) + y_d[\frac{1}{T^2} + \frac{\dot{a}_3}{T}]}{\dot{a}_3} \]  
(5.21)
Therefore in discrete-time domain with the Euler law, the following approximation is defined,

\[ \dot{v}(t) \approx \frac{v(k) - v(k - 1)}{T} \approx u(t) \quad (5.22) \]

Then, for the control implementation, it is employed a linear combination \( u(t) \approx \beta_1 v(k) - \beta_2 v(k - 1) \), such as, if \( \beta_1 = \beta_2 = \frac{1}{T} \), it is obtained \( u(t) \approx \dot{v}(t) \).

So, to gain some degree of flexibility for control design, \( \beta_1 \) and \( \beta_2 \) are used as free parameters. The linear combination is a difference between the present-sample \( v(k) \) and the past-sample \( v(k - 1) \), this means a time-differentiation approximation technique. Thus, if \( \beta_1 = 1 \) and \( \beta_2 = 0 \), we obtain the case where \( u(t) = v(k) \).

On the other hand, the Adaptive Mechanism is designed for the parameterized equation (5.20) and the same technique explained in Section 2.2.1 and implemented also for the Van der Pol Oscillator. Hence, the dynamic parameter estimation system is given by:

\[
\begin{align*}
\dot{\hat{a}}_3 &= -\gamma_e u_{f1} [\hat{a}_3 u_{f1} + \hat{A}_1 y_{f1} + \hat{A}_2 y_{f2} - y] \\
\dot{\hat{A}}_1 &= -\gamma_e y_{f1} [\hat{a}_3 u_{f1} + \hat{A}_1 y_{f1} + \hat{A}_2 y_{f2} - y] \\
\dot{\hat{A}}_2 &= -\gamma_e y_{f2} [\hat{a}_3 u_{f1} + \hat{A}_1 y_{f1} + \hat{A}_2 y_{f2} - y]
\end{align*}
\]  
\( (5.23) \)

### 5.2.2 Driver Block with Dynamic Hysteresis

Once the Model Predictive Control and the Adaptive Mechanism were stated, it is now necessary to set the model reference that will be programmed inside the Driver Block. In this particular case, it is proposed to use a dynamic model hysteresis as the equation executed by this block. The motivation of this is that the Driver Block may generate hysteresis reference trajectories to work along with the system to drive the control signal in a smooth manner. The hysteresis model to be used is the one given in (3.2):

\[ \dot{z}_{hm}(t) = a_{hm}[-z_{hm}(t) + b_{hm}\text{sgn}(x_{hm}(t) + a_{hm}\text{sgn}(z_{hm}(t)))] \quad (5.24) \]

In this design it is selected the input \( x_{hm}(t) \) as the velocity information from the process, this is \( x_{hm}(t) = \dot{y}(t) \). Moreover, the information required from the plant is double: first, the position because the Driver Block needs to know where is the actual position of the base to generate a realizable reference signal; and, second, the velocity because it is needed from the
hysteresis model in equation (5.24). Hence, the output Driver Block equation is proposed as follows:

\[ y_d(k+1) = \sigma_1 \dot{y}(k) + \sigma_2 y(k) + \sigma_3 z_{hm}(k) \]  

(5.25)

where \( \sigma_1, \sigma_2 \) and \( \sigma_3 \) are selected gains to make the system stable and without overshoot \[3\]. Evidently, \( \dot{y}(k), y(k), \) and \( z_{hm}(k) \) are the sampled signals in discrete-time domain. The term \( \sigma_1 \dot{y}(k) \) is a kind of damping force useful to attenuate vibrations of the structure. Finally, and because we are dealing with a regulation problem, the user set point \( y_r(t) \) is set to zero.

Additionally, as was mentioned before, in this specific case it was necessary to place the HDM block at the parameter signal \( \hat{a}_3 \) that makes the division in the control law in equation (5.21). With this action, the division by zero is avoided and, moreover, the persistent excitation condition is present in the whole closed-loop system. Then, the new control law is:

\[ v(k) = \frac{y(k)[\frac{a}{\tau^2} - \hat{a}_1 \frac{1}{T} + \hat{a}_2] + \frac{y(k-1)}{\tau^2} + \frac{\hat{a}_3 z_{HDM}}{T} v(k-1) + y_d[\frac{1}{\tau^2} + \frac{a}{T}]}{\frac{\hat{a}_3 z_{HDM}}{T}} \]  

(5.26)

Finally, Figure 5.9 depicts the block diagram that summarizes the implementation of the whole Adaptive-Predictive control technique above explained.

### 5.2.3 Numerical Experiments

Here it is presented the results that validate that the implemented control technique achieves the control objective of the base-isolated system. This
performance is compared to the open-loop response. The simulations were carried out in Simulink. The following values were selected as ‘true’ parameters for the system and the Bouc-Wen model \([14, 113]\): \(m = 156 \times 10^3\) Kg, \(k_i = 6 \times 10^6 N/m\), \(c = 2 \times 10^4 Ns/m\), \(\alpha_i = 0.6\), \(D_i = 0.6 m\), \(A_i = 1\), \(\beta_i = 0.1\), \(\gamma_i = 0.5\), \(n = 3\) and zero initial conditions. The values in equation (5.23) are: \(\lambda_1 = 10\), \(\lambda_2 = 5\), \(\gamma_c = 0.01\), and with initial conditions \(a_3(0) = 0.1\), \(A_1(0) = A_2(0) = 0\). Besides, the values used for the Driver Block in equation (5.25) are: \(a_{hm} = 0.01\), \(b_{hm} = 100\), \(\sigma_1 = 100\), \(\sigma_2 = -1000\), \(\sigma_3 = -1\), \(ahm = 10\), and with initial condition \(z_{hm}(0) = 0.001\). The sampling period \(T\) implemented is 0.01s. Finally, the HDM block here implemented uses the relay hysteresis system with the values in the Matlab/Simulink format: \(\text{switch on/off} = \{1, -1\}\), \(\text{output on/off} = \{10, 0.1\}\); and the filter transfer function is given by \(G(s) = \frac{1}{s+1}\). Additionally, the perturbation force used for simulations is the ground acceleration of El Centro earthquake, whose time history is displayed in Figure 5.10.

Figure 5.11 shows the response of the base-isolated displacement in open-loop and under the Predictive Control design. Here it is clearly notable that the displacement is significantly reduced when the control scheme is used. From these results it is conclusive that the control objective is satisfactorily achieved. Finally, the control signal is depicted in Figure 5.12.

As a brief comment from the above presented experiments, it is concluded that the proposed Adaptive-Predictive control algorithm has the expected performance since the main control objective is successfully achieved. The control algorithm provides hysteresis projection commands that fit with the natural hysteresis behavior of the base-isolated system. Moreover, since it is
Figure 5.11: Output response of the base-isolated displacement with El Centro earthquake.

Figure 5.12: Control signal for the base-isolated system.
employed only one-sample-period time for future projection, the Adaptive-
Predictive strategy is very simple to implement.

5.2.4 An On-line Statistic Fault Detection Algorithm for the
Base-isolated System

This section proposes a novel on-line fault detection system [120]. The
importance of this approach is that, within a controlled system, an adequate
fault detection may give extra information about what is occurring inside
the controlled system. Here, the proposed fault detection technique is im-
plemented for the base-isolated structure since it is a complex system from
which the model parameters not always could be available. Besides, since the
control algorithm is designed from the linearized model, it could lose impor-
tant information from the real plant. This fault detection approach is based
on statistical analysis since data analysis discipline is nowadays very popular,
mainly because it provides methods to organize and summarize data and to
draw conclusions about the information contained in the dataset.

The development of fault detection systems has an important role in engi-
neering applications, primarily in the industrial sector [121]–[123]. Generally
speaking, this is because an early and adequate fault detection strategy al-
 lows to take appropriate actions on time to avoid future serious problems,
such as the deterioration of machines, human risk, production reduction, or
increase in maintenance costs [124], [125].

From the dynamic system point of view, a fault may occur in the process
that can be interpreted as changes in any parameter of the process model
[126]. This kind of fault is considered in this section and may describe, for
instance in mechanical systems, deteriorations of the plant such as rupture,
fatigue or clogging [119], [127], [128]. Most of the fault detection methods
use a tuned mathematical model of a given process as a reference [119], [124],
[129], [130]. This is typically called the healthy model and it serves to obtain
a residual signal, which is the difference between the process output response
and the healthy model output. By using this signal, it is possible to do a
residual evaluation to set a threshold to infer when the fault may appear
[119], [124], [128], [130]. This idea is posed in this approach, where, on one
side, the residual signal, here renamed as error signal, is employed to pro-
gram a healthy threshold. On the other side, the error signal is processed by
the proposed on-line statistic estimator scheme. This scheme analyzes the
residual signal by using the \textit{variance} to detect when the prescribed threshold is overcome.

First of all, it is resorting to the Adaptive-Predictive control obtained in previous Section 5.2. Secondly, the control scheme is modified in order to add the fault detection algorithm. Figure 5.13 shows how the control system is now implemented. In this figure $e(t)$ represents the error signal as the difference between the actual process output, $y(t)$, and the output of the healthy model, $y_h(t)$. Note that both responses are obtained influenced by the same external perturbation $f(t)$. Furthermore, both systems receive the same control action $u(t)$. For this implementation, first is suggested the healthy model as a suitable linear model obtained from the original plant (5.17) as follows:

$$\ddot{y}(t) + c\dot{y}(t) + \alpha_i k_i y(t) = f(t) + u(t) \quad (5.27)$$

Afterwards, in order to handle the error signal, the statistic estimator algorithm is designed and proposed as it is summarized in Figure 5.14. The first stage of this scheme refers to continuously collecting a set of $n$ data by using a sample rate $T_s$. The sample rate serves to acquire and build data sets from the error signal. Then, the statistic estimator calculates the variance parameter for each data set of $n$ samples. Figure 5.15 outlines the algorithm above described, which is repeated until the complete error signal is evaluated. Finally, the threshold decision block contains a previously settled healthy threshold. Thus, by comparing the calculated variance values to this threshold level, a fault inference can be done.

The sample variance is a measure of variability with respect to its average value. This statistic metric is important since, in this application, the variance measures the residual signal variability and this signal is modified by the

Figure 5.13: The healthy model implanted in the control scheme.
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Figure 5.14: The statistic estimator block diagram.

Figure 5.15: The on-line statistic estimator algorithm with \( n = 20 \) samples.

external perturbation, in this case an earthquake. And it is also sensitive to a possible fault in the system. The mathematical expression of sample-variance is

\[
s^2 = \frac{\sum (x_i - \bar{x})^2}{n - 1}\]

(5.28)

where \( n \) is the number of data in a sample, \( x_i \) is a taken data from it, and \( \bar{x} \) is the sample mean.

System Training Stage

The purpose of the training stage is to obtain the healthy threshold. To do this, the control diagram given in Figure 5.13 is required. For this stage, first, different perturbations in the system are used to obtain different responses, and then it is selected the perturbation that provides the error signal with more distribution of its data. Then, it is made the assumption that this signal is the adequate to set the healthy threshold. Therefore, the training stage was developed as follows. First of all, four real earthquake data, shown in Figure 5.16, are individually employed as external perturbations. The objective is to generate four different error signals to select the one to establish the healthy threshold. These signals are analyzed by employing the
traditional statistic boxplots. These graphical tools allow to describe prominent features of the data. In particular, an important feature is the number of data and how far are these from the mean value. Figure 5.17 shows the boxplots of each error signal obtained with the corresponding earthquake: Kobe, El Centro, Nishi-Akashi and Chi-Chi [120].

The boxplots given in Figure 5.17 highlight the fact that the error signal obtained by using the Kobe earthquake has a significant number of outliers and further away from the average value. That is, it is considered that it is the worst scenario talking about external perturbation. For this reason, the error signal obtained with the Kobe earthquake is here considered the best option to set the healthy threshold. This error signal is examined through the statistic estimator (see Figure 5.14 and 5.15). Then, the maximum and the minimum variance values calculated are those that will set the threshold as it is shown in Figure 5.18.

Summarizing, the proposed statistic fault detection strategy consists of the following elements:

1. A suitable healthy model.
2. An on-line statistic estimator to analyze the error signal.
3. A healthy threshold obtained through a training stage.

The numerical experiment results are presented next. First, it will be shown that the designed Adaptive-Predictive control has a good performance in
Figure 5.17: Boxplots of the signal error for each earthquake.

Figure 5.18: Sample-variance analysis from Kobe error signal and the estimated healthy threshold.
accomplishing the control objective of attenuating displacement. The experimentation stage is done by employing the four earthquakes depicted in Figure 5.16. These seismic perturbations will be invoked to validate the proposed fault detection strategy and it will be seen that the healthy threshold previously set always is overcome when a faulty system is called up.

In order to execute the numerical experiments that validate both the control design and the fault detection algorithm, a fault is modeled [119], [120]. This fault represents a change in the material stiffness of the base-isolated system and it may be translated into a change of the base shape due to deterioration or rupture [118], [119]. The fault is captured by adding an additional term $\Delta A_i$ to the nominal value of $A_i$ in equation (5.18). The mentioned modeled fault is presented in Figure 5.19. Note that the fault is invoked at ten seconds, and removed at 20 seconds of the running process.

In the numerical experiments, the following true values for the Bouc-wen model in equation (5.18) are set [74], [113], [119]: $m = 156$ x $10^3$ Kg, $k_i = 6 \times 10^6$ N/m, $c = 2 \times 10^4$ Ns/m, $\alpha_i = 0.6$, $D_i = 0.6$ m, $A_i = 1$, $\beta_i = 0.1$, $\gamma_i = 0.5$, $\bar{n} = 3$ and zero initial conditions. The values in the Adaptive Mechanism in equation (5.23) are: $\lambda_1 = 10$, $\lambda_2 = 5$, $\gamma_e = 0.01$, and initial conditions $b_1(0) = 2$, $A_1(0) = 0.8$ and $A_2(0) = 1.5$. Moreover, the values used for the Driver Block equation (5.25) are: $\sigma_1 = 100$, $\sigma_2 = -1000$, $\sigma_3 = -100$. The sampling period time $T$ implemented to design the control scheme is 0.01 s (see Figure 5.13).

The first result is the one obtained by implanting the fault and by using
the data of the Kobe earthquake. The open-loop and closed-loop output response is depicted in Figure 5.20(a). This graphic shows the time history of the base displacement when the earthquake goes into action. Clearly, the closed-loop response has a better performance since the displacement is reduced. Furthermore, from this result it is possible to affirm that the controlled system is robust to faults since its performance is adequate even under a fault in the process. On the other hand, the variance analysis of the error signal produced between the output system response with fault and the output of the healthy model is presented in Figure 5.20(b). From this, it is notable that the healthy threshold is overcome when the fault appears at 10 seconds, just as was expected. Moreover, the output responses and variance analysis also are presented for the rest of the earthquakes. On one hand, the graphics in Figure 5.21 are the results obtained with the data of Chi-Chi earthquake. Secondly, the results by employing the Nishi-Akashi earthquake data are shown in Figure 5.21. Finally, the respective results by using El Centro earthquake are displayed in Figure 5.23.

All the numerical experiments above presented highlight the fact that the controlled system has the expected performance even when there is a fault in it, since the control objective of attenuating the base displacement is achieved. Additionally, the variance analysis allows to confirm, as was assumed, that the healthy threshold is overcome just when the fault occurs.
Figure 5.21: (a) Sample-variance analysis under the Nishi-Akashi earthquake without fault in the system. (b) Open-loop and closed-loop responses for the faulty case. (c) Variance analysis of the Nishi-Akashi error signal under the faulty model.
Figure 5.22: (a) Sample-variance analysis under the Chi-Chi earthquake without fault in the system. (b) Open-loop and closed-loop responses for the faulty case. (c) Variance analysis of the Chi-Chi error signal under the faulty model.
Figure 5.23: (a) Sample-variance analysis under El Centro earthquake without fault in the system. (b) Open-loop and closed-loop responses for the faulty case. (c) Variance analysis of El Centro error signal under the faulty model.
5.2.5 Conclusion from the Experiments

The experiments above presented allow to draw some significant conclusions. First, this example evidences the importance of adequate selecting the linear model with which the control design is implemented. Moreover, this case highlights the fact that the control proposal is simple even if the system to be controlled is a complex one, just as the case of the base-isolator. On the other hand, with this system, two approaches were tested. Firstly, the modulation block with hysteresis may be inserted in a different stage of the control scheme, as long as it provides the persistent excitation condition to the complete closed-loop system. Secondly, it was proven the idea of design the Driver Block as a system with hysteresis, in order this may work along with the hysteresis in the plant. The results were satisfactory since the control objective of mitigating the displacement of the base under an earthquake is accomplished. Additionally, the fault detection algorithm here proposed demonstrated to be useful to detect a fault in the process. As a near future work, it is expected to test this algorithm with the idea that it may work for different systems, due to its basic behavior is simple.

5.3 Final Chapter Remarks

In this chapter two cases were presented. Both cases were invoked to validate the control approach at a numerical level using Matlab/Simulink. The first case demonstrated how the HDM block works to eliminate the parameter drift induced by a time-delay added at the output of the process. This example resorted to the Van der Pol system, which is represented by a nonlinear mathematical model that, due to its characteristics, is very susceptible to be an unstable system. Moreover, its response corresponds to a non-minimum phase system that is a common control challenge. On the other hand, the example of the designed control for a base-isolated system also evidenced a satisfactory performance by accomplishing the regulation control objective. Besides, in this case it was shown how the hysteresis implanted within the Driver Block helps to join the closed-loop performance and the natural hysteresis behavior of the process to be controlled. Moreover, also this validation case served to propose a fault detection algorithm as a complement of the control strategy, which was successfully applied. As was seen in this chapter, these two first implementation cases were carried out at a simulation level. Therefore, it was necessary to validate the control technique also at an experimental level as it will be exposed in the next chapter.
In this chapter it is presented the experimental implementations of the Hysteresis Adaptive-Predictive control approach. These are settled in the field of power electronics.

The first one is the implementation of the control strategy to a DC-DC buck converter which has the aim of regulating the output voltage even when the system is subjected to different external perturbations. The designed control for this system is implemented in an experimental platform, where different scenarios were tested to confirm the adequate performance of the control proposal. Additionally, previous to the experimental implementation, numerical results were also obtained to support the experimental results.

On the other hand, also in the field of power electronics, a single-phase inverter is invoked to validate the control technique. In this specific case, the modulation stage is carried out by designing an adaptive hysteresis modulation, which is another important contribution of this thesis. Finally, this control is also implemented in a simulation level and in an experimental platform to test the performance.

6.1 An Adaptive–Predictive Control Scheme with Dynamic Hysteresis Modulation Applied to a DC–DC Buck Converter

This section exposes the implementation of the Adaptive-Predictive control technique with modulation hysteresis to a DC-DC buck converter.
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In recent years, the power electronic field has had an enormous growth, mainly in the branch of regulation, conversion and distribution of energy [131], [132]. This, due to the high demand of electrical and electronic applications that require devices that execute these tasks. Among all the variety of power electronics devices, the DC–DC converters are one of the most common and most studied by engineers and researchers [131].

The DC-DC converters constitute an important control challenge due to their switching nonlinear and time-varying characteristics, the fast changes in their reference voltage, their high sensitive to the frequently changing load conditions, their very small sampling period and the changes in the system parameters related to external perturbations [133]–[135]. In general, the main objective of DC–DC converters is to ensure stability with an adequate dynamic response in order to achieve a desired load output voltage by guaranteeing a good performance while optimizing the utility life of the electronic components [133]. One of the most common DC–DC converters is the buck converter, which is the one treated in this section. It basically consists on step down the output voltage on the load with respect to the input voltage. This converter has been employed in the realization of battery chargers [136], [137], and battery-operated portable equipment, due to its simple structure and low-cost [138], [139]. Besides, in the automotive field, the buck converter is widely used. One example of it is its bidirectional version for applications in dual battery system for hybrid electric vehicles [140], [141]. Furthermore, in the management of energy, the DC–DC converters have been adopted along with an adequate control technique, to improve the optimization of the total cost of fuel cell/battery in hybrid electric vehicles [142], [143]. Last but not least, in the renewable energies area, the DC-DC converters also have won popularity, for instance, to feed power from distributed generators into smart grids [144] and to improve the efficiency of energy provided by photovoltaic panels through maximum power point tracking techniques [44], [145], [146].

6.1.1 DC-DC Buck Converter Modeling

A conventional electronic circuit of the buck converter is shown in Figure 6.1. It is mainly composed of an input voltage source \( E \), a switch device \( S \), a diode \( D \), an inductor \( L \), a capacitor \( C \), and finally the load, which usually is a resistor \( R \). Based on circuit analysis and under ideal assumptions, the buck converter dynamic model may given by [147]:

\[ \text{[Equation]} \]
where, \( z_1 = i_L \) is the inductor current, \( z_2 = V_o \) is the output voltage and \( u \) is the switching control input. Here it is assumed that the circuit is in Continuous Conduction Mode (CCM), this is, the minimum instantaneous value of the inductor current does not drop to zero even in load variation conditions.

The following state normalization by using the time scale transformation \( \tau = \frac{t}{\sqrt{LC}} \), may be introduced [134]:

\[
\begin{align*}
    x_1 &= \frac{z_1}{E} \sqrt{\frac{L}{C}}, \\
    x_2 &= \frac{z_2}{E} 
\end{align*}
\]  

Therefore, the normalized model that will serve for control design purposes is given by [147]:

\[
\begin{align*}
    \dot{x}_1(t) &= -x_2(t) + u(t) \\
    \dot{x}_2(t) &= x_1(t) - \frac{x_2(t)}{Q} \\
    y(t) &= Ex_2(t)
\end{align*}
\]  

where \( Q = R \sqrt{C/L} \) and \( y(t) \) is the output equation. Hence, \( x_1(t) \) and \( x_2(t) \) are now the normalized state variables, the inductor current and output voltage, respectively.

6.1.2 Adaptive-Predictive Control Mathematical Development

From the system in equation (6.3) it is possible to obtain the parameterized transfer function, which will be later useful to design the Predictive Model and the Adaptive Mechanism of the control scheme. The parameterized
transfer function to \( (6.3) \) can be stated by its relation, in Laplace domain, between the output process \( Y(s) \) and the input control \( U(s) \) as follows:

\[
G(s) = \frac{Y(s)}{U(s)} = \frac{a_1}{s^2 + a_2 s + a_3} \tag{6.4}
\]

where \( a_1, a_2 \) and \( a_3 \) are the plant parameters to be estimated by the Adaptive Mechanism, and then employed by the Predictive Model. Additionally, note that equation \( (6.4) \) is a second order transfer function that will facilitate to conceive the control design described in previous sections, and it is suitable to obtain an outstanding control performance for the buck converter.

Once the transfer function is stated, it is now possible to continue with the control design just as was carried out in previous examples. First of all, through the Euler discretization law applied to the transfer function in \( (6.4) \) it is obtained the discrete-time representation to establish the predictive model. Then, the predictive control law results as follows:

\[
u(k) = \frac{y_d(k+1)\left[\frac{1}{2T} + \frac{\hat{a}_2(k)}{T}\right] + y(k)\left[-\frac{2}{T} - \frac{\hat{a}_2(k)}{T} + \hat{a}_3(k)\right] + y(k-1)\hat{a}_1(k)}{\hat{a}_1(k)} \tag{6.5}\]

On the other hand, the Adaptive Mechanism also is obtained from the management of the function in \( (6.4) \), and by following the same process that in the previous examples. First, the stable second order filters are selected as:

\[
G_{F1}(s) = \frac{s}{s^2 + \lambda_1 s + \lambda_2} \quad G_{F2}(s) = \frac{1}{s^2 + \lambda_1 s + \lambda_2} \tag{6.6}
\]

Afterwards, the Gradient Algorithm law, as it was established in \( (2.10) \), is applied in order to get the dynamic model that does the parameter estimation task as it is presented following:

\[
\begin{align*}
\dot{\hat{a}}_1 &= -\gamma u_f [\hat{a}_1 u_f + \hat{A}_2 y_{f1} + \hat{A}_3 y_{f2} - y] \\
\dot{\hat{A}}_2 &= -\gamma y_{f1} [\hat{a}_1 u_f + \hat{A}_2 y_{f1} + \hat{A}_3 y_{f2} - y] \\
\dot{\hat{A}}_3 &= -\gamma y_{f2} [\hat{a}_1 u_f + \hat{A}_2 y_{f1} + \hat{A}_3 y_{f2} - y] \tag{6.7}
\end{align*}
\]

Finally, resorting to the Adaptive -Predictive control strategy with hysteresis modulation, it is now required the dynamic hysteresis model that composes the Hysteresis Delta Modulator (HDM). For this specific example it is proposed to use the following hysteresis equation:

\[
\dot{z}(t) = a_{hm}[-z(t) + b_{hm}sgn(x(t) + a_{hm}sgn(z(t)))] \tag{6.8}
\]
Table 6.1: Buck converter parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC input voltage</td>
<td>50V</td>
</tr>
<tr>
<td>Switching frequency</td>
<td>20kHz</td>
</tr>
<tr>
<td>Inductor L</td>
<td>0.004 H</td>
</tr>
<tr>
<td>Capacitor C</td>
<td>2.5 µF</td>
</tr>
<tr>
<td>Load resistor R</td>
<td>22.2 Ω</td>
</tr>
<tr>
<td>Resistor in inductor</td>
<td>0.04 Ω</td>
</tr>
<tr>
<td>Diode snubber resistance</td>
<td>0.1Ω</td>
</tr>
<tr>
<td>Diode snubber capacitance</td>
<td>20 µF</td>
</tr>
</tbody>
</table>

where $a_{hm}$ and $b_{hm} \in R^+$ are the hysteresis loop parameters and $z(t)$ is the internal variable of the hysteresis model. On the other hand, $\alpha_{hm}$ is the constant-transition rate.

### 6.1.3 Numerical Results

The experiments are carried out in Matlab/Simulink 2018b. Furthermore, the realistic buck converter parameters used for these simulations are obtained from a real DC-DC setup and listed in Table 6.1 [148]. The snubber values for the diode were tuned by trial and error by considering the buck converter switching frequency. In addition, the parameters of the control scheme are set as follows: $\alpha_{hm} = 5$, $a_{hm} = 5$, $b_{hm} = 0.1$, $\gamma = -0.001$, $\lambda_1 = 10$, $\lambda_2 = 5$, $\alpha_1 = \alpha_2 = 100$, $\beta_1 = 200$. These parameters were tuned by the trial and error procedure by fulfilling the criteria of stability for the filters and the Driver Block equation. Finally, the sample time $T$ is set to 0.05 ms. In Figure 6.2, it is shown the Simulink model of the buck converter employed to implement the experiments.

Firstly, the control performance is evaluated when the reference voltage has step changes. This scenario is realistic, for instance, when the user changes the reference value according to a required application of the buck converter. In these experiments, the reference voltage is altered by step changes every second from 15 V, to 20 V, to 25 V. In Figure 6.3 it is possible to observe that the control performance is satisfactorily executed since the different values of reference voltage are achieved in fast time and without overshoots. Note that the oscillation condition at the output response is due to the hysteretical nature of the closed-loop system and it does not compromise the performance of the converter controller. In fact, depending on the application, the oscillations might be attenuated by employing adequate filters, among other
Additionally, in order to illustrate the actuation of the control law, the PWM signal (see Figure 6.2) was filtered by using a low-pass filter \( G_{PWM}(s) = \frac{10}{s + 10} \). This was done since at first glance the control action in the PWM signal is not perceived. Hence, the Figure 6.4 is a manner of guaranteeing that the controller goes into action every time the reference signal is updated.

In the following experiment, a step down change from 50 to 40 V at the input voltage occurs at 0.5 seconds. This kind of scenario is important to consider since it is a realistic situation when the voltage supply to the converter is subject to variable voltage conditions such as voltage drop or overloading, or when the voltage supply does not have a control stage to maintain the input voltage to the converter regulated. One example of this scenario could be a DC-DC power converter used in a photovoltaic system. The result of this experiment is shown in Figure 6.5. From this, it is possible to observe that the needed time to reach the reference voltage (20 V) is approximately 5 milliseconds. Moreover, when the input voltage changes from 50 V to 40 V at 0.5 seconds, the system takes approximately the same time to retrieve the voltage reference value.

On another side, the numerical experiment results with a step change in the converter load are following presented. Just as the previous experiments, the variation in the load is also a realistic case in DC-DC converters applica-
Figure 6.3: (a) Output voltage response with step changes in the reference voltage. (b) (c) (d) The corresponding zoom-in versions.

Figure 6.4: Filtered PWM signal.
Figure 6.5: (a) Output voltage response with a step down change in the input voltage. (b) (c) The corresponding zoom-in versions.
Figure 6.6: (a) Output voltage response with a step up change in the load. (b) (c) The zoom-in versions.

Figure 6.7: (a) Estimated parameters when a step change load occurs at 0.5 seconds. (b) The corresponding zoom-in graphic.
Figure 6.8: (a) Output voltage response with a step change in the inductor. (b) (c) The corresponding zoom-in graphics.
tions. For instance, when an inductive motor linked to the DC-DC converter is broken down, the load seen by the converter will vary from its original value. In this simulation, the change in the load is invoked at 0.5 seconds, from $22.2\Omega$ to $27.2\Omega$, and the reference voltage is $25$ V. Additionally, it is shown the response of the process estimated parameters $\hat{a}_1$, $\hat{a}_2$ and $\hat{a}_3$. This is useful to observe two important keys of the Adaptive Mechanism: 1) the dynamic response of the parameters, and 2) the utility of this block of giving information about the parameters variation to infer when an abrupt change occurs in the process. In this experiment, the value of the gain $\gamma = -1000$ is greater than in the previous simulations to accelerate the dynamic of the adaptive system since it normally is slower than the control scheme dynamic [106]. The process output response is presented in Figure 6.6. On the other hand, the estimated parameters are depicted in Figure 6.7 where it is possible to note the variation in the estimated parameters $\hat{a}_2$ and $\hat{a}_3$ when the change in the load is invoked.

Moreover, for the following numerical analysis, a fault in the inductance $L$ was introduced at 0.5 seconds. This fault was simulated by abruptly change the value of the inductance from $0.002$ H to $0.004$ H. The reference value is $25$ V. Figure 6.8 exposes the output voltage response. Additionally, in this experiment it is also shown the estimated parameters behavior in Figure 6.9, where it is observable the parameters reaction when the fault in the inductor occurs.

Figure 6.9: (a) Estimated parameters with an induced error in the inductance value. (b) The zoom-in graphic.

Furthermore, one of the most important current application of DC-DC converters is in the field of renewable energies. Therefore, a following numerical
experiment by using a PV system is presented. In this experiment, the input voltage of the DC-DC buck converter is provided by a photovoltaic panel as it is shown in Figure 6.10. The implemented PV array is the SunPower SPR serie 305-E, included in the library Simscape in Simulink. This array consists of strings of 66 PV modules connected in parallel. Each string consists of 5 modules connected in series. For this experiment, the condition of temperature was fixed at 28°C and the irradiance seen by the PV panel was modeled as shown in Figure 6.11. This was programmed with changes that may emulate shading conditions. The reference voltage was fixed at 90 V and the parameters of both the control scheme and the buck converter, are the same used in the previous exposed numerical experiments. Figure 6.12(a) shows the input voltage of the converter provided by the PV panel under
the changes in the irradiance. On the other hand, Figure 6.12(b) shows the converter output voltage where it is worth to notice that the reference value is achieved even under the different values of the irradiance in the PV panel.

6.1.4 Experimental Results

Finally, in order to experimentally validate the proposed Predictive Control, a variety of experiments were carried out by using a benchmark platform located at the Electrical Energy Laboratory (EELAB) in Ghent University. The parameters of each component are the same listed in Table 5.1. The setup is the one presented in Figure 6.13, which is a three-phase inverter described in [150], [151]. However, for these experimental purposes, it was adjusted such that only one leg is used to get a buck converter configuration where the proposed control algorithm is implemented. The setup is integrated with a DSC Texas Instrument processor, model TMS320F28335. This processor provides a clock speed of 150 MHz and a floating-point unit [148], [150].

The results obtained with the proposed technique are compared with the results obtained by employing a common PI controller. The parameters of the PI controller are $k_i = 0.999 \text{ rad/s}^2$ and $k_p = 0.001 \text{ rad/s}$. Worth mentioning, that for the experimental implementation, the Adaptive Mechanism stage was not programmed, instead of it, constant values were employed to program the Predictive Control in equation (6.5). This is possible since, if the dynamic of the Adaptive Mechanism is slow (due to a small value of $\gamma$),
the estimated parameters can be conceived as constant values, and under an ideal assumption, they are the nearest possible to the nominal process parameters. For these experiments, the estimated parameters are set \( \hat{a}_1 = 0.1, \hat{a}_2 = 4 \) and \( \hat{a}_3 = 10 \). On the other hand, the values for the AP control scheme are \( \alpha_{hm} = 8, b_{hm} = 5, \alpha_1 = \alpha_2 = 10 \) and \( \beta_1 = 20 \).

In Figure 6.14, the response of the output voltage (Ch1: yellow signal) is depicted when the reference voltage of the buck converter has a step change from 0 V to 20 V. The time per division in Figure 6.14(a) is 500 microseconds, on the other hand, in Figure 6.14(b) is 5 milliseconds. In this Figure it is also shown the load current (Ch2) and the filtered inductor current (Ch3). From here, it is notable that the time that takes the output voltage in achieving the stable reference value in both cases, the PI controller and the proposal AP control, is similar. However, the response with the proposed control technique is better than the one with the PI controller since this last one has an over damped response. A similar conclusion can be deduced from the experiment when the reference voltage has a step change from 20 V to 0 V in Figure 6.15. Here, the time per division is 1 millisecond and 10 milliseconds, respectively. Signals blue (Ch2) and magenta (Ch3) are the measured
Figure 6.14: Output voltage response (Ch1), load current (Ch2) and filtered inductor current (Ch3), under a step up change in the reference voltage from 0 V to 20 V. (a) Results employing the PI controller with time per division 500 microseconds. (b) Results with the proposed AP controller and time per division 5 milliseconds.

Figure 6.15: Output voltage response (Ch1), load current (Ch2) and filtered inductor current (Ch3), under a step down change in the reference voltage from 20 V to 0 V (a) Results employing the PI controller with time per division 1 millisecond. (b) Results with the proposed AP controller and time per division 10 milliseconds.
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Figure 6.16: Output voltage response (Ch1), filtered current inductor (Ch3) and input voltage (Ch4), under a step up change in the input voltage from 50 V to 100 V and time per division 25 milliseconds. (a) Results employing the PI controller. (b) Results with the proposed AP controller.

Figure 6.17: Output voltage response (Ch1), filtered current inductor (Ch3) and input voltage (Ch4), under a step down change in the input voltage from 100 V to 50 V and time per division 25 milliseconds. (a) Results employing the PI controller. (b) Results with the proposed AP controller.
Figure 6.18: Output voltage response (Ch1), and inductor current (Ch2) under a step up change in the load from 22.2Ω to 25.2Ω. (a) Results with the PI controller and time/div 1 millisecond. (b) The zoom version with time per division 100 microseconds. (c) Results with the proposed AP controller and time/div 5 milliseconds. (d) The zoom version with time per division 2.5 milliseconds.

current through the load and in the inductor converter, respectively. Note that in these experiments the voltage probe was scaled by two the original measured value.

Furthermore, the results following presented were obtained by inducing a step change in the input voltage from 50 V to 100 V and vice versa. The reference value was set at 25 V. Figure 6.16 gathers the results when the input voltage has a step up change. On the other hand, Figure 6.17 recovers the results when the input voltage varies from 100 V to 50 V. In both cases, by employing both control techniques, the results are very similar. The system barely notes the change and it maintains the output voltage (Ch1) at
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Figure 6.19: Output voltage response (Ch1), and inductor current (Ch2) under a step down change in the load from $25.2\Omega$ to $22.2\Omega$. (a) Results with the PI controller and time/div 2.5 milliseconds. (b) the zoom version with time per division 250 microseconds. (c) Results with the proposed AP controller and time/div 5 milliseconds. (d) The zoom version with time per division 1 millisecond.
Figure 6.20: Output voltage response (Ch1), inductor current (Ch2), and load current (Ch3) under a step up change in the inductor from 2 mH to 4 mH. (a) Results with the PI controller and 2.5 milliseconds per division. (b) The zoom version with 55 microseconds per division. (c) Results with the proposed AP controller and 5 millisecond per division. (d) The zoom version with time per division 1 millisecond.
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Figure 6.21: Output voltage response (Ch1), inductor current (Ch2), and load current (Ch3) under a step down change in the inductor from 4 mH to 2 mH. (a) Results with the PI controller and 250 microseconds per division. (b) Results with the proposed AP controller and 2.5 milliseconds per division.

the desired value. Additionally, the green signal (Ch4) is the input voltage to the buck converter and the magenta signal (Ch3) is the converter current. Finally, the blue signal (Ch2) shows the moment when the change in the input voltage occurs. From Figure 6.17, the measured inductor current shows that there is a spike with a high $di/dt$. This may be a normal response since there is energy accumulated in the capacitor, then when an abrupt step down is induced in the input voltage, the system needs to spend this amount of energy instantaneously, consequently a peak current occurs. Thus, it is worth to mention that this transient does not result into a change of the output voltage and it is presented in both control algorithms.

In other experiment, a step change in the load is induced from 22.2 Ω to 27.2Ω and vice versa. First, when the step up change is invoked, the time per division in the results with the PI control technique is 1 millisecond and 100 microseconds in the zoom version. On the other hand, the time per division for the results with the AP proposal, is 5 milliseconds and 2.5 milliseconds in the zoom version. From Figure 6.18, it is visible that the time in achieving the reference voltage value is a bit faster with the PI controller. Nevertheless in contrast with it, the response of the AP controller does not present the overshoot unlike the case with the PI control. In this figure, the green signal (Ch4) is used to identify when the change in the load occurs. The set of graphics in Figure 6.19 presents alike results obtained by doing the step down change in the load. In these results, the time per division for the PI case is 2.5 milliseconds and 250 microseconds in the zoom versions.
Moreover, the time per division for the AP case is 5 milliseconds and 1 millisecond in the zoom version.

Finally, the set of graphics in Figure 6.20 depicts the experiment results when a step up change in the inductor is triggered from 2mH to 4mH. Although this scenario may not be present in practice, since an abrupt change in the inductor may mean the converter is completely broken down, it is a good experiment to validate robustness of the control technique. This experiment was done by switching the corresponding transistor in the setup to make the adequate array with the inductors. In this specific experiment, the AP control has a faster response (5 milliseconds/div and 1 millisecond/div in the zoom version) than the PI case (2.5 milliseconds/div and 55 microseconds/div in the zoom version). Moreover, the PI controller results contain more overshooting. In these experiments, the green signal (Ch4) represents the precise moment when the inductors are switching. On the other hand, Figure 6.21 depicts the results by doing the step down change in the inductor. Note that in this case, for both controllers, the system barely notices the change. Here, the time per division is 250 microseconds and 2.5 milliseconds, respectively.

6.1.5 Conclusions from the Experiments

The above exposed validation case has demonstrated that the proposed control approach is a simple manner to accomplish the main power control objective of the DC-DC converters. That is, to efficiently regulate the output voltage of the DC-DC converter to a desired value even when the system is subjected to the commonly existing perturbations, such as variation in the input voltage, fast changing in the reference command voltage, or a possible fault in some of the buck-process parameters. The proposed Predictive Control scheme has been experimentally evaluated in a benchmark platform to be robust under different faulty scenarios. Moreover, the exposed results, both numerical and experimental, show that the control objective is quickly accomplished, which is a notable and always required property in the field of DC-DC converter applications. Furthermore, if a comparison between the results from numerical experiments and real implementation is made, it can be seen that the time response is slower in the real cases. This difference is mainly because the simulation model uses ideal conditions, while in the case of the real implementation, the system is subjected to different conditions, for instance, the signal-processing time, the speed of the controller processing unit and the optimal useful life of the actuators, among other characteristics.

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Nubia Ilia Ponce de León Puig
always presented in real control systems. Nevertheless, even in the real implementation, the proposed technique provides acceptable results in the time response and in the robustness of the controller. Note that the output voltage with the control proposal has more oscillations than the response with the PI controller, this is because of the hysteresis within the AP control scheme, and it is considered that according to the application, this ripple behavior may be easily filtered. On the other hand, as was presented in this section, the conventional PI controller is a good option to accomplish the objective, however this kind of controller has a limited behavior when the system is subjected to external perturbations, for instance when the value of the load varies (Figure 6.18). Additionally, it is worth mention that the output voltage obtained with the control proposal contains more oscillations, which is a characteristic inherit from the hysteresis system. However, this signal can be easily filtered according the necessities of the system. As it was shown in the experimental results, the AP control technique works better than the case with the PI controller when the parameters of the system are subjected to changes, external perturbations or faults. A reason for this may be that the HDM block fulfills its aim of providing the condition of modulating the control signal according to the closed-loop requirements. For this reason, in general, the exposed proposal can be considered as a better option since the AP control technique is more robust than the PI controller.

6.2 Adaptive-Predictive Control Strategy with Adaptive Hysteresis Modulation Applied to a Single-Phase Inverter

In a previous section it was presented the results of applying the proposed control strategy to a conventional DC-DC buck converter. Now, by following the power electronics path, and the current environmental scenario regarding the impact of renewable energies, this section presents the design of an Adaptive-Predictive control scheme by adding an adaptive hysteresis modulation, and then applied it to an electronic single-phase inverter.

It is well known that nowadays the generation and distribution of clean energies from renewable sources (solar, wind, hydro) is spreading all over the world [152]. In the field of power distribution systems, one of the crucial tool is the power inverter stage. Its main function is to change a DC input voltage source to a symmetric AC output voltage supply [153]. Typically, it
is employed as a DC-AC interface between the renewable source supply and the electrical grid, although, it also may be employed as an Uninterruptible Power System (UPS), in induction heating systems, and for variable speed in motor propulsion, among other industrial applications [153], [154].

In order to achieve high performance in the electrical distribution of quality energy, the inverter has to accomplish certain requirements such as a fast dynamic response, robustness to perturbations, none tracking error, low total harmonic distortion [154], [156], and to defeat the voltage unbalance and over-voltage perturbations [157], [158]. To accomplish the above mentioned keys, some steps are necessary to go on. First of all, the grid synchronization is a vital item in electrical grid distribution systems [159]. If the output inverter is not synchronized with the linked grid, large voltage transients may appear and may damage the system [156]. Hence, the goal of the synchronization stage is to generate the reference signal that meets with the grid demands: controlled grid voltage amplitude, phase and frequency [156], [159], [160]. In this regard, the Phase-Locked-Loop (PLL) systems are one of the most popular devices to do the synchronization task, this due to their robustness and accuracy [161]. On the other hand, the control of power flow and quality energy, also are important keys for the energy distribution systems [150]. This means that the power exchange between the distribution system and the grid has to be performed in a controlled manner while the harmonics in the source current and voltage injected, produced by the interfacing between the inverter and the grid, have to be mitigated [158]. The Total Harmonic Distirbution (THD) is a power quality criteria denoting the harmonics content in the distribution system signals and it should be below 5% to guarantee energy quality [156], [162]. Finally, the faults detection in the Distributed Generation (DG) plants has gained lot of attention since the inverter should not be disconnected from the grid every time a short duration fault occurs like voltage sags and dips. However, the DG should be disconnected in case of severe faults to avoid dangerous situations [156]. For this reason, an adequate fault detection system is increasingly important in inverter systems. To fulfill the inverters control objective there are some techniques well established that have proven to be functional options. The main ones are: the Sliding Mode Control (SMC) [155], [163], [165], Proportional-Integer (PI) controllers [161], [166], [167], hysteresis current control [82], [168], [169], Model Predictive Control (MPC) [170], [174], among others.

For this specific implementation case, the Adaptive Predictive control approach is invoked with the novelty of adding an adaptive hysteresis modulation stage. This is, the hysteresis modulation block uses information from
the current state of the process output and from the grid to adapt the hysteresis parameters according to the occurred changes. Hence, with this, it is expected that the closed-loop controlled system will have a better performance. The experiments carried out at a simulation and experimental level do validate the performance of the proposal, as will be later presented.

6.2.1 Single-Phase Inverter Model Simplification

The schematic diagram of a generic single-phase full-bridge inverter connected to a LC filter is shown in Figure 6.22 [154]. A constant DC-bus input voltage, $V_{dc}$, is connected on the left side, the grid voltage, $V_g$, is linked to the four transistors arrangement through a LC filter with an internal resistance $R$. Moreover, $i_s$ is the current through the inverter.

The mathematical model of the single-phase inverter may be approximated to the DC-DC buck converter model due to its similarities with it [135]. Hence, for the control design of the single-phase inverter, here it is resorting to the normalized DC-DC buck converter model. By assuming that the circuit is in continuous conduction mode, the model yields [147]:

$$
\dot{x}_1(t) = -x_2(t) + u(t)
$$
$$
\dot{x}_2(t) = x_1(t) - \frac{x_2(t)}{Q}
$$

(6.9)

where $x_1(t)$ and $x_2(t)$ are the normalized state variables: the normalized inductor current and output voltage, respectively. Additionally, $u(t)$ is the control input, and $Q$ is a value that collects the parameters of the filter [147].

Figure 6.22: Schematic diagram of a controlled single-phase full-bridge inverter [175].
As in the previous cases, it is required the parameterized transfer function. Hence, the system in equation (6.9) is transformed to its representation in Laplace domain, and then, it is parameterized as follows:

\[ G(s) = \frac{a_1}{s^2 + a_2s + a_3} \]  

(6.10)

where \( a_1, a_2, a_3 \) are now the parameters that collect the nominal values of the actual single-phase inverter. These parameters will be later estimated by the Adaptive Mechanism.

The above equation is a mathematical model approximation for a single-phase inverter. This renders the control design simple to conceive. In this regard, the control objective, which is to track the reference current imposed by the grid connected to the inverter and to regulate the voltage supply, is effectively accomplished. Since the transfer function in (6.10) is the same that the one used to design the control scheme applied to the DC-DC buck converter, in this case it is assumed that the control law and the Adaptive Mechanism system will be the same provided in equation (6.5) and in the system (6.7), respectively. Nevertheless, in this case the Driver Block and the Hysteresis Modulator are designed in a different manner as explained next.

### 6.2.2 The Driver Block Conception

As was stated before, the Driver Block is the system that generates the reference trajectory to induce the output process evolve smoothly even when the system is subjected to external perturbations or changes in the operation point [9], [10], [14]. In the fact of the application here addressed, the Driver Block is built in a quite different form as compared to the other cases presented in this thesis. First, it is required the Driver Block generates the reference current to make sure that the total consumed/injected current in the grid meets the signal requirements: a perfect wave sine with specific amplitude and phase, and low distortion. This is typically necessary in distribution grid applications where high power is required [153]. Furthermore, the implementation of this block, for this specific instance, uses information from the output process, but also from the grid connected to the inverter that may change abruptly due to perturbations or user manipulations. In this manner, the performance of the Driver Block helps to accomplish the objective of adjusting the inverter current according to the changes in the grid and in the process output.
In order to produce the signal that fulfills the requirements of the grid and creates the perfect sine wave to be the reference current, it is necessary to extract the phase angle and the amplitude of the voltage grid. To do this, a Phase-Locked-Loop (PLL) system is used to calculate the phase angle. On the other hand, the amplitude is obtained by the calculation of the grid voltage mean value. Once the information requested is completed, the final reference current is calculated with the following formula:

\[ i_r(t) = V_{ga} \sin(w_1)g_1 \]  

(6.11)

where \( V_{ga} \) is the amplitude of the fundamental grid voltage, \( w_1 \) is the angle phase obtained from the PLL. Additionally, \( g_1 \) is the fundamental conductance which directly controls the fundamental active power on the inverter. This value is based on the amount of available power in the input source, and it may be calculated with the output power and voltage. Its sign indicates if the grid will be consuming or supplying power.

According to the Driver Block aim, it is a design principle that the desired output belongs to a desired trajectory that drives the process output with a smooth behavior without abrupt control actions but, at the same time, rapidly and without overshoots. Thereby, it is proposed the following Driver Block equation:

\[ y_d(k + 1) = \alpha_1 y(k - 1) + \alpha_2 y_r(k) + \beta_1 y_d(k) \]  

(6.12)

Note that the reference current \( i_r(t) \) is now the set point \( y_r(k) \), which is directly manipulated in discrete-time by the above Driver Block equation. On the other hand, \( y(k - 1) \) is the past state of the output process, this is, the current \( i_s \). Moreover, \( \alpha_1, \alpha_2 \) and \( \beta_1 \) are selected to avoid overshoots. In order to clarify the implementation of the Driver Block for this specific case, Figure 6.23 is presented.
6.2.3 The Adaptive Hysteresis Modulation System

The motivation from were the idea of the adaptive hysteresis emerged is based on hysteresis current controllers [168]. These typical controllers have been widely employed for inverters due to its simplicity [168]. Basically, a hysteresis controller first compares the reference current to the measured one. This action produces an error signal that is compared with settled upper and lower limit values of the hysteresis controller. Based on that, the switching logic is properly changed. For instance, the canonical behavior of a hysteresis controller with a fixed band is represented in Figure 6.24. Although these controllers are very common, they still have some notable disadvantages, one of the most outstanding is their variable switching frequency that may make harder to filter out the resulting voltage harmonics created by the inverter itself [178], [179]. Also, if the switching frequency is quite high, it may mean significant switching losses. A solution of that issue has been the adaptive hysteresis control, which adapts the hysteresis band to ensure semi-constant switching frequency [178].

In this section a novel hysteresis modulation stage is proposed based on the conventional adaptive hysteresis current controller [168]. This stage is implemented in the control scheme, after the predictive control law. In this manner the closed-loop control performance will be notably improved. To do this, the following dynamic hysteresis equation is evoked one more time in this work:

\[ \dot{z}(t) = \alpha_{hm}[-z(t) + b_{hm}\text{sgn}(x(t) + a_{hm}\text{sgn}(z(t)))] \]  \hspace{1cm} (6.13)

Nevertheless, the equation above is modified to be the adaptive hysteresis system. To do this, the parameter \( b_{hm} \) will be now recalculated in every sampling time. Thus, the conventional derivative adaptive hysteresis equa-
CHAPTER 6. EXPERIMENTAL IMPLEMENTATION CASES

The development to get the equation (6.14) can be seen in [168]. Here, a small modification to the equation (6.14) is done. That is, the first term of the equation is substituted by a constant parameter $\phi_{AC}$, which is a factor selected under the user criterion. Thus, the new variable parameter $b_{hm}$ to obtain the band hysteresis is given by:

$$b_{hm}(t) = \phi_{AC}(1 - m^2(t))$$  \hspace{1cm} (6.16)

On the other hand, in this proposal, the parameter $a_{hm}$ will be the magnitude value of the calculated reference current ($V_{ga}$). As was explained before, this magnitude value is provided by implementing a Phase-Locked-Loop system. Hence, by doing the above, the hysteresis system in (6.13) is now an adaptive system version that depends on the updated values of the input and output process. Moreover, the hysteresis band has its own dynamic since it is recalculated by using the differential of the current reference. Within the Adaptive-Predictive control scheme, the equation (6.13) with the new terms $b_{hm}$ and $a_{hm}$ is implemented to be the hysteresis modulator, where its input, $x(t)$, is the predictive control law ($u(k)$) and its output is now the renewed control law delivered to the plant and the Adaptive Mechanism ($u_{hm}(k)$). In order to clarify the control scheme previously developed, Figure 6.25 depicts the block diagram of the whole control scheme.

6.2.4 Numerical Results

The diagram designed in Simulink and employed to generate the numerical simulations is presented in Figure 6.26. Here it is possible to note that a controlled voltage source and a sine wave generator is used to simulate harmonics in the grid. This scheme is a LC configuration with grid impedance and bipolar modulation. Also, a resistive load with internal inductance is connected to the grid, and a capacitance filter is connected between the grid...
Figure 6.25: Block diagram of the control scheme with adaptive hysteresis modulation applied to a single-phase inverter.

Figure 6.26: Inverter setup in Matlab/Simulink.

and the inverter. On the other hand, the inductor has been split in two parts, however this will not have any effect on the control performance. Additionally, in the DC side, a voltage source is connected. The ‘true’ parameters of the inverter are presented in Table 6.2. Finally, the value of the controller parameters are: $\gamma = 10$, $\lambda_1 = 50$, $\lambda_2 = 100$, $\alpha_{hm} = 20$, $\alpha_1 = 0.1$, $\alpha_2 = 0.85$, $\beta_1 = 0.05$ and $\phi_{AC} = 10$.

For the simulations presented here, the value of $g_1$ is set as negative, so that the inverter behaves as a supplier to the grid. However, it has been seen that this value can be calculated to be varied according to the voltage source [177]. During the simulation, the value of $g_1$ is updated from $-0.2$ to $-0.4$ at 0.25 seconds, which can be seen as a validation of the control design when a perturbation occurs in the grid voltage.
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Table 6.2: Inverter and controller parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC input voltage</td>
<td>200 V</td>
</tr>
<tr>
<td>Switching frequency</td>
<td>20 kHz</td>
</tr>
<tr>
<td>Grid voltage peak</td>
<td>50 V</td>
</tr>
<tr>
<td>Voltage frequency</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Inductor L</td>
<td>0.004 H</td>
</tr>
<tr>
<td>Capacitor Ca2</td>
<td>5(\mu)F</td>
</tr>
<tr>
<td>Load resistor R</td>
<td>0.470(\Omega)</td>
</tr>
</tbody>
</table>

As mentioned before, for the reference current calculation, a Phase-Locked-Loop block is employed. This calculates the magnitude and the angle phase of the voltage grid. With this information, the equation (6.11) is implemented in a Simulink subsystem where the signals are only updated at zero-crossing. Another important remark to do regarding the implementation is that a PWM signal generator was used to give the inverter its switching state. This is a standard PWM signal generator carrier-based with triangular waveform.

The result in Figure 6.27 shows the reference current generated by the implemented Driver Block and the inverter output current. With this result, it is possible to validate that the output accomplishes the objective of tracking the reference current. Additionally, Figure 6.28 depicts the output current and the reference current at the time when the value of \(g_1\) changes. From here is notable that the controller is robust, since, even when the reference current changes due to external perturbation or the user needs, the control objective of tracking the reference current is still accomplished.

Furthermore, Figure 6.29 shows the FFT analysis plot of the output current. Here, it is observed from this graphic that the THD is lower than 5%. Thus the quality of the signal fulfils the minimum requirements. Moreover, it has less harmonic content than the reported in current hysteresis controller and Proportional Integral current control applications [168]. Finally, the voltage supplied to the grid is depicted in Figure 6.30 where it is observable that the objective of regulating the voltage is also well accomplished.

6.2.5 Experimental Results

The experimental results are presented in this subsection. The platform that validates the proposed control technique is the one used for the DC-DC case presented in section 6.1 located at Ghent University in the Electrical Energy
Figure 6.27: (a) Reference current and inverter output current waveforms. (b) Zoom-in version.

Figure 6.28: Inverter output current when the parameter $g_1$ changes.

Figure 6.29: FFT analysis of the output current.
Laboratory. This experimental benchmark is shown in Figure 6.31. The parameters of the system are the previously listed in Table 6.2.

The experimentation stage is carried out by implementing the control proposal and a conventional PI controller. This with the aim of comparing the results between these two control techniques. Besides, the control scheme is applied to the system when it has a load connected to it and when it does not. In this manner, the experimentation validates the control performance of the proposal in different realistic scenarios.

The first results are exposed in Figure 6.33. In this figure it is shown the voltage at the load (Ch1), the current at the load (Ch2), and the output voltage (Ch4). These experiments were obtained with 102 V at the input and a current of 0.25 amperes and 0.5 amperes, respectively. On the other hand, from the scenario where there is no load and the inverter is connected directly to the grid, the results in Figure 6.34 are presented. To do these experiments a grid simulator was used, which is shown in Figure 6.32. The results in Figure 6.34 present the current grid (Ch2) and the voltage at the grid (Ch4) for different values of current input: 0.25 A, 0.5 A, 0.8 A and 1 A, respectively.

In the same way, experiments by using the proposed technique were performed to obtain the following results. First, Figure 6.35 shows the results when the inverter is connected to the load. Secondly, the results when the inverter is connected to the grid are depicted in Figure 6.36. In these last results one may highlight the curly behavior at the current signal caused by the hysteresis system. This is a typical response in controllers based on hysteresis [168], [169]. The experiment stage has proved that both implemented
Figure 6.31: Experimental platform for the single-phase inverter experiments.

Figure 6.32: Three-Phase inverter simulation system.
controllers work as expected. Nevertheless, it is necessary to validate that the signals meet the requirements to supply a realistic grid. Thus, it is presented Table 5.3 where all the measurements from the experiments are summarized. Here, the minus signum at the power column indicates that the inverter is supplying power to the grid. Moreover, the column of the harmonics content at the output voltage indicates that in both cases the signal meets the requirements of the grid, even when at first sight the signals with the hysteresis Adaptive-Predictive control have more oscillations.

Table 6.3: Measurements from the experiments.

<table>
<thead>
<tr>
<th>Input Current (A)</th>
<th>Controller</th>
<th>Power (W)</th>
<th>Voltage THD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>PI</td>
<td>-16.79</td>
<td>2.54%</td>
</tr>
<tr>
<td></td>
<td>A-P Hysteresis</td>
<td>-17.42</td>
<td>1.82%</td>
</tr>
<tr>
<td>0.5</td>
<td>PI</td>
<td>-37.8</td>
<td>0.46%</td>
</tr>
<tr>
<td></td>
<td>A-P Hysteresis</td>
<td>-38.79</td>
<td>1.68%</td>
</tr>
<tr>
<td>0.8</td>
<td>PI</td>
<td>-64.02</td>
<td>1.54%</td>
</tr>
<tr>
<td></td>
<td>A-P Hysteresis</td>
<td>-64.51</td>
<td>1.84%</td>
</tr>
<tr>
<td>1</td>
<td>PI</td>
<td>-82.42</td>
<td>1.74%</td>
</tr>
<tr>
<td></td>
<td>A-P Hysteresis</td>
<td>-82.36</td>
<td>2.45%</td>
</tr>
</tbody>
</table>
6.2.6 Conclusions from the Experiments

In this section it was resorted to a single-phase inverter to apply the Adaptive-Predictive Hysteresis control proposed in this thesis. However, this case has the particularity that the Hysteresis Modulation stage is composed by an adaptive hysteresis system. Hence, the hysteresis depends on the actual state of the system, making this an adequate and successful strategy to accomplish the control objective. Moreover, it is notable that in this case, the modulation stage does not contain the integrator path since, due to the adaptive hysteresis performance, the output of the modulation stage is a kind of train of pulses signal that is subsequently manipulated by the PWM signal generation. Finally, it is worth mention that it is well-known that the conventional PI controller does not guarantee null error for a sinusoidal input. Hence,
Figure 6.35: Results with the A-P Hysteresis controller and a load connected to the inverter: Voltage at the load (Ch1), current at the load (Ch2), and grid voltage (Ch4). (a) With input current 0.25 A. (b) With input current 0.5 A.

It is considered for future work to make a comparison study by employing P-resonant or PI resonant controllers. Also, as a possible future work it is considered that the control could be more explored considering a capacitor in the input voltage with a PV array, in which the injected power is related to the extraction of the maximum power in the PV array.

6.3 Final Chapter Remarks

The content of this Chapter is of utmost importance for the present thesis because it was tested and validated the proposal of a novel control technique. This is, the Adaptive-Predictive control with the hysteresis modulation stage. Two systems were invoked to assess the control technique, which are present in the current state-of-the-art in control applications. These cases were the control applied to the DC-DC buck converter and to the single-phase inverter, respectively. In both cases, the control strategy proved to work as expected by adequately accomplishing the control objectives in the experimental platform. Furthermore, for the instance of the single-phase inverter, an adaptive hysteresis was stated with the aim of auto-tune the parameters of the hysteresis block that modulates the control signal.
Figure 6.36: Results with the A-P Hysteresis controller and the inverter connected to the grid: output current (Ch2), and grid voltage (Ch4). (a) With input current 0.25 A. (b) With input current 0.5 A. (c) With input current 0.8 A. (d) With input current 1 A.
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Chapter 7
Conclusions

7.1 Discussion of Results

Although the specific results were remarked at the end of each chapter, this section presents an overall discussion of the most remarkable results obtained in this thesis.

Initially, the results from the proposed Maximum Power Point Tracking algorithm presented in Chapter 3 are discussed. In this respect there are many keys that stand out. First, the experiment demonstrated that the invoked hysteresis model is appropriate and practicable, thus fulfilling the main objective of this proposal. However, in a more experimental sense regarding to the renewable energy application, the comments are varied and significant. The designed benchmark platform is witty since the DC conversion stage is implemented with a DC-motor linked to a variable resistance. With this, the load seen by the PV panel is adjusted according to the control action on the DC-motor. This control action is obviously generated by the Maximum Power Point Tracking (MPPT) algorithm, which in this case is the proposed hysteresis algorithm. Here the aim was to build a cheap and simple experimental test platform that may be useful not just for the hysteresis algorithm but for other MPPT algorithms in the state-of-the-art, as long as they meet with the system requirements. In Appendix A, the electronic diagrams and code programs are presented as a guide for who is interested in recreating this experiment. On the other hand, and talking about the results, it is important to recall that the blinking phenomenon appearing at the output voltage is due to the half-wave rectifier implemented to change the light intensity levels. In this regard, it is considered that the platform gives an extra challenge to the algorithm, since this is a perturbation that can be interpreted, for instance, as a fast shading condition. Moreover, from
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the results it is notorious that the conventional and well-known Perturb &
Observer algorithm works well as expected, however it presents more over-
shoot at the voltage and current signals than the case with the proposed
hysteresis algorithm, and more important, the power is nearest its maximum
point when the hysteresis algorithm is used.

Concerning Chapter 4, it was demonstrated with a numerical experiment
that the Hysteresis Delta Modulator (HDM) block provides a signal with
enough harmonic content to improve the parameter estimation of a non-
minimum phase system. For this experiment the three hysteresis systems
presented in Chapter 3 were invoked. It was verified that the case when
the proposed hysteresis model is used gives the best estimation of the pa-
rameters. Nevertheless, it is important to highlight that the values of the
hysteresis parameters were selected by trial and error and were the same for
each hysteresis model. Hence, it is valid to consider that the three hysteresis
models may be adequate as long as the parameters are appropriately tuned
for each specific case. It was seen throughout the thesis that, for the im-
plementation cases, just the hysteresis model presented in equation (3.2) is
used for experimentation. This is because this may be seen as an interme-
date model between the simple relay one and the proposed one. With this, it
is assumed that the implementation will be very similar for the three cases
since all of them have the same basis of modelling.

Once the control proposal was stated in Chapter 4, then the validation cases
were implemented at a numerical level, which are exposed in Chapter 5. The
engineering systems were the Van der Pol oscillator and a base-isolated sys-
tem. First, the Van de Pol oscillator was interesting because it was possible
to show the sensitivity of the system to become unstable. In this specific case,
it was observed that the closed-loop system has a bursting response, hence
a parameter drift performance, when a small time-delay is added at the out-
put process. It was proved that the Adaptive-Predictive control without the
hysteresis modulation works adequately when the time-delay is not present,
but when the delay is added at the output process the control performance
is deteriorated. The solution to this issue was to insert the proposed HDM
block within the control structure. Thereby, the parameter drift was elimi-
nated and the control objective was achieved. This implementation may be
considered simple but it was useful to prove that the proposed control works
as expected. Moreover, the Van der Pol oscillator is a nonlinear system that
through the years has been invoked to validate different control techniques
due to its peculiar characteristics.
Secondly, the base-isolated system is also called on in Chapter 5. This is a significant engineering system due to its nonlinear characteristic that is mainly represented by a hysteresis model. However, by invokig the control approach, the task of controlling this kind of system is more simple to carry out. Another important key of this experiment is that it was demonstrated that the HDM block may be inserted in a different stage of the control scheme as long as it provides the persistent excitation condition to the whole closed-loop system. This allows to conclude that the hysteresis modulator is easily handled according to the system requirements. On the other hand, this case was useful to validate the proposal of the Driver Block with hysteresis. Additionally, with the idea of proposing a complete control scheme, it was suggested an statistical fault detection algorithm, which demonstrated to work as expected. In these experiments different earthquakes were used to validate the control scheme. From here, it is possible to observe that when the fault comes in, the response in open-loop presents an upset from the rest position which is amended in the closed-loop version. Hence, the control proposal is robust to faults.

Regarding the experimental implementations of the controller, these cases were presented in Chapter 6. First of all, it is important to remark that since the experiment with the suggested MPPT algorithm was carried out, it raised the idea that one remarkable application for the Adaptive-Predictive Hysteresis controller is in the field of power electronics. This is because the hysteresis response is a kind of train of pulses, which is very common in the way that the switch devices are controlled in this field. Therefore, a DC-DC buck converter was invoked as a test case, as well as a single-phase inverter. Talking about the DC-DC buck converter, the results are wide. First, it was observable that the control objective of regulating the output voltage is successfully accomplished in fast time and with no overshoot. Furthermore, in the output response the curly behavior is also presented, however it may be easily filtered when the application requires. Additionally, for this case was possible to validate the control technique in a real platform and compare the results obtained with a conventional PI controller. The comparison study shows that the control proposal may be as viable as any other technique.

On the other hand, with the single-phase inverter case, similar conclusions can be drawn. First, it was numerically and experimentally validated that the control approach was achieved. In this case it was also proposed an Adaptive-Hysteresis modulator. This idea arose from the observed necessity in the previous cases of adequately tuning the parameters of hysteresis according to the system. Hence, it was necessary to suggest an automated way
CHAPTER 7. CONCLUSIONS

of adjust these parameters. In the example of the single-phase inverter, it was proved that the Adaptive-Hysteresis can do this task. From these results it is conclusive that the proposed control strategy has a good performance in accomplishing the control objective of tracking the reference current. The experiments were carried out in the same platform that the DC-DC buck converter.

7.2 Future Research

As a near future work, first it is expected to experimentally implement the Adaptive-Predictive Hysteresis with the Adaptive Mechanism. This because, as it was seen in the two experimental cases, the DC-DC converter and the single-phase inverter, the stage of parameter estimation was not programmed. Instead of it, constant values for the parameters were selected and programmed. This showed to be functional. However, if the Adaptive Mechanism is implemented, this may give extra information of the process state. Another important area of improvement is related to the selection of the parameters of the hysteresis system used within the modulation block. This means auto-tune the parameters according to the application. A first approximation of this idea was presented in Section 6.2. Nevertheless, this approach was first thought for this specific application. Hence, as a future work, it is planned to prove if the proposed adaptive hysteresis will work for any kind of application or if it will be necessary to make some modifications to obtain a general Adaptive Hysteresis Modulation that tune its parameters itself. Additionally, another important future work is to make improvements regarding the hysteresis within the Driver Block and to implement this approach in a real engineering system. This with the aim to validate the feasibility of the algorithm to fit in any digital microprocessor.

7.3 Summary and General Conclusions

This thesis has been motivated by the interest in developing a control strategy that takes advantage of the Predictive Control attributes and may manage systems that are more complex every day. These systems are typically represented by a nonlinear mathematical model that is too complex to fit in some of the control strategies currently existing. Hence, it is required that the control algorithms are more simple to understand and implement. Therefore, the main contribution of this thesis is to propose a control design based
on the nowadays popular Predictive Control strategy by adding hysteresis. With this, the present thesis addressed different cases of study to validate the performance of the proposal.

From the initial idea of proposing a novel control technique that uses hysteresis, to obtaining the results exposed here, the methodology was carried out as follows. First, three hysteresis mathematical model were presented. Then, it was verified the performance of a hysteresis mathematical model when implemented in an experimental application. Since the three hysteresis models presented in Section 3.2 have the same modelling basis, this implementation allowed to entail that the three models may be feasible. For this task, an experimental platform was designed from scratch. This benchmark was conceived within the renewable energies field. As seen in Chapter 3, this platform allows to verify that indeed the hysteresis mathematical model is feasible, since the programming stage was easily achieved. Moreover, the model could be adequately altered to fit with the implementation system requirements. The experiment proposed an algorithm to extract the maximum power point from a photovoltaic panel. The algorithm was proposed directly as an hysteresis model that uses the information from the PV panel, voltage and current. With this, the objective was accomplished, since it was able to handle the hysteresis model to fit with the power requirements. Moreover, the algorithm was programmed in an Arduino board, which is a very simple and accessible technology. The results from this experiment were satisfactory, not only because the hysteresis model was shown to be feasible, but also because the proposed algorithm worked correctly at an experimental level by using a real photovoltaic panel.

Afterwards, the aim of this work was to adequately insert the hysteresis system within a Predictive Control scheme. This was done by resorting to the theoretical knowledge of the Predictive Control mathematical foundation. For instance, it was analysed that within an Adaptive-Predictive scheme, the persistent excitation condition is required to guarantee the convergence of the parameters. With this idea and with the knowledge of the hysteresis response, the conception of designing a modulator signal with hysteresis that provides the needed condition raised, as it was presented in Chapter 4.

On the other hand, possibly the most relevant share of this thesis was to validate the proposal by invoking typical engineering systems. The idea was to test if the approach is adequate to accomplish certain control objectives. Moreover, it was expected to check if, in addition to meeting the control objectives, the proposals help to solve recurring problems in the control area.
such as bursting or parameter drift. Additionally, it is well known that, within the Predictive Control, the model reference is important since it allows to smoothly drive the output system to a desired set-point or to track the desired performance. In this thesis it is presented the use of hysteresis as the model reference within the Driver Block since it may provide the smooth response without overshoots through the well selection of its parameters. As presented in Chapters 5 and 6, the applications go from the conventional and well-known Van der Pol Oscillator to more complex systems as a base-isolated, a DC-DC buck converter and a single-phase inverter.

Summarizing the conclusion from the numerical and experimentation cases, the following points stand out:

- In all cases the control objective is successfully achieved, and in most of them, the performance stands out over other techniques in the state-of-the-art.

- The control approach is easily implemented and understandable. Furthermore, the proposal is feasible even for nonlinear systems, since the design is based on a linear approximation.

- It is proven that the hysteresis model is easily implemented in a cheap and accessible technology as it is the Arduino electronic board. With this it is concluded that not much resource is required to implement the proposal. Even it may be cheaper than other techniques that need powerful computer processors to do its work.

- The selected application cases were intentionally subjected to typical issues commonly presented in engineering applications. From this, it could be proven that the approach successfully works under the circumstances such as delay, parameter drift and bursting.

Finally, to conclude this section, the following points highlight the main tangible contributions of this thesis:

- A new control strategy based on Predictive Control that uses hysteresis to improve the control performance.
• Practical implementation cases that can be easily followed to be a guide for other applications.

• A complete theoretical, numerical and experimental document that can be a useful guidebook for those interested in Predictive Control and its applications.
Appendix A
Experiment Implementation of the PV-MPPT Algorithms

This Appendix details the experiment with the PV panel and the proposed MPPT algorithm in section 3.3.1. Firstly, it is explained each stage of the general designed platform where the experiment was carried out. This platform is the one shown in section 3.3.1 in Fig. 3.8. Here, the platform is summoned one more time in Fig. A.1 for the purposes of this appendix. Then, the technical specifications needed to implement the MPPT algorithms are explained in the next points by following the objective of each stage [88]:

![Figure A.1: Overview scheme of the experimental platform.](image)

- **Stage A:** This stage consists on the *irradiation control* that allows to have two different levels of light in the lamp. The designed electronic circuit to do this task is depicted in Fig. A.2. Here, it is employed an Arduino UNO, labeled as *Board 1*. In this stage, a *repetitive blinking*...
APPENDIX A. EXPERIMENT IMPLEMENTATION OF THE PV-MPPT ALGORITHMS

Figure A.2: Electronic circuit to automatically control the bulb time-varying intensity \([88]\) is induced as a consequence of the implemented half-wave rectifier. Due to PV panels are too sensitive to this kind of light perturbation, the experiment platform is able to emulate, for instance, a fast shading light condition \([89], [94]\). Note that this stage is independently designed from the other stages that integrate the PV-MPPT system.

- **Stage 1:** This stage consists of the electronic implementation shown in Fig. A.3 which instruments the PV voltage and PV current signals to be readable by a second Arduino UNO (Board 2). This is because the Arduino board reads voltages in the range of 0–5 V and the employed PV panel can produce up to 17 V. Hence, it is necessary a stage for the signals coupling.

- **Stage 2:** This stage is captured in the Board 2 where the MPPT algorithms are coded. The programmed codes for experimental implementation are presented in the sub appendix A.1. Both algorithms,
Figure A.3: Electronic circuit for PV outputs’ data processing and control signal instrumentation [88]
the P&O method and the hysteresis approach, generate a reference command signal (named here $X := X(t)$), which assists with accomplishing the maximum power point tracking. Moreover, in this stage also is coded the control algorithm for the DC-motor as was explained in section 3.3.1.

- **Stage 3:** This phase consists of an electronic instrumentation to correctly drive the DC motor. The PWM control signal generated in Stage 2 ($u_{PWM}$) is an uni-polar one since Arduino outputs are limited to positive voltage values. Nevertheless, the DC motor must be able to turn in both senses to increase or decrease the potentiometer resistance linked mechanically to it. For this reason, this stage converts the uni-polar signal to a bipolar one without losing the original control signal information.

The final developed platform is shown in Fig. A.4. Clearly, this experimental benchmark has notable advantages with respect to other experimental realizations [86], [88], [90], [96], such as:

1. It uses low cost electronic components.
2. The hardware deployment requires a small area.
3. It is easy to build.
4. It uses an open-source software.

The components that constitute the benchmark platform are listed following:

2. An Arduino Uno board (labeled here as *Board 1*) to automatically control the intensity light of the bulb.
3. A lamp with a 100 W bulb to emulate the irradiation variation and shading conditions.
4. A 22 Ω shunt resistance used to instrument the supplied PV current to the load.
5. A motorized-potentiometer constituted by a DC motor mechanically linked to a 5 kΩ potentiometer. This potentiometer emulates the load seen by the PV panel.

6. A second Arduino Uno board (labeled here as Board 2) where the MPPT control algorithm is implemented.

7. An electronic instrumentation development to couple the inputs and output signals to/from Board 2.

Finally, here also are presented the tables that contains the measurements values used to obtain the characterization of the employed PV panel. These characteristic curves were previously presented in section 3.3.1.
**APPENDIX A. EXPERIMENT IMPLEMENTATION OF THE PV-MPPT ALGORITHMS**

Table A.1: Measured values for the high irradiation level on the PV panel.

<table>
<thead>
<tr>
<th>External Load (Ω)</th>
<th>PV Voltage (V)</th>
<th>PV Current (mA)</th>
<th>PV Power (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.03</td>
<td>0.0092</td>
<td>0.0095</td>
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<tr>
<td>220</td>
<td>2.14</td>
<td>0.0094</td>
<td>0.0201</td>
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<td>0.0094</td>
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<tr>
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<td>0.0083</td>
<td>0.0877</td>
</tr>
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<td>10.41</td>
<td>0.0083</td>
<td>0.0867</td>
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<tr>
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<td>10.8</td>
<td>0.0082</td>
<td>0.0891</td>
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<tr>
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<td>12.17</td>
<td>0.0078</td>
<td>0.0955</td>
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<td>2330</td>
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<td>0.0976</td>
</tr>
<tr>
<td>2560</td>
<td>15.45</td>
<td>0.0060</td>
<td>0.0938</td>
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<tr>
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<td>0.0053</td>
<td>0.0843</td>
</tr>
<tr>
<td>3270</td>
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<td>0.0049</td>
<td>0.0794</td>
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<tr>
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<td>16.03</td>
<td>0.0048</td>
<td>0.0781</td>
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<tr>
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</tr>
<tr>
<td>4700</td>
<td>16.47</td>
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<td>0.0590</td>
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</table>
Table A.2: Measured values for the low irradiation level on the PV panel.

<table>
<thead>
<tr>
<th>External Load (Ω)</th>
<th>PV Voltage (V)</th>
<th>PV Current (mA)</th>
<th>PV Power (W)</th>
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</thead>
<tbody>
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<tr>
<td>270</td>
<td>1.63</td>
<td>0.0069</td>
<td>0.0114</td>
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<tr>
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<td>2.33</td>
<td>0.0069</td>
<td>0.0232</td>
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<td>560</td>
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<tr>
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<td>10.64</td>
<td>0.0053</td>
<td>0.0570</td>
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<td>0.0589</td>
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<tr>
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<td>11.5</td>
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<td>0.0589</td>
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<td>12.45</td>
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<td>4700</td>
<td>15.30</td>
<td>0.0033</td>
<td>0.0511</td>
</tr>
</tbody>
</table>
APPENDIX A. EXPERIMENT IMPLEMENTATION OF THE PV-MPPT ALGORITHMS

A.1 Program Codes

A.1.1 Arduino Program to Implement the Perturb and Observer Algorithm

```
#include <PWM.h>

// Variables to process power data.
float potA=0, pot, deltaPot, deltaPotN;
// Control variable.
float uPWM=0;
// Reference command signal generated by the P&O algorithm.
float X;
// Variables to process voltage data.
float Vref, VrefA=0, deltaVref;
// Variables to read PV voltage and PV current values.
float voltage, current;
// Variables to process the read values.
float voltageValue, corrienteValue;

void setup() {
    pinMode(0,INPUT); // Pin to read voltage.
    pinMode(2,INPUT); // Pin to read current.
    pinMode(9, OUTPUT); // Pin to write output control.

    // Timer initialization.
    InitTimersSafe();
    // Instruction to set the PWM frequency at 40 KHz.
    bool success=SetPinFrequencySafe(9, 40000);
}

void loop() {
    // Read the voltage and scale it into the Arduino range (0–1023).
    voltageValue=analogRead(0);
```
voltage=voltageValue*(5.0/1023.0);
//Calculate the real PV voltage according to 
//external electronic instrumentation.
voltage=voltage/0.468;

//Read the current and scale it into the Arduino range (0−1023).
correnteValue=analogRead(2);
current=correnteValue*(5.0/1023.0);
//Calculate the real PV current according to external 
//electronic instrumentation.
current=current/36.96;

pot=voltage*current;          //Calculate PV power.
deltaPot=pot−potA;            //Calculate power difference.

//Calculate sign of power difference.
if (deltaPot > 0){deltaPotN=1;}
else {deltaPotN=−1;}

deltaVref=voltage−VrefA;      //Calculate voltage difference.
//P&O algorithm to obtain the reference command signal.
X=deltaVref*deltaPotN;

uPWM=20*(voltage−10+X)+127;  //Calculate the final control signal.

analogWrite(9,round(uPWM));   //Writes the final control 
//signal at Pin 9.

//Update power and voltage.
potA=pot;
VrefA=voltage;
}

A.1.2 Arduino Program to Implement Our Hysteresis MPPT 
Algorithm

//Arduino library included to operate the PWM output frequency.
#include <PWM.h>
APPENDIX A. EXPERIMENT IMPLEMENTATION OF THE PV-MPPT ALGORITHMS

// Variables to process power data.
float potA=0, pot, deltaPot, deltaPotN;
// Control variable.
float uPWM=0;
// Variables to process voltage data.
double deltaVolt, voltA;
// Variables to read PV voltage and PV current values.
int voltage, current;
// Hysteresis algorithm variables.
double sgnPot, sgnz, z, xaf, xd;
// Reference command signal generated by the hysteresis algorithm.
float X=0.1;
// Variables to process the read values.
float voltageValue, corrienteValue;
// Hysteresis algorithm constants.
double timeChange=0.1, a=1, b=1, alpha=10;

void setup() {
    pinMode(0,INPUT); // Pin to read voltage.
    pinMode(2,INPUT); // Pin to read current.
    pinMode(9, OUTPUT); // Pin to write output control.

    // Timer initialization.
    InitTimersSafe();
    // Instruction to set the output frequency at 40 KHz.
    bool success=SetPinFrequencySafe(9, 40000);
}

void loop() {

    // Read the voltage and scale it into the Arduino range (0–1023).
    voltageValue=analogRead(0);
    voltage=voltageValue*(5.0/1023.0);
    // Calculate the real PV voltage according to external electronic instrumentation.
    voltage=voltage/0.468;

    // Read the current and scale it
corrienteValue=analogRead(2);
current=corrienteValue*(5.0/1023.0);
//Calculate the real PV current according to
//external electronic instrumentation.
current=current/36.96;

pot=voltage*current; //Calculate PV power.
deltaPot=pot-potA; //Calculate power difference.
deltaVolt=voltage-voltA; //Calculate voltage difference.

//Calculate sign of power difference.
if (deltaPot > 0){sgnPot= 1;}
else {sgnPot= −1;}
//Hysteresis MPPT algorithm.
z=deltaVolt*a*sgnPot;

if (z > 0){sgnz= 1;}
else {sgnz= −1;}

//Hysteresis dynamic equation to generate the reference
//command signal.
xd=X+timeChange*(alpha*(-X+b*sgnz));

//Calculate control signal.
uPWM=20*(voltage−(10+X))+127;

//Write the final control signal at Pin 9.
analogWrite(9,round(uPWM));

//Update variables.
potA=pot;
voltA=voltage;
X=xd;
APPENDIX A. EXPERIMENT IMPLEMENTATION
OF THE PV-MPPT ALGORITHMS


BIBLIOGRAPHY


Hysteresis Predictive Control Design with Applications


