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Thème :

Simulation and implementation of Model Predictive Current Control and Artificial neural network based on MPCC of a Three-Phase, Two Level, Inverter-Fed RL-Load

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ملخص:

إن الهدف الرئيسي من هذا الموضوع يتلخص في دراسة وتنفيذ التحكم التنبؤي استنادا على النموذج (MPC) ثم على الشبكات العصبونية الاصطناعية المطبقة على المحركات الكهربائية ومحولات الطاقة الكهربائية بغرض تحسين أداء أنظمتنا. نبدأ دراستنا بنبذة حول المحولات المصفوفية والتحكم التنبؤي من خلال تقديم بعض الطوبولوجيات من MC ، منظور حول الذكاء الاصطناعي وخاصة الشبكات العصبية, بعض تطبيقات التحكم التنبؤي وتحسيناته وأخيرا لمحة على الشبكات العصبونية الاصطناعية. تم تطبيق التحكم التنبؤي المستند على النموذج MPCC ثم على الشبكات العصبونية الاصطناعية على شحنة RL التي يؤذيها مموج في البداية.

كلمات مفتاحية:

مموج مصفوفي (MC)، آلة لا تزامنية، التحكم التنبؤي (MPC)، دالة التكلفة ، الشبكات العصبونية الاصطناعية

Résumé :

L'objectif principal de ce sujet est d'étudier et implémenter la commande prédictive à base du model (MPC) puis à base des réseaux de neurones appliqué aux convertisseurs de puissance pour améliorer les performances de nos systèmes. Nous commençons notre étude par un état de l'art sur les convertisseurs matriciels, l'intelligence artificielle et la commande prédictive. Ensuite, la commande prédictive du courant à base du modèle (MPCC) puis à base des réseaux de neurones artificiels a été appliquée à une charge RL alimentée par un onduleur Une comparaison entre les deux commandes proposées a été établie.

Mots clés :

Convertisseur Matriciel, la commande prédictive à base du modèle, fonction de coût.

Abstract:

The main objective of this topic is to study and implement predictive control based (MPC) model, neural networks applied to electrical drive and power converters, in order to improve performances of our system. We begin our study with a state of the art on matrix converters and predictive control. Then, the model predictive current control (MPCC) and artificial neural networks based MPCC (ANN-MPCC) were applied to an RL charge fed by a two-level inverter. A comparison between the two proposed strategies was introduced for each test.

Key words:

Matrix Converter (MC), Model Predictive Control (MPC), cost function

Acknowledgment

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Dedication

First of all, I would like to thank all the persons who never stopped to support me, to believe in me, to watch over my success from a very young age, to whom I owe what I became today, and what I will become in the future, my family.

I dedicate this work
To my brother OMAR who was always there for me, whom I hope to be proud of me.

To my grandmother, May Allah prolongs her life and grants her health.
To my uncle AMINE, my confident, the person who always takes care of me, my God bless him.

To my confident friends SAMIA and HANANE.
To my childhood friend SAMY.
To my best friend Amel who never stopped believing in me and for her precious help as partner.
To My friends Yahia and Juba.

SAMY

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List of symbols and acronyms

MC : Matrix Converter

IMC : Indirect Matrix Converter

DMC : Direct Matrix Converter

SMC : Sparse Matrix Converter

MIMC : Multilevel Indirect Matrix Converter

2LVSI : Two-Level Voltage Source Inverter

MPC : Model Predictive Control

MHPC : Model Heuristic Predictive Control

DMC : Dynamic Matrix Control

GPC : Generalized Predictive Control

P-DPC : Predictive Direct Power Control

MPCC : Model Predictive Current Control

MPTC : Model Predictive Torque Control

ANN : Artificial neural network

ANN-MPC : Artificial neural network based model predictive control

ANN-MPCC: Artificial neural network based model predictive current control

ANN-MPTC: Artificial neural network based model predictive torque control

FNN : Feed forward back-propagation neural network

PNN : Perceptron neural network

FITNET : Fitting application neural network

NFTOOL : Network-fitting tool

NNTOOL : Neural network tool

T_s : Sampling period

FCS-MPC : Finite Control Set-Model Predictive Control

FACTS : Flexible AC Transmission Systems

StatComps : Static synchronous compensators

APF : Active Power Filter

THD	: Total Harmonic Distortion
V_{DC}	: DC source voltage
M	: Neutral point of the inverter
N	: Neutral point of the load
PMSG	: Permanent Magnet Synchronous Generator
φ_r	: Rotor flux
φ_s	: Stator flux
i_s	: Stator current
i_r	: Rotor current
v_s	: Stator Voltage
v_r	: Rotor voltage
L_m	: Magnetizing inductance
L_s	: Stator inductance
R_s	: Stator resistance
L_r	: Rotor inductance
R_r	: Rotor resistance
M_s	: Mutual inductance between two stator windings
M_r	: Mutual inductance between two rotor windings
M_{sr}	: Magnitude of the inductance between the stator and the rotor
Ω	: Mechanical speed
J	: Moment of inertia of the mechanical shaft
T_{em}	: Electromagnetic torque
T_L	: load torque
k_f	: Dry friction coefficient
ω	: Rotor angular speed
p	: Number of pole pairs
ξ	: damping coefficient
ω_n	: Natural circular pulse
Q	: Reactive Power

$\boldsymbol{R_f}$: Filter resistance

$\boldsymbol{L_f}$: Filter inductance

$\boldsymbol{C_f}$: Filter capacitance

$\boldsymbol{\alpha}$: Temperature coefficient

$\boldsymbol{T}$: Temperature

$\boldsymbol{\lambda}$: weighting factor

General introduction

General introduction

The use of power converters has become very popular in the recent decade with a wide range of applications, including drives, energy conversion, traction, and distributed generation. The control of power converters has been extensively studied, and new control schemes are presented every year, power electronics circuits have proved indispensable in many areas because they convert electrical power from one form to another, such as ac-dc, dc-dc, dc-ac, or even ac-ac with a variable output magnitude and frequency [1].

Many control strategies for power electronics have been proposed that have been shown to be reasonably effective. Mainly, these are strategies based on linear controllers combined with nonlinear techniques, such as pulse width modulation (PWM). However, controllers of this type are usually tuned to achieve optimal performance only over a narrow operating range; outside this range the performance is significantly deteriorated. Therefore, the problems associated with many applications and their closed-loop controlled performance still poses theoretical and practical challenges. Furthermore, the advent of new applications leads to the need for new control approaches that will meet the increasingly demanding performance requirements.

A control algorithm that has been recently gaining more popularity in the field of power electronics is model predictive control (MPC) [2, 3]. This control method, which has been successfully used in the process industry since the 1970s, has attracted the interest and attention of research and academic communities due to its numerous advantageous features, such as design simplicity, explicit inclusion of design criteria and restrictions, fast dynamics and inherent robustness. In addition, the emergence of fast microprocessors has increasingly enabled successful implementation [7, 6, 5, 4].

Recently, several studies have suggested the application of the technique of artificial intelligence like neural networks, fuzzy logic and genetic algorithms to replace hysteresis controller and switches statement of the inverter[12][6]. The artificial neural networks (ANNs) are capable of learning the desired mapping between the inputs and outputs signals of the system without knowing the exact mathematical model of the system. The ANNs are excellent estimators in nonlinear systems [11]

Artificial neural networks are introduced also to replace the model predictive control. The ANN are used for their properties of learning capability and generalization to improve the control performance of the system and to overcome the disadvantages of the MPC.

This thesis is organized into four chapters; they are summarized as follows:

The first chapter is dedicated to an overview of the matrix converters by citing the different topologies proposed in the literature then, the principal drawback of the model predictive torque control (MPTC) then a global perspective about artificial intelligence in power electronics. The chapter is concluded with an overview of artificial neural network.

The second chapter is devoted to the analysis and the simulation of predictive current control applied to a two-level three-phase inverter feeding an RL-load with evaluation of performance's purposed strategy.

The Third chapter is devoted to the analysis and the simulation of neural network based predictive current control applied to a two-level three-phase inverter feeding an RL-load with evaluation of performance's purposed strategy. A comparison between the two strategies is established.

The last chapter of this thesis is dedicated to the real implementation of both MPCC and neural networks based predictive current control strategies in a CDER laboratory in order to verify the theorical and simulations results. This final chapter is also concluded with a comparison between the two strategies.

The general conclusion concerns a brief synthesis of the work carried out with the main obtained results and some perspectives.

Chapter one

State of the art: model predictive control based on neural network

CHAPTER ONE

Introduction

Model predictive control (MPC) has become one of the well-established modern control methods for converter topologies, where a high-quality voltage with low total harmonic distortion (THD) is needed. Although it is an intuitive controller, easy to understand and implement, it has the significant disadvantage of requiring a large number of online calculations for solving the optimization problem. On the other hand, the application of model-free approaches such as those based on artificial neural networks approaches is currently growing rapidly in the area of power electronics and drives. Broadly speaking, the use of neural networks for the control of dynamical systems was proposed in the early nineties[13].

This chapter is divided into two main parts, the first is devoted to the state of the art of the converter, and the second part is devoted to the state of the art of the Model Predictive Control (MPC) based on neural network. Where some converter topologies, some applications of the control strategy were presented, and an overview of the neural network as an enhancement of MPC.

I.1 State of the art of the matrix converter

I.1.1 Introduction

In recent years, the application of variable speed drives in industrial and commercial facilities has been increased greatly. Hence, the need of AC-AC conversion that converts three-phase input to the three-phase load, becomes essential in order to get variable frequency amplitude and phase for several applications. The AC to AC converters receive power from the input source and distribute it to the three-phase output with desired voltage and frequency. To improve the characteristics efficiency and the consistency of the systems, various power converter circuits are presented nowadays.[1]

Matrix converter (MC) is an all-switch power converter with interesting properties such as controllable input power factor, bidirectional power flow, and high-quality input and output currents. Moreover, because of the absence of the bulky DC link energy storage components, it benefits from the possibility of a compact design. There are two main types of the MC, namely, direct matrix converter (DMC) and indirect converter (IMC). The appliance of those converters are extensive: motor drive, FACTS devices, distributed generations systems, and wind energy conversion systems.[2]

I.1.2 Matrix Converter Topologies

The matrix converter consists of 9 bi-directional switches that allow any output phase to be connected to any phase. The circuit scheme is shown in Figure I.1:

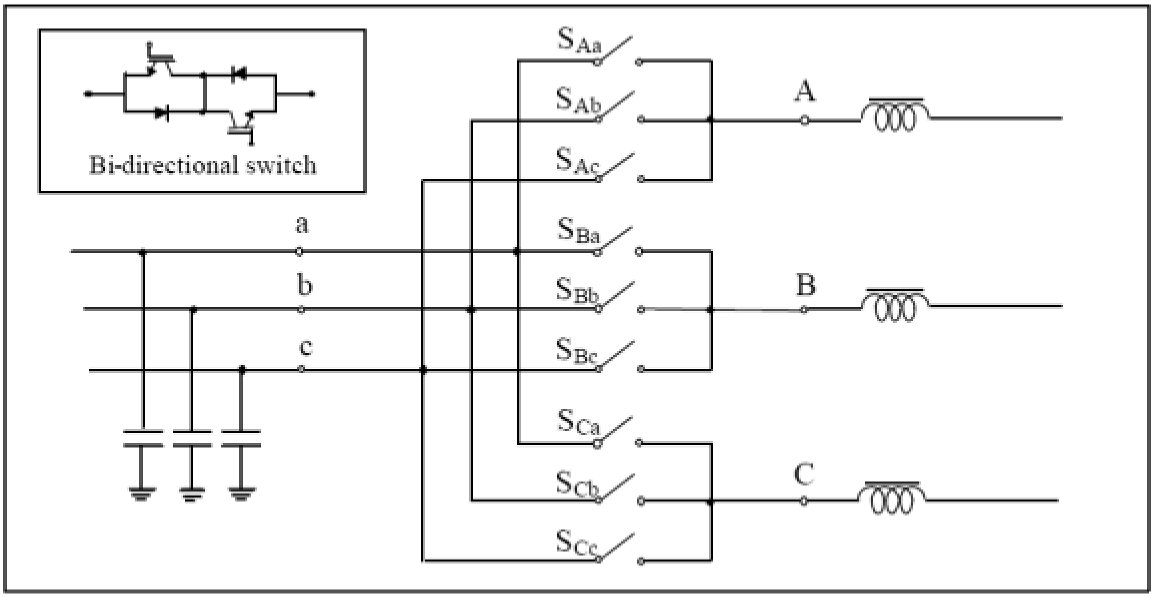


Figure I- 1 : Circuit scheme of a three phase to three phase matrix converter. a,b,c are the input terminals. A,B,C are the output terminals.

The input terminals of the converter are connected to a three-phase voltage-fed system, usually the grid, while the output terminal is connected to a three-phase current-fed system, like an induction motor might be.

The capacitive filter on the voltage-fed side and the inductive filter on the current-fed side represented in the scheme of Figure I.1 are intrinsically necessary. Their size is inversely proportional to the matrix converter switching frequency.

With nine bi-directional switches, the matrix converter can theoretically assume 512 (2^9) different switching states combinations. But not all of them can be usefully employed.

Regardless to the control method used, the choice of the matrix converter switching states combinations to be used must comply with two basic rules. Taking into account that the converter is supplied by a voltage source and usually feeds an inductive load, the input phase should never be short-circuited and the output currents should not be interrupted. From a practical point of view, these rules imply that one and only one bidirectional switch per output phase must be switched on at any instant. By this constraint, in a three phase to three phase matrix converter, there are 27 permitted switching combinations.

I.1.3 Matrix Converter classification

There are to main types for the MC, direct matrix converter (DMC) and indirect matrix converter (IMC). The appliance of those converters are extensive: motor drive, FACTS devices, distributed generation systems, and wind energy conversion systems.

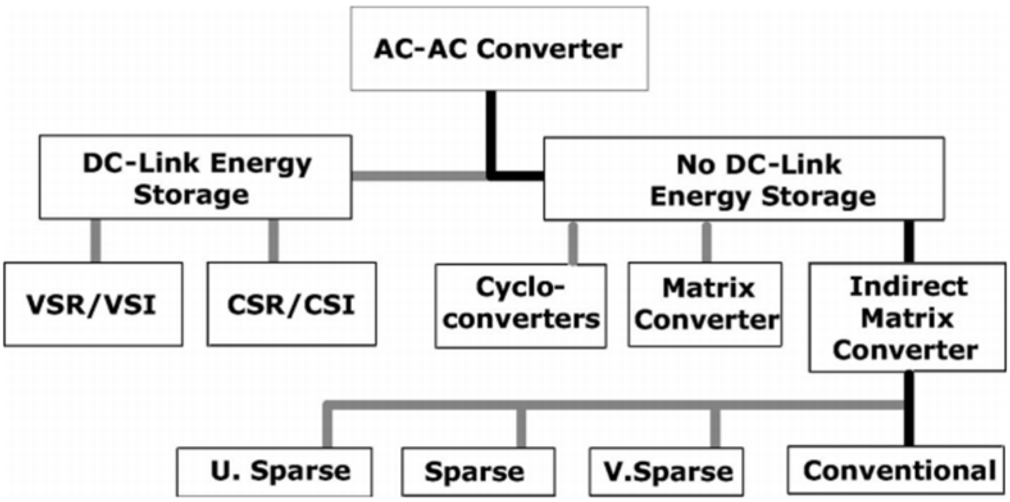


Figure I- 2: Classification of Power Converters

I.1.3.1 Direct Matrix converters

The additional direct AC power converters are the matrix converter (MC). The conventional matrix converter is made up of nine switches that connect each input phase to each output phase. With proper switching pattern, the output voltage control, current phase angle and input power factor can be obtained, Figure I-3 shows the elementary circuit of direct matrix converter.[14]

The most promising characteristics of MC are that : it does not have any limitations on the output frequencies, the input power from the input voltage source to the output three phase loads can be transferred directly, with the elimination of inductors and capacitors at the DC link as shown in Figure I-3:

It affords three-phase AC to three phase AC single conversion. Furthermore, the size and volume of the converter can be mostly reducedby using direct matrix converter.

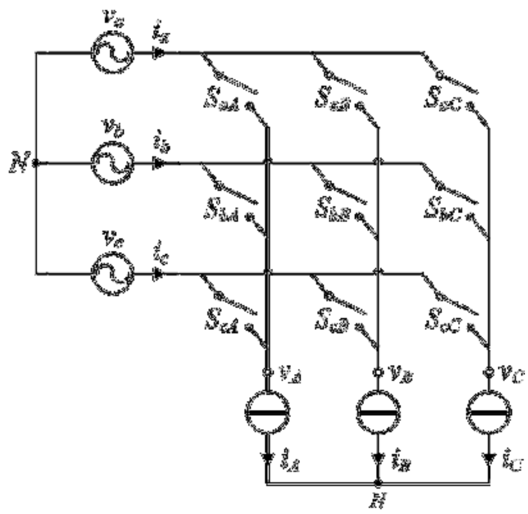


Figure I- 3: Direct Matrix Converter (DMC)

I.1.4 Indirect Matrix Converters

The improved topology called indirect Matrix converter is established on the concept of virtual DC link which is used to control the Matrix Converter. Hence, there is no energy storage element between the input and output side. The advantages of Indirect Matrix Converter compared to direct Matrix Converter are that : the commutation problem of power switches is solved and all the switches are switched ON and OFF at zero current.

Even though both matrix converters show dissimilarities in the circuit configuration, modulation techniques, efficiency and complexity, they also afford similar characteristics such as sinusoidal input as well as output currents and power flow at both directions with similar number of power semiconductor switches.[1]

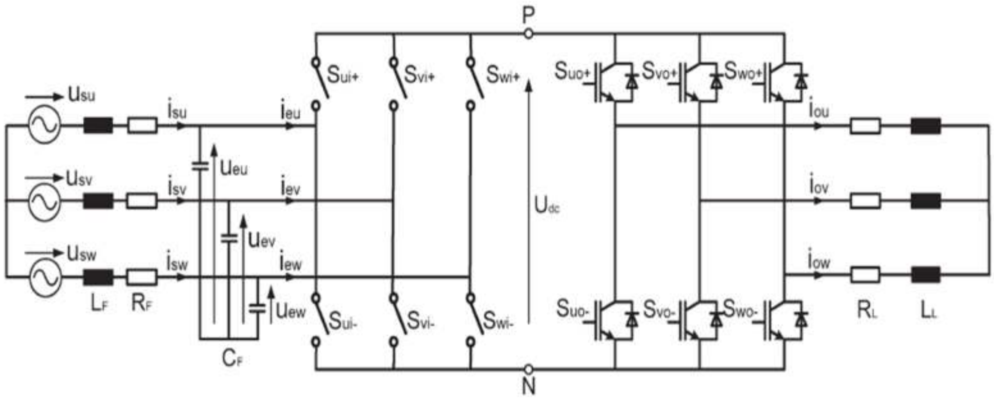


Figure I- 4: Indirect Matrix Converter (IMC)

I.1.5 Structures of Indirect Matrix Converters

I.1.5.1 Conventional Indirect Matrix Converters

The electrical grid supplies the rectifier with AC power that passes in the first place by the input filter to be dealt with as a clean power energy. Afterwards the rectifier modifies this energy to a DC form power energy. The DC bus, which in place is responsible to provide the DC energy to the inverter stage, is of virtual nature since it misses any type of bulky storage components [3]. The rectifier stage, which is formed of six bidirectional switches, provides a factious DC link voltage with a variable average. The other six unidirectional switches forming the inverter stage

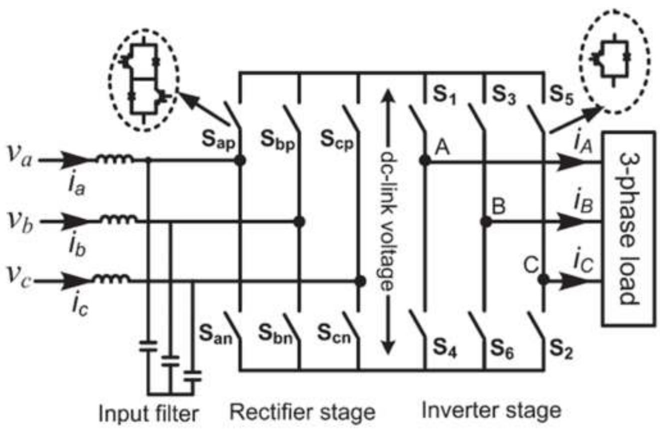


Figure I- 5: Structure of a conventional Indirect Matrix Converter

I.1.5.2 Sparses Indirect Matrix Converters

The main issue of the conventional IMC is the switching problem because of the difficulty of working with the 4-dials switches in their safety zones. As a solution, a zero DC-link current switching is implemented or a protection circuit is added. These solutions were introduced in the indirect matrix converter topology that also uses 18 IGBT semiconductors and 18 diodes arranged in a way that the rectifier and inverter stages are distinct. Several topologies were derived from indirect converters: the Sparse topology (15 IG Y semiconductors), the Very-Sparse topology (12 IGBT semiconductors), and the unidirectional Ultra-Sparse topology (9 IGBT semiconductors). These converters present the possibility to access the DC link between the inverter and the rectifier stage, which makes their control more flexible. Furthermore, they involve a smaller number of switches and consequently they are more compact, less expensive, easier to control than the conventional topology and more efficient since the switching losses are also reduced.[4]

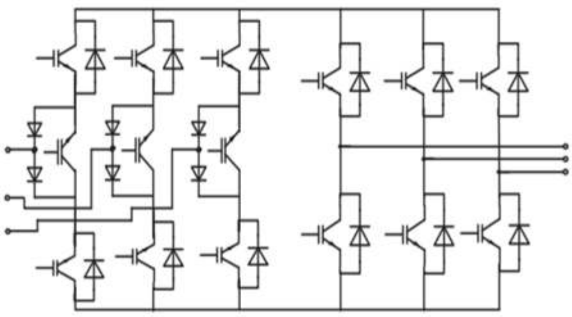


Figure I- 6: Sparse Matrix Converter (SMC)

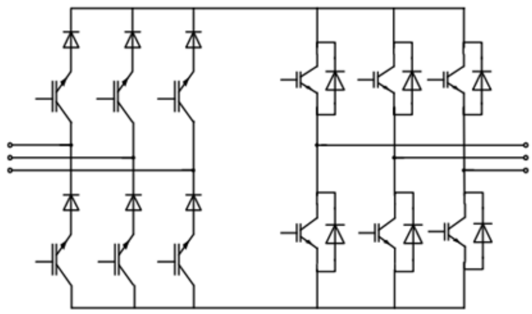


Figure I- 7: Very sparse Matrix Converter

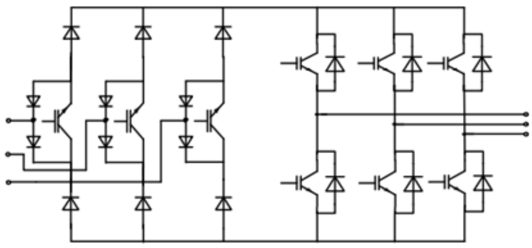


Figure I- 8: Ultra sparse Matrix Converter (USMC)

I.1.5.3 Multilevel Indirect Matrix converters

The multilevel indirect matrix converter (IMC) is a merit of power converter for feeding a three-phase load from three-phase power supply because it has several attractive features such as: Sinusoidal input/output currents, bidirectional power flow, and long lifetime due to the absence of bulky electrolytic capacitors. As compared to the conventional IMC, the multilevel IMC provides high output performance by increasing the level of output voltage.

Over the past few years, there has been a significant effort towards addressing the technical challenges associated with the development of topology and control of the multilevel IMC. The conventional multilevel IMC topology was firstly introduced in, which is based on the traditional IMC, but with a rear-ends six-switch inverter replaced by a three-level neutral-point-clamped (NPC) inverter as shown in Fig, Then, the new multilevel IMC based on the combination of conventional NPC and cascaded-rectifier is presented in in order to improve the voltage transfer ratio [5].

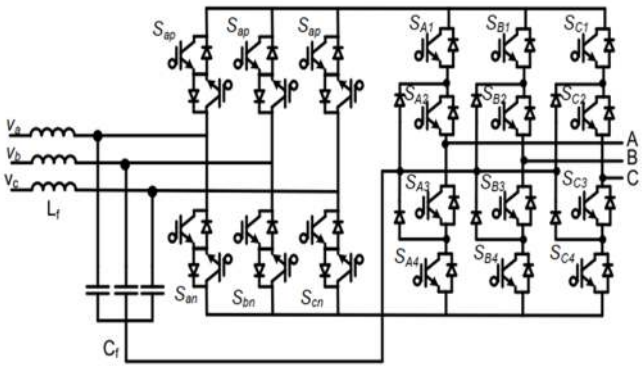


Figure I- 9: Multi level IMC

I.2 State of the art of Model Predictive Control

I.2.1 Introduction

Predictive control has been considered as a part of optimal control theory since 1960s [6]. The model predictive control (MPC), a branch of predictive control, has found growing applications in motor drives and power electronics MPC implies the idea of employing a model of a plant under control to predict the future behavior of the model control system's output. The prediction provides the capability to solve optimal control problems for minimizing the tracking error of the predicted output with respect to a desired reference [7]. During the last two decades, several reviews have been conducted of the MPC literature from various points of view. One of the earliest survey studies reviewed MPC theory and design techniques[8]. A part of that review deals with the robustness issues, indicating that this has been an important topic since the very beginning. Robust MPC theory and implementation methods are presented and surveyed in[8], [9], The theory allows for the systematic handling of system uncertainties. The early approach of robust MPC is based on min-max optimal control problem formulations in which the controller acts according to the worst-case evaluations of the cost function.

The application of MPC method in its different forms is also addressed in the field of drives and power electronics, including active filters, distributed generation, and renewable energy, …etc.

I.2.2 Development of MPC (History)

According to authors research, the MPC was the first used in industry such as oil and petrochemical industries, which dates back to the 1950s as a computer based supervisory control. At that time, MPC was a promising control strategy yet it wasn't widely embraced by other process industries due to the computational power needed for the MPC until the mid-1970s, when several other techniques were introduced like: Model Heuristic Predictive Control (MHPC) and Dynamic Matrix Control (DMC). These two control algorithms were developed into Generalized Predictive Control (GPC) which is more robust compared to the MHPC and DMC [10].

In the second decade of the MPC development, during the late 1980s, researchers founded a theoretical approach for the MPC: the discrete-time state-space representation model:

$$\begin{cases} x[i+1] = Ax[i] + Bu[i] \\ y[i+1] = Cx[i] + Du[i] \end{cases}$$

During this decade, researchers showed interest in studying the stability of the MPC for the first time. Which can be proved by considering the cost function of the MPC as a Lyapunov function. The cost function is introduced in the next paragraph

I.2.3 Working Principal of MPC

Predictive control covers a very wide class of controllers that have found rather recent application in power converters. A classification for different predictive control methods is shown in the following Figure:

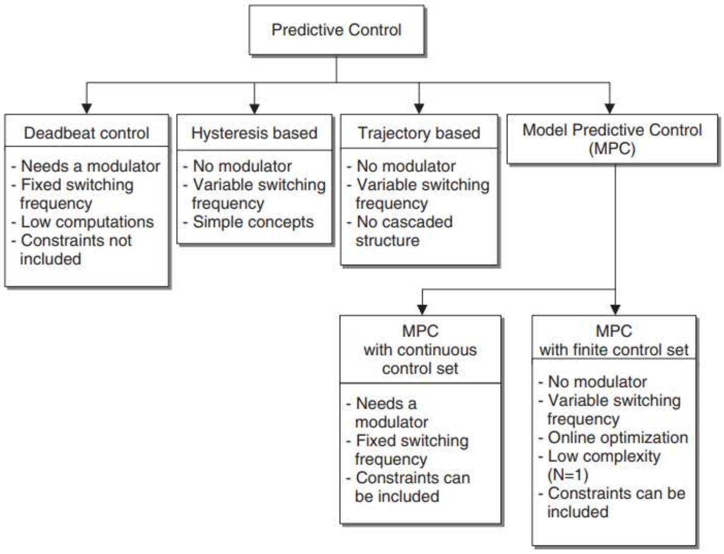


Figure I- 10: Classification of predictive control methods used in power electronic

variables are forced to follow a predefined trajectory. In deadbeat control, the optimal actuation is the one that makes the error equal to zero in the next samplingtime. A more flexible criterion is used in model predictive control (MPC), expressed as a cost function to be minimized.

The difference between these groups of controllers is that deadbeat control and MPC with continuous control set need a modulator in order to generate the required voltage. This will result in having a fixed switching frequency. The other controllers directly generate the switching signals for the converter, do not need a modulator, and present a variable switching frequency.

Nonlinearities in the system can be included in the model, avoiding the need to linearize the model for a given operating point, and improving the operation of the system for all conditions. It is also possible to include restrictions on some variables when designing the controller. These advantages can be very easily implemented in some control schemes, such as MPC, but are very difficult to obtain in schemes like deadbeat control. [6]

I.2.4 Principle of Model-Based Predictive control

The methodology of all the controllers belonging to the MPC family is characterized by the following strategy, represented in figure

$$\hat{x}(k+1) = A\hat{x}(k) + Bu(k)$$
$$\hat{y}(k) = C\hat{x}(k) + Du(k)$$

Where $x(k)$ and $\hat{x}(k+1)$ are the system state vectors at the current and next instants, respectively. Also $u(k)$ and $y(k)$ are input and output vectors, respectively, at the current instant. A, B, C, and D are the states matrix, control matrix, the output matrix and disturbance matrix, respectively. An objective function J which is a function of system states and inputs, is defined to formulate the system's desired performance as:

$$J = f\big(x(k), u(k), \dots \dots \dots .., u(k+N)\big)$$

Where N is a postitive number known as the prediction horizon and is the number of future instances over which the control can predict the system's performance. The vector $u(k+N)$ is the system input at the instance $k+N$ .The sequence of the inputs prior to $u(k+N)$ is also included in J, as shown in figure below:

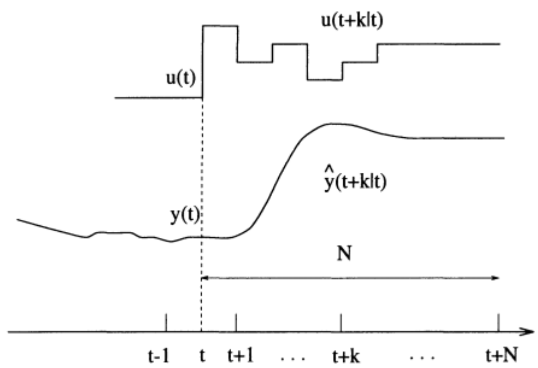


Figure I- 11: Working principle of MPC

MPC defines the control action by minimizing a cost function that describes the desired system behavior. This cost function compares the predicted system output with a reference. The predicted outputs are computed from the system model. In general, for each sampling time, the MPC controller calculates a control action sequence that minimizes the cost function, but only the first element of this sequence is applied to the system. Although MPC controllers solve an open-loop optimal control problem, the MPC algorithm is repeated in a forward horizon fashion at every sampling time, thus, providing a feedback loop and potential robustness with respect to system uncertainties [36].

I.2.5 MPC's Elements

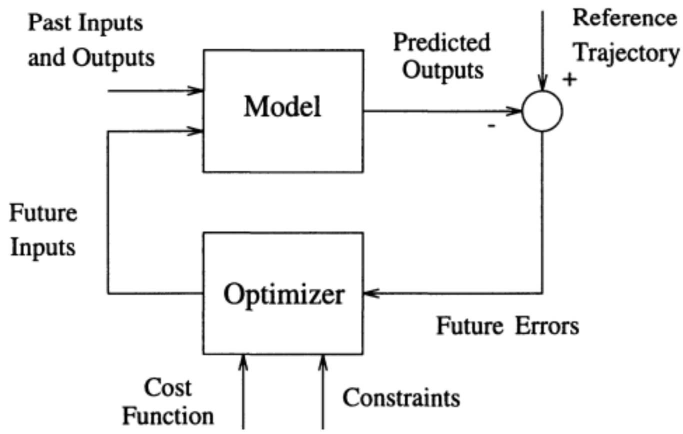


Figure I- 12: Basic structure of MPC

All the MPC algorithms possess common elements and different options can be chosen for each one of these elements giving rise to different algorithms. These elements are:

- Prediction Model
- Objective Function
- Obtaining the control law

I.2.6 Prediction Model

The model is the corner-stone of MPC [33]; a complete design should include the necessary mechanisms for obtaining the best possible model, which should be complete enough to fully capture the process dynamics and should also be capable of allowing the predictions to be calculated and at the same time, to be intuitive and to permit theoretic analysis.
Practically every possible form of modeling a process appears in a given MPC formulation, the following being the most commonly used:

- Transfer function.
- State space.

Non-linear models can also be used to represent the process but the problem of their use springs from the fact that they cause the optimization problem to be more complicated. Neural nets [40]as well as fuzzy logic [41] are other forms of representation used in some applications.

I.2.7 Objective Function

The various MPC algorithms propose different cost functions for obtaining the control law. The cost function definition is one of the most important stages in the design of an MPC, since it allows not only to select the control objectives of the application, but also to include any required constraints that represents the desired behavior of the system [42]. This function considers the references, future states (or predicted states), and future actuations. In case of a multivariable system, the cost function may be written as

$$J = \sum_{j=N1}^{N2} [w(k+j) - \hat{y}\,(k+j)]^2 + \lambda \sum_{j=1}^{Nu} [\Delta u(k+j-1)]^2 +$$

With $\Delta u(k+j)$=0 for j = Nu

While:

$\hat{y}$: is the predicted output. Δu: Control increment, w: The order, N_1, N_2: Prediction horizons to the output, N_u:Prediction horizon to the control, λ: weighting factor

The weighting factor allows for adjusting the importance of each controlled variable according to its priority in the scope statement

The selected actuation is the one that minimizes the cost function, it is stored so that it can be applied to the converter in the upcoming sampling period [43]

I.2.8 Obtaining the control law

In order to obtain values u (t + k | t) it is necessary to minimize functional J. To do this the values of the predicted outputs y(t + k | t) are calculated in function of past values of inputs and outputs and of future control signals, making use of the model chosen and substituted in the cost function, obtaining an expression whose minimization leads. An analytical solution can be obtained for the quadratic criterion if the model is linear and there are not constraints, otherwise an iterative method of optimization should be used [44].

If the system is not linear but nonlinear ,we can use linear MPC and still benefit from the proprieties of the convex optimization problem , the available method to use this case are the adaptive and gain scheduled MPC , the way these controllers deal with a nonlinear system is based on linearization. If the system is nonlinear and that cannot be approximated well then we have to use nonlinear MPC, this method is the most powerful on as, it uses the most powerful on as, it uses the most accurate representation of plant.

I.2.9 The major problem of the MPC

The Model Predictive Control (MPC) is a well-established technique for process control that has been applied to electrical systems, so after the three decades of the gradual development, so what remains now? [45]

At present, the MPC suffer from many problems, such as the lack of systematic handling of uncertainty. Therefore, it is necessary to improve the prediction accuracy for mismatched prediction models. The other problem is how to design the cost functions and the weight coefficients [46] [47] .One of the other drawback of MPC is that it requires the optimization problem to be solved online

All this makes the existing MPC algorithms suffer from a major challenge: relatively low computation efficiency [48] and huge amount of real-time calculations [13].

I.2.10 MPC in power electronics

Variants of MPC have thenceforth been developed and implemented in power converters and used in applications such as electrical drives, static synchronous compensators (STAT-COMs), high voltage dc (HVDC) systems, flexible ac transmission systems (FACTS), and uninterruptible power supplies (UPS), to name a few [10],[11]

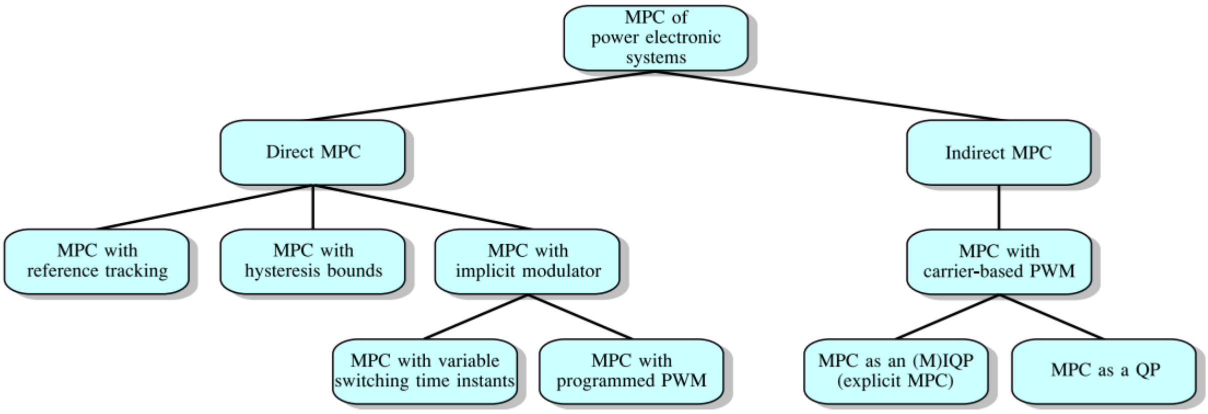
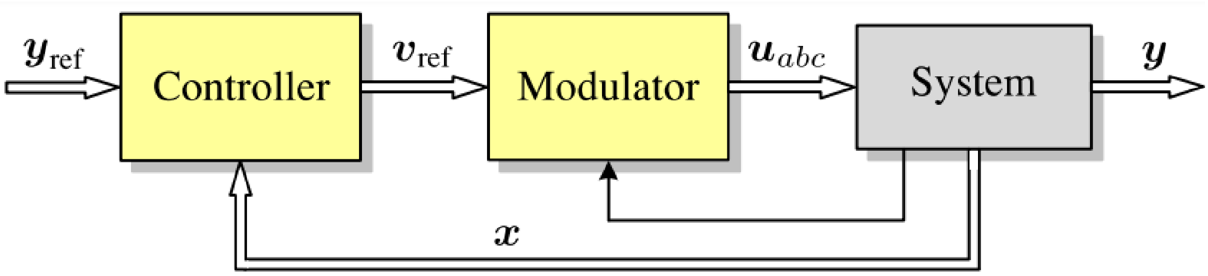
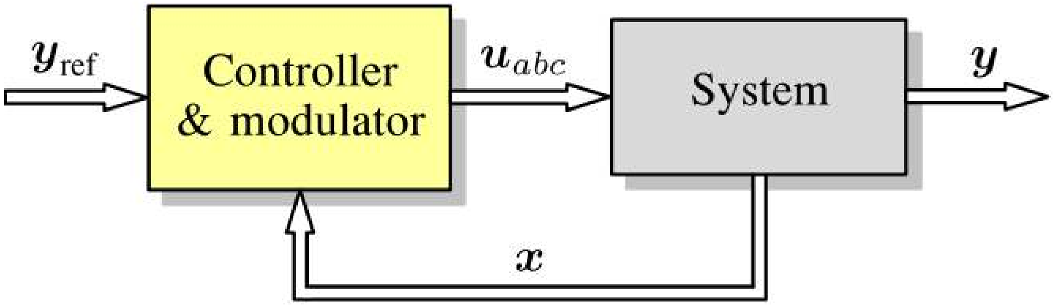


Figure I- 13: MPC of Power Electronic Systems.

MPC schemes for power electronics can be classified into two main categories depending on whether they employ a separate modulator or not. In the former case, MPC is implemented as an indirect controller, i.e., the controller computes the modulating signal/duty ratio which is fed into a modulator for generation of the switching commands, see Figure-14 (a). Hence, the control action is a real-valued vector. On the other hand, when MPC is designed as a direct controller, the control and modulation problems are formulated and solved in one computational stage, thus, not requiring a dedicated modulator, See Figure I-14 (b). Consequently, the elements of the control input vector are the switching signals, implying that it is an integer vector



(a) Indirect control scheme



(a) Direct control scheme

Figure I- 14: **Main controller structures of MPC**

The aforementioned MPC algorithms can be further divided into smaller groups as shown in Figure I-13 Direct MPC-based schemes include controllers with reference tracking, hysteresis bounds and implicit modulator. Direct MPC with reference tracking, also known as finite control set MPC (FCS-MPC),is the most favored method in academia due to its well-reported advantages such as its intuitive design procedure and straightforward implementation [12], [13]-[14]. The aim is to achieve regulation of the output variables along their reference trajectories by manipulating the converter switches, and thus directly affecting their evolution. This variant of direct MPC, however, comes with pronounced computational complexity which can potentially lead to computationally intractable optimization problems. Moreover, researchers often-knowingly or not—resort to design simplifications that detract from its effectiveness and result in inferior performance compared with conventional control techniques, see the paper [15].

Direct MPC with hysteresis bounds was the first rudimentary version of this type of controllers developed for power electronic converters [16],[17]-[18]. This algorithm employs hysteresis bounds within the variables of interest, such as the stator currents, or the electromagnetic torque and stator flux magnitude of a machine, need to be constrained. Later, more sophisticated derivatives were devised which adopt a variety optimization criteria and/or nontrivial prediction horizons [19]-[20]. Moreover, the versatility of the method in discussion allowed for different types of hysteresis bounds that affect the system performance in terms of, e.g. harmonic distortions or switching losses [17],[21],[22].

Finally, the third group of direct MPC strategies can be further divided into two subgroups. The first one includes methods that manipulate not only the switching signals, but also their application time in an attempt to emulate the behavior of pulse width modulation (PWM) techniques. More specifically, these methods—and in contrast to the aforementioned direct MPC strategies—introduce the concept of variable switching time instants by changing the state of the switches at any time instant within the sampling interval. This is done by computing both the optimal switch positions and the associated duty cycles [23]-[24]. In doing so, higher granularity of switching is introduced enabling the reduction of the harmonic distortion in the variables of concert. Moreover, some of these methods achieve operation of the power converter at a fixed switching frequency, thus resulting in deterministic switching losses.[25],[24],[26],[27]-[28].

The second group consists of direct MPC methods that are combined with programmed PWM [29], i.e., modulation methods that forgo a fixed modulation interval. The switching pattern and the switching instants are computed offline based on some optimization criteria, such as minimization of the current total harmonic distortion (THD) and/or the elimination of specific harmonic. Programmed PWM is implemented in the form of selective harmonic elimination (SHE) [30],[31] , or optimized pulse patterns (OPPs) [32],[33]. The idea of manipulation of the switching instants of OPPs in a predictive fashion was introduced in [34],[35] and [36],[36] for stator current and stator flux reference trajectory tracking, respectively. These methods, however, lack the recording horizon policy and do not distinguish between the fundamental and the ripple components thus complicating the observer design [37]. To address these issues, more sophisticated MPC algorithms for the control of OPPs deemed necessary, leading to the methods presented. Moreover, SHE with MPC is presented, e.g., in [38],[39]. Owing to the nature of the programmed modulation methods these MPC-based strategies achieve very low harmonic distortions, but they are fairly elaborate since fast closed-loop control is challenging.

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I.3 Artificial Intelligence in power electronics

I.3.1 Introdution

Today, artificial intelligence (AI) is spreading rapidly and is one of the most important areas of research in the past few decades[40], [41]. The goal of AI is to support intelligent systems with human-like learning and thinking abilities. It has enormous advantages and has been successfully used in numerous industrial fields, including image classification, speech recognition, autonomous vehicles, computer vision, and more. Power electronics benefit from the huge development potential of artificial intelligence. Wide range of applications, including power module heatsink[42] design optimization, multi-color light-emitting diode (LED) [43], maximum power point tracking (MPPT) control for wind energy conversion systems[44], [45], inverter anomaly detection[46], remaining useful life (RUL) prediction for supercapacitors[47], etc. . Through the implementation of artificial intelligence, the power electronic system has become self-aware and self-adaptive, and therefore, the system autonomy can be improved[48].

Meanwhile, the rapid development of data science, including sensor technology, Internet of Things (IoT), edge computing, digital twin[49] , and big data analytics[50] , [51], provides various data for power electronic systems. Different stages of their life cycle. The ever-increasing amount of data opens up enormous possibilities and lays a solid foundation for artificial intelligence in power electronics. AI can use data to improve product competitiveness through global design optimization, intelligent control, system state estimation, etc. As a result, power electronics research can be conducted from a data-driven perspective, which is especially beneficial for companies dealing with complex and challenging cases.
The realization of artificial intelligence in the field of power electronics has its characteristics different from other technical field, such as image classification. Therefore, an overview of AI in power electronics is needed to advance collaborative research and interdisciplinary applications.

I.3.2 Application of AI for power electronic systems

Figure bellow gives a summary of the methods, the functions, and the application of AI for power electronics. It can be seen that AI has been extensively applied to the three distinctive life-cycle phases of power electronic systems, including design, control, and maintenance.

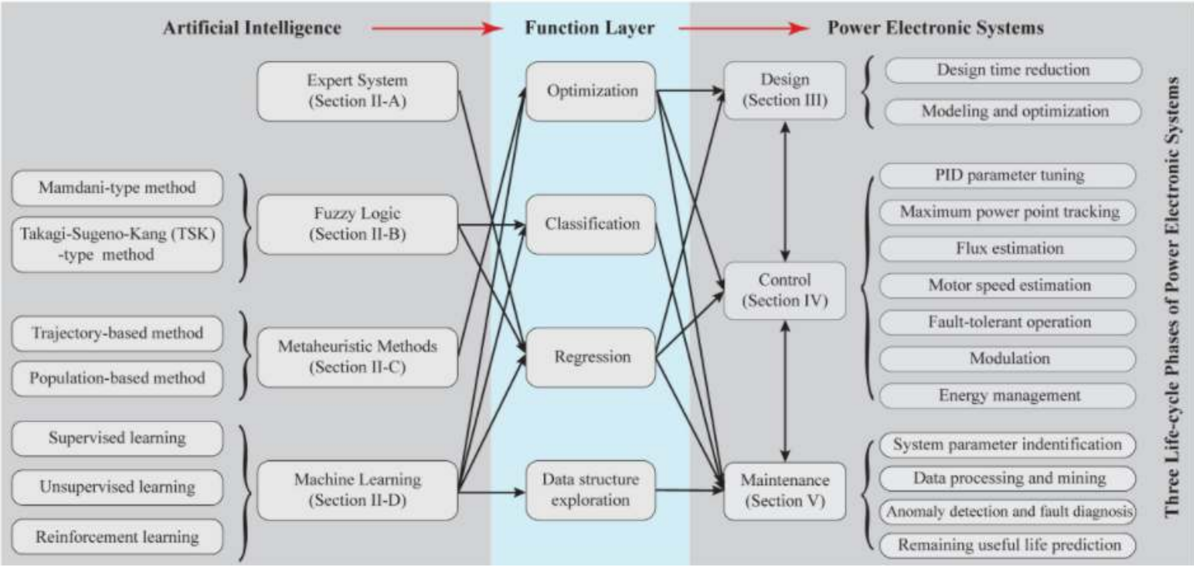


Figure I- 15: **AI for Power Electronic Systems**

As a functional layer between AI and power electronic applications, the essential functions of AI are categorized as optimization, classification, regression, and data structure exploration[48].

- Optimization: It refers to find an optimal solution maximizing or minimizing objective functions from a set of available alternatives given constraints, equalities, or inequalities that the solutions have to satisfy.
- Classification: It deals with assigning input information or data with a label indicating one of the k discrete classes. Specifically, anomaly detection and fault diagnosis in maintenance is a typical classification task to determine fault label with condition monitoring information.
- Regression: By identifying the relationship between input variables and target variables, the goal of regression is to predict the value of one or more continuous target variables given input variables.
- Data Structure Exploration: It consists of data clustering that discovers groups of similar data within a dataset, density estimation determines the distribution of data

I.3.3 AI Clasification

The AI methods in power electronics can be generally categorized as expert system, fuzzy logic, metaheuristic methods and machine learning.

- **Expert System**

Expert system is the earliest method in AI that is effectively implemented in industrial applications[52]. The expert system [53]-[54] is essentially a database that integrates the expert knowledge in a Boolean logic catalog, based on which the IF-THEN rules in human brain reasoning are simulated. It is an intelligent system simulating the inference process that answers the why-and-how inquires based on the database. The database is from either field expert experience or simulation data, facts, and statements.. The technical details of expert system are given in, and several exemplary applications can be found in.

- **Fuzzy Logic**

Similar to expert system, fuzzy logic is also a rule-based method while it extends the Boolean logic into a multivalued case. Fuzzy logic is an ideal tool to tackle system uncertainties and noisy measurements [55],[56]. Instead of using the precise input crisp value directly, fuzzification is first performed with the fuzzy sets consisting of several membership functions to a range of 0-1. The fuzzy input signals are then aggregated with fuzzy rules in the inference step. subsequently performed on the inference step. Defuzzification is subsequently performed on the inference result by considering the degree of fulfillment and output a crisp value. As a result, the crisp value is manipulated in a fuzzy space that completes nonlinear mapping between the input and output with elaborately designed.
In most applications, a fuzzy logic method mainly consists of four parts : fuzzification, rule inference, knowledge base and defuzzification [57].

- **Metaheuristic Methods**

The term metaheuristic was coined by Glover (1986) and combines the prefix meta- (meaning "after" or "beyond", in an upper level) with heuristic ("to find" or "to discover"). In classical optimization methods, the exact optimal solution is found in a finite (although often prohibitively large) amount of time. In contrast, metaheuristic methods are aimed at finding a solution that is "good enough" in a computing time that is, "small enough"; therefore providing a better tradeoff between solution quality (i.e., accuracy) and computing time [58].

Many metaheuristic algorithms have been developed in the last decades. Genetic algorithms (GA) and particle swarm optimization (PSO) have been widely applied because they have demonstrated main advantages[59].

- **Machine Learning**

Machine learning is designed to automatically discover principles and regularities with experience from either collected data or interactions by trial-and-error. For applications, in power electronics, it is categorized and supervised learning, unsupervised learning, and reinforcement learning (RL).

1) Supervised Learning:

With the trainig dataset consisting of input-and-output pairs, the supervised learning aims to establish the mapping and functional relationships between the inputs and outputs implicitly. This feature is especially useful for cases in power electronics where system models are challenging to formulate

Generally, supervised learning methods can be categorized into connectionism-based methods (i.e., NN method), probabilistic graphical methods, and memory-based methods (i.e., kerlen method).

2) Unsupervised Learning:

Compared to the supervised learning where the dataset is input-and-output pairs, unsupervised learning has no output data for the learning target during the learning process. Generally, the tasks of unsupervised learning in applications of power electronics can be categorized as data clustering and data compression.[72]

I.4 Recurrent neural network (RNN)

I.4.1 Introduction

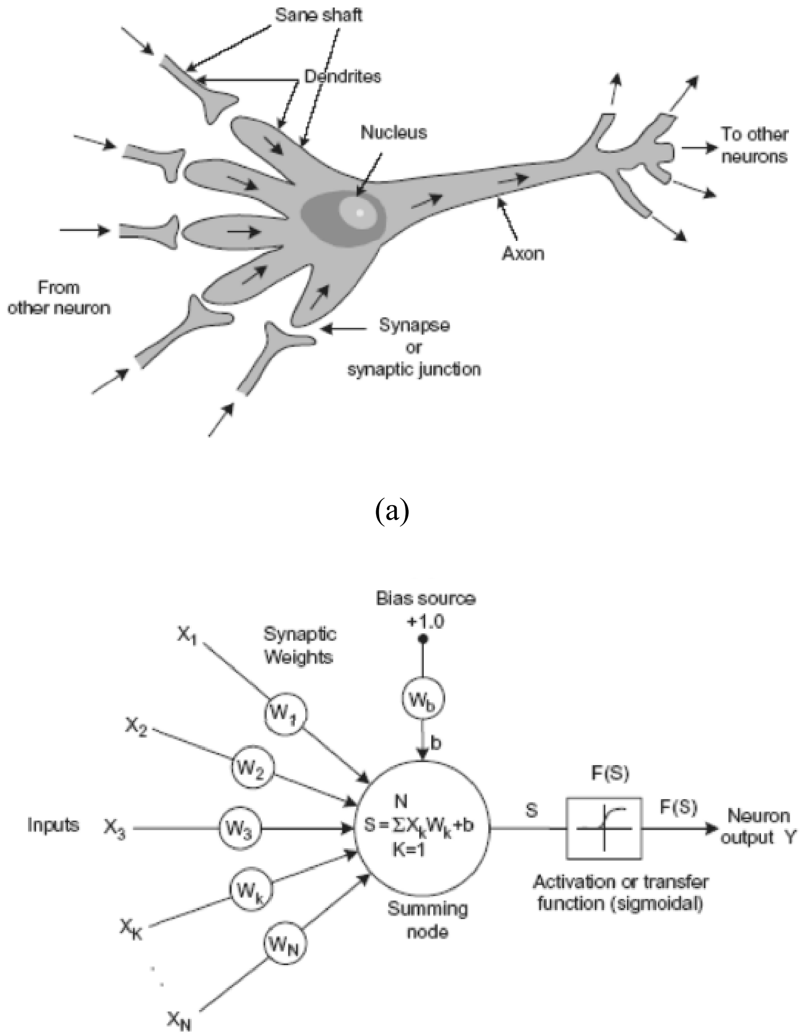
In recent years, the neural-network-based control technique has represented an alternative method to solve the problems in control engineering. The most useful property of neural networks in control is their ability to approximate arbitrary linear or nonlinear mapping through learning. It is because of the above property that many neural-network-based controllers have been developed for the compensation for the effects of nonlinearities and system uncertainties in control systems so that the system performance such as the stability, convergence, and robustness can be improved [60].

It can be seen from the recent development of the neural-network-based control systems that, by suitably choosing neural-network structures, training methods, and sufficient past input and output data, the neural networks can be well trained to learn the system forward dynamics to predict the future behavior of the system for the predictive control and model following control, or to learn the inverse dynamics for inverse control. However, the stability, error convergence, and robustness have not been fully proved for these off-line trained neural-network-based control systems because of the high nonlinearity of the neural networks and the lack of feedback[60].

I.4.2 Structure of a neuron

I.4.2.1 Biological and Artificial Neurons

ANN consists of a number of artificial neurons that are interconnected together. The structure or artificial neuron is inspired by the concept of biological neuron shown in Fig. 8(a). Basically, it is the processing element in the nervous system of the brain that receives and combines signals from other similar neurons through thousands of input path called dendrites. Each input signal (electrical in nature), flowing through dendrite, passes through a synapse or synaptic junction as shown.



(a)

(b)

Figure I- 16: **(a) Biological neuron, (b) Artificial neuron model.**

The junction is an infinitesimal gap in the dendrite which is filled with neurotransmitter fluid that either accelerates or retards the flow of the signal. These signals are accumulated in the nucleus (or soma), nonlinearly modified at the output before flowing to other neurons through the branches of axon as shown. The adjustment of the impedance or conductance of the synaptic gap by the neurotransmitter fluid contributes to the "memory" or "intelligence" of the brain. According to the theory of the neuron, we are led to believe that our brain has distributed associative memory or intelligence characteristics which are contributed by the synaptic junctions of the cells. It may be interesting to note here that when a human baby is born, it has around 100 billion neurons in the brain. Typically, from the age 40, around one million neurons die every day.

The model of an artificial neuron that closely matches the biological neuron is shown in Figure-16(b). Basically, it has op-amp summer-like structure. The artificial neuron (or simply neuron) is also called processing element (PE), neurode, node, or cell. Each input signal (continuous variable or discrete pulses) flows through a gain or weight (called synaptic weight or connection strength) which can be positive (excitory) or negative (inhibitory), integer or noninteger. The summing node accumulates all the input-weighted signals, adds to the weighted bias signal b, and then passes to the output through the nonlinear (or linear) activation or transfer function (TF) as shown.

I.4.3 The construction of ANN systems

In general, ANN systems are capable of "learning" trends in a given data set and establishing input–output relationships based strictly on a "test" set of data.

The basic element in neural network systems is called a neuron. The neuron accepts one input x , and produces an output value y, based on the (generally) nonlinear function. However, there is no way to determine beforehand which choice of this function will produce the best results for a particular problem. A complete multilayer neural network system is constructed by combining neurons in series (from left to right) and parallel (from top to bottom). [59]

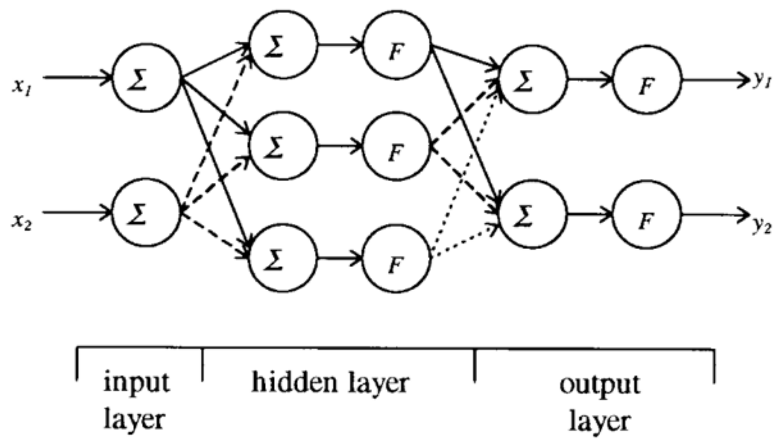


Figure I- 17: A three-layer neural network system

A layer is defined to be a set of parallel-connected neurons, or "nodes." The hidden and output layers are identical in both form and functionality; they give the network its ability to "learn" complex nonlinear relationships between inputs and outputs. [59]

I.4.3.1 The ANN's working principle

ANN's perform their calculations using the nonlinear functions and simple multiplying factors, called weights that are associated with a pathway between any two neurons. In its basic form, this model can be expressed as an iterative composition of input-output functions of the form [60]

$$f(\vec{x}) = h\left(w_0 + \sum_{i=1}^{M} w_i x_i\right)$$

Where $h(x)$ is an activation function , $\vec{x}= \{x_1, x_2, \cdots, x_M\}$ is the input vector of the ANN with M elements, w_i are the weights for each input xi , and w_0 is a bias or correction factor. The objective of the ANN training phase is to optimize some cost function by finding optimal values for the w_i and w_0 [60]. The weights are updated in a manner such that the complete network "learns" to produce a specific output for a specific input. The process of adjusting the weights to achieve a specified accuracy level is referred to as "training." [61]

I.4.3.2 Activation functions

Several common type activation functions used in artificial neuron are shown in Fig 9. These are defined respectively, as linear (bipolar), threshold, signum, sigmoidal (or log-sigmoid), and hyperbolic tan (or tan-sigmoid).

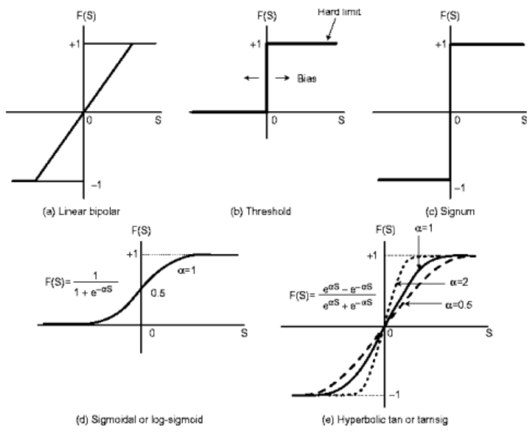


Figure I- 18: Several actiation functions of artificial neurons.

I.4.3.3 The training of ANN

The major justification for the use of ANN's is their ability to "see" and "learn" relationships in complex data sets that may not be easily perceived by human engineers. An ANN system performs this function as a result of "training" which, in words, is a process of repetitively presenting a set of training data (typically a representative subset of the complete set of data available) to the network and adjusting the weights so that each input data set produces the desired output [61].

I.4.3.4 Learning Algorithm Categorization

Neural networks are trained by two main types of learning algorithms: supervised and unsupervised learning algorithms.

Supervised Learning: a supervised learning algorithm adjusts the strengths or weights of the inter-neuron connections according to the difference between the desired and actual network outputs corresponding to a given input. Thus, supervised learning requires a "teacher" or "supervisor" to provide desired or target output signals. The network employs a special one-step procedure during "learning" and an iterative procedure during recall.[62]

Unsupervised Learning: unsupervised learning algorithms do not require the desired outputs to be known. During training, only input patterns are presented to the neural network which automatically adapts the weights of its connections to cluster the input patterns into groups with similar features. [62]

I.4.3.5 Classes of neural network

a- The feed-forward neural net

FNN tend to be straightforward networks that allow signals to travel one way only, from input to output. There are no feedback (loops); i.e. the output of any layer does not affect that same layer. Most of the works on nonlinear MPC (NMPC) use FNN, for example In [63] , S.Tiwari, R. Naresh, and R. Jha realize a neural network model predictive controller, by using the FNN, for predictive control of the power system to improve its transient stability. Yan and Wang in [64] introduce a robust MPC based on a FNN The results show that this robust MPC could improve computational efficiency and shed a light for real-time implementation. However, the main drawback of FNN that their capability for representing nonlinear systems is limited [58]

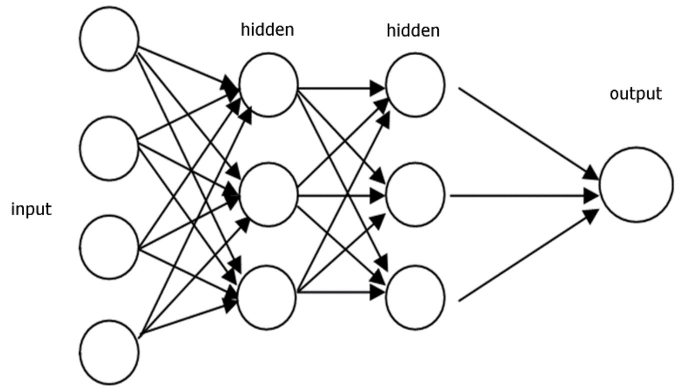


Figure I- 19: The feed-forward neural network

b- The recurrent neural net

RNN can have signals traveling in both directions by introducing loops in the network. They are capable of providing long-range predictions even in the presence of measurements noise due to their structures. Therefore, RNN are better suited to model nonlinear systems for MPC. Pan and Wang in [65] use an echo state network to identify unknown nonlinear dynamical systems for NMPC. The results show that the echo state network-based NMPC can reach the global convergence. RNN improved performance in terms of global convergence and reduced model complexity [66]. Examples of recurrent networks include the Hopfield network [Hopfield, 1982], the Elman network [Elman, 1990] and the Jordan network [Jordan, 1986]. [62]

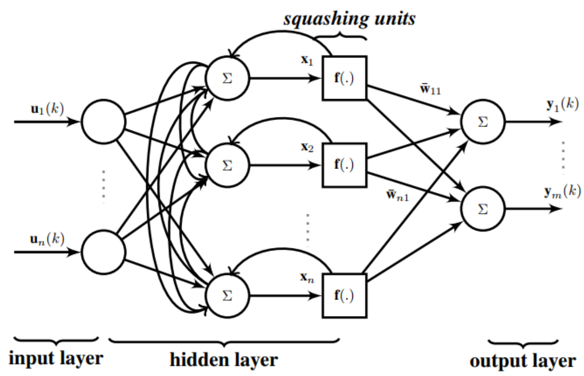


Figure I- 20: Simple recurrent neural network

c- Self-organizing neural network

The class of methods that have been often termed "self-organizing maps" (SOM) involve iterative procedures for associating a finite number of object vectors (inputs) with a finite number of representational points [67]. A self-organizing neural network consists of two parts: main part and control part. The main part, structurally, is the same as an ordinary 3-layered feed-forward neural network, but each neuron in its hidden layer contains a signal from the control part, the main part is trained by a supervised learning and learns input-output mapping. The control part consists of a self-organizing map (SOM) network [68] whose outputs associate with the hidden neurons in the main part one by one and control the firing strength; the control part is trained by an unsupervised learning [69].

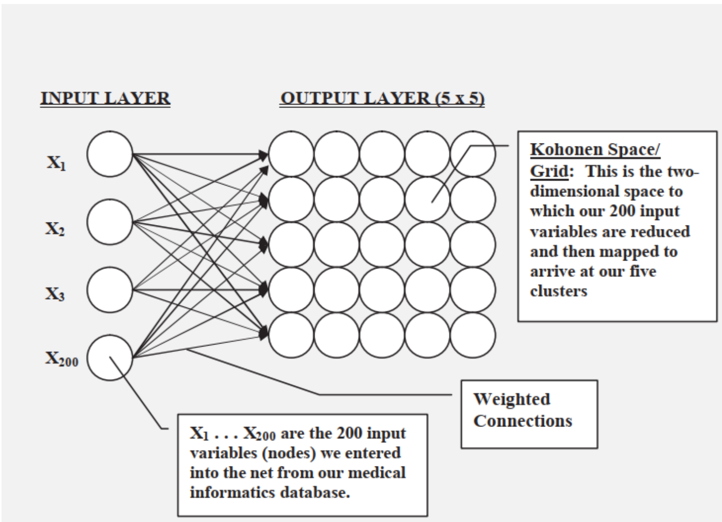


Figure I- 21: Diagram of a Self-Organizing Map

I.4.4 How ANN Systems are applied

ANN systems must be applied to problems for which a suitable amount of training data exists; it may come from historical records from measured data. The system will only perform as well as it has been trained [61]. In our case, the objective is to drive a three- phase's inverter. Therefore, we use MPC as an expert or a teacher for generating the data required for training off-line the proposed neural network using standard supervised learning, under full state observation of the system, once the off-line training is performed, the trained ANN can successfully control the output voltage of the inverter, without the need of using MPC at test time.

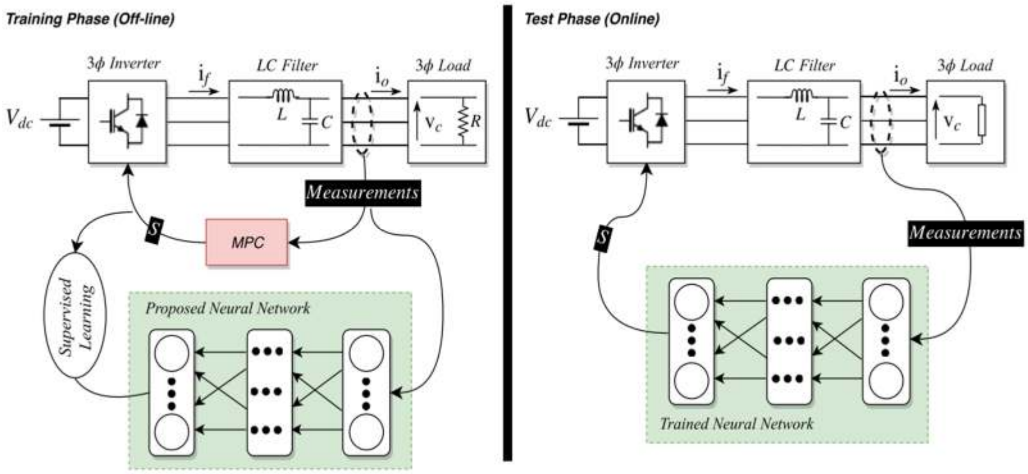


Figure I- 22: An overview of the proposed control strategy

I.5 Conclusion

In this chapter, we presented an overview of the state of the art of the major elements our work.

At the beginning, we talked about the AC-AC converters which are divided into direct and indirect converters, which have different structures where each one has its special requirements and issues.

Secondly, a section briefly describes the model predictive control, including a historical development, its working principle with some examples of its applications. Then we gave a global perspective about the use of artificial intelligence in power electronic field.

The MPC suffers from the concern of the relatively low computation efficiency. Therefore, we highlight the methods of performance's improvement of the MPC, the neural network is one of the most promoted solution. The last section was dedicate to present an overview of ANN and how it could improve the model predictive control.

Chapter two

A Model Predictive Current Control of a Three-Phase, Two Level, Inverter-Fed RL-Load

CHAPTER TWO

Introduction

Current control of a three-phase inverter is one of the most important and classical subjects in power electronics. And with the technological advancement in microprocessors, interest has been shown to Model Predictive Current Control (MPCC).

This chapter presents an MPC scheme for a three-phase, two (level, inverter-fed RL-load. The modeling of the two-level voltage source (2LVSI) and of the load will be presented, the working principle will be explained and both simulation and experimental results will be shown.

II.1 Model Predictive Current Control

In model Predictive Current Control (MPCC), the current is the variable that should be controlled. In order to control it, we use the model of the system (inverter+load) to predict at each sampling period all the possible output current values according to each possible switching state of the inverter and compare them to a reference. The predicted value that optimizes a predefined optimization criterion (the cost function) will be selected, and the corresponding switching states will be applied

II.2 System modeling

II.2.1 Inverter model

The power circuit of the three-phase inverter converts electrical power from DC to AC from using the electrical scheme shown in Figure II.1. Considering that the two switches in each inverter phase operate in a complementary mode in order to avoid short-circuiting the DC source, the possible switching states are reduced to 8, they are shown in Table II.1.

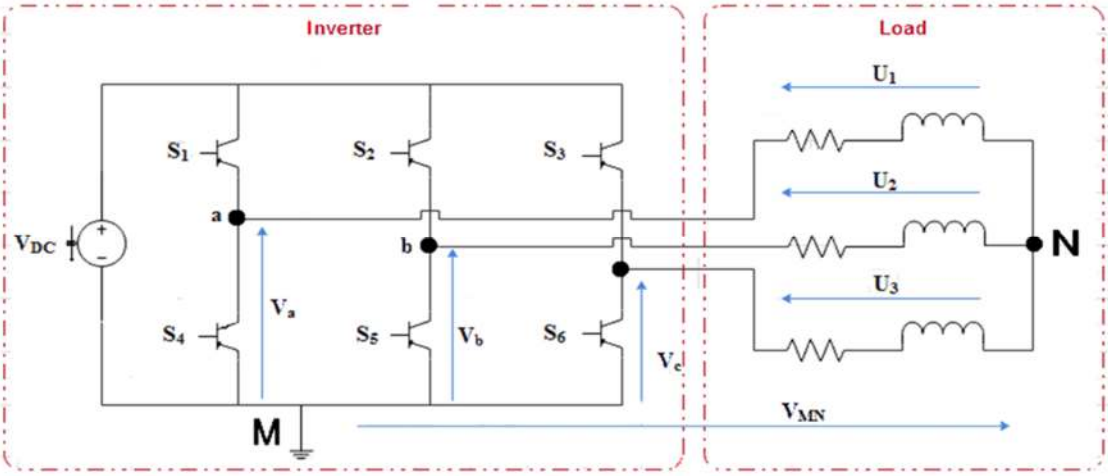


Figure II- 1 : Voltage source inverter power circuit

Where

- V_{DC} is the DC source voltage.
- v_a, v_b and v_c are the phase-to-neutral (M) voltages of the inverter
- u_1, u_2 and u_3 are the phase-to-neutral (N) voltages of the load
- S_1, …, S_6 are the gate signals

The power switches operate in a complementary mode; thus, the connection function can be expressed as follows:

$$S_a = \begin{cases} 1 \text{ if } S_1 \text{on and } S_4 \text{off} \\ 0 \text{ if } S_1 \text{off and } S_4 \text{on} \end{cases}$$

$$S_b = \begin{cases} 1 \text{ if} S_2 \text{on and} S_5 \text{off} \\ 0 \text{ if} S_2 \text{off and} S_5 \text{on} \end{cases} \tag{II.1}$$

$$S_c = \begin{cases} 1 \text{ if} S_3 \text{on and} S_6 \text{off} \\ 0 \text{ if} S_3 \text{off and} S_6 \text{on} \end{cases}$$

By applying Kirchhoff's first law we get:

$$\begin{cases} u_1 = v_{MN} + v_a \\ u_2 = v_{MN} + v_b \\ u_3 = v_{MN} + v_c \end{cases} \tag{II.2}$$

Adding the three equations we get:

$$v_{MN} = -\frac{1}{3}(v_a + v_b + v_c) \tag{II.3}$$

Replacing v_{MN} in (II.2) and considering that the load is balanced, we result in the following system that will be implemented in MATLAB:

$$\begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} = \frac{1}{3} V_{DC} \begin{pmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{pmatrix} \begin{pmatrix} S_a \\ S_b \\ S_c \end{pmatrix} \tag{II.4}$$

Table II- 1: Feasible switching states of the two-level four-leg inverter

S_a	S_b	S_c	u_1	u_2	u_3
0	0	0	0	0	0
1	0	0	$\frac{2}{3}V_{DC}$	$\frac{-1}{3}V_{DC}$	$\frac{-1}{3}V_{DC}$
1	1	0	$\frac{1}{3}V_{DC}$	$\frac{1}{3}V_{DC}$	$\frac{-2}{3}V_{DC}$
0	1	0	$\frac{-1}{3}V_{DC}$	$\frac{2}{3}V_{DC}$	$\frac{-1}{3}V_{DC}$
0	1	1	$\frac{-2}{3}V_{DC}$	$\frac{1}{3}V_{DC}$	$\frac{1}{3}V_{DC}$
0	0	1	$\frac{-1}{3}V_{DC}$	$\frac{-1}{3}V_{DC}$	$\frac{2}{3}V_{DC}$
1	0	1	$\frac{1}{3}V_{DC}$	$\frac{-2}{3}V_{DC}$	$\frac{1}{3}V_{DC}$
1	1	1	0	0	0

II.2.2 Load model

The application of Kirchhoff's first law to the RL-load in Figure II.1 gives:

$$\begin{cases} u_1 = L\dfrac{di_a}{dt} + Ri_a \\ u_2 = L\dfrac{di_b}{dt} + Ri_b \\ u_3 = L\dfrac{di_c}{dt} + Ri_c \end{cases} \tag{II.5}$$

In order to obtain a model for this RL load for simulation in MATLAB/Simulink environment we need to transform (II.5) into Laplace domain as transfer functions:

$$\begin{cases} \dfrac{i_a}{u_1} = \dfrac{1}{sL + R} \\ \dfrac{i_b}{u_2} = \dfrac{1}{sL + R} \\ \dfrac{i_c}{u_3} = \dfrac{1}{sL + R} \end{cases} \tag{II.6}$$

For discretizing the system (II.5) the forward Euler method is used. Which is easy to implement and is accurate when sampling period T_s is small enough So $\frac{di}{dt}$ is replaced by $\frac{i(k+1)-i(k)}{T_s}$ and after some arrangements, (II.5) becomes:

$$\begin{cases} i_a[k+1] = \left(1 - \dfrac{RT_s}{L}\right) i_a[k] + \dfrac{u_1 T_s}{L} \\ i_b[k+1] = \left(1 - \dfrac{RT_s}{L}\right) i_b[k] + \dfrac{u_2 T_s}{L} \\ i_c[k+1] = \left(1 - \dfrac{RT_s}{L}\right) i_c[k] + \dfrac{u_3 T_s}{L} \end{cases} \tag{II.7}$$

Where, in the control algorithm, $\mathrm{i_a}[\mathrm{k}]$ is evaluated as the measured current of phase a at the sample k and $\mathrm{i_a}[\mathrm{k}+1]$ is evaluated as the predicted value of the current of phase a at the samplek $+ 1$.

II.2.3 Model predictive control

In this section the goal is to control the load current. MPC exploits the discrete-time model of the inverter to predict the future behavior of the current, for each switching state. Thereafter, the optimum switching statex_{opt} is selected, based on the minimization of the cost function, and directly fed to the power switches of the converter in each sampling interval Ts. [71]

We choose the cost function to be minimize so as to achieve the lowest error between the predicted current and the reference values; which is expressed as:

$$J = |i_a[k+1] - i_a^*[k+1]| + |i_b[k+1] - i_b^*[k+1]| + |i_c[k+1] - i_c^*[k+1]| \qquad \text{(II.8)}$$

Where $i_a^*[k+1], i_b^*[k+1]$ and $i_c^*[k+1]$ are the reference values of the phase currents at the sample $k+1$.

The MPC steps can be described in the algorithm shown in Figure II.2. The algorithm starts with the measurement current at the beginning of the sampling time. Once the variables are available, the model is evaluated for the first switching state obtaining the predicted variables, which are used in the cost function. Depending on the result, the switching state is selected or discarded and the loop is repeated. Once the switching states were evaluated, the selected switching state is applied to the converter.

The MPCC scheme uses finite number of valid switching states of the inverter in order to find the x_opt by using the following steps:

- Step 1: Measure load current $i[k]$and read input reference $i^*[k+1]$
- Step 2: For each switching state, calculate the output voltage of the inverter $v[k]$ using the inverter model
- Step 3 : Predict the current of the next sampling period $i[k+1]$ using the load model.
- Step 4: Evaluate the cost function, or error, for each prediction as, for instance:

$$J = |i[k+1] - i^*[k+1]|$$

- Step 5: Select the switching state that minimizes the cost function, S_{opt}, and store it so that it can be applied to the converter in the next sampling period.

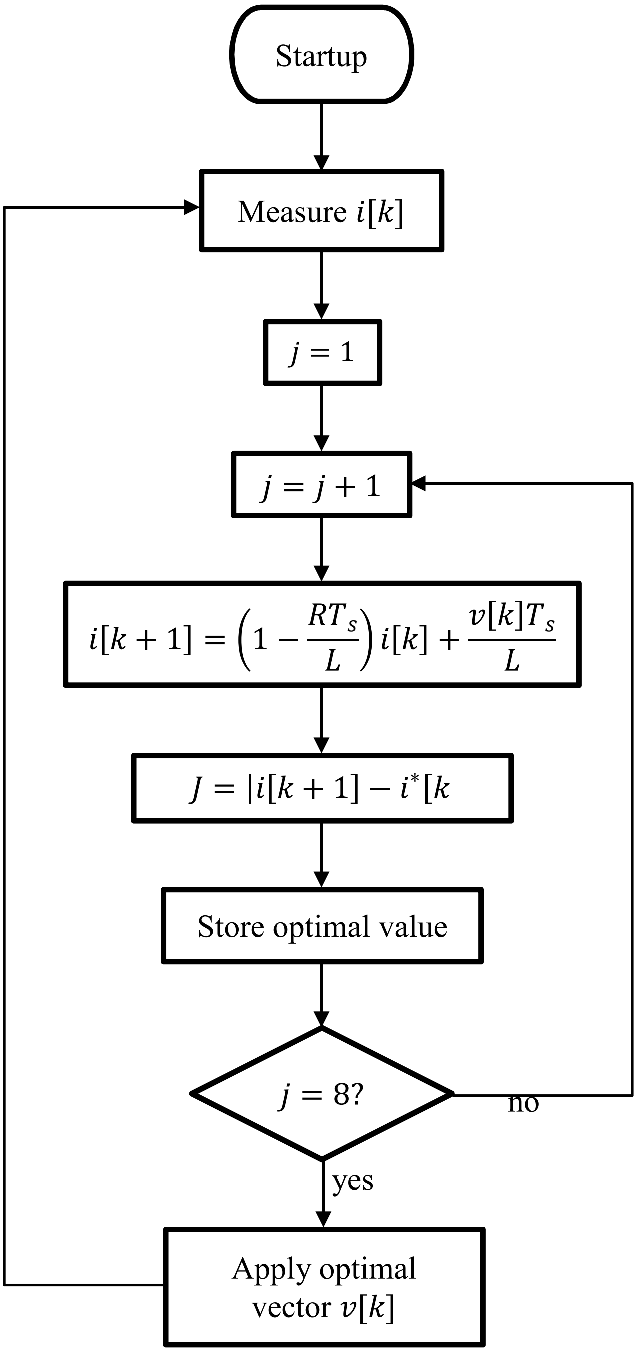


Figure II- 2 : Flow diagram of MPCC

Then in implementation, we should express, the currents and the output voltage of the inverter in $\alpha\beta$ coordinate system, to simplify and minimize the computation time as follow

$$v = \frac{2}{3}(v_a + av_b + a^2 v_c) \tag{II.9}$$

$$i = \frac{2}{3}(i_a + a i_b + a^2 i_c) \tag{II.10}$$

Where:

$a = e^{\frac{j2\pi}{3}} = -\frac{1}{2} + j\frac{\sqrt{3}}{2}$

$i_\alpha = Re(i)$

$i_\beta = Im(i)$

Instead of calculating the output voltage of the inverter for each possible switching state at every iteration, we can calculate them in advance and apply them to the load model.

Table II- 2: Possible switching states and output vector voltage

S_a	S_b	S_c	v
0	0	0	$v_0 = 0$
1	0	0	$v_1 = \frac{2}{3}V_{DC}$
1	1	0	$v_2 = \frac{1}{3}V_{DC} + j\frac{\sqrt{3}}{2}V_{DC}$
0	1	0	$v_3 = \frac{-1}{3}V_{DC} + j\frac{\sqrt{3}}{2}V_{DC}$
0	1	1	$v_4 = \frac{-2}{3}V_{DC}$
0	0	1	$v_5 = \frac{-1}{3}V_{DC} - j\frac{\sqrt{3}}{2}V_{DC}$
1	0	1	$v_6 = \frac{1}{3}V_{DC} - j\frac{\sqrt{3}}{2}V_{DC}$
1	1	1	$v_7 = 0$

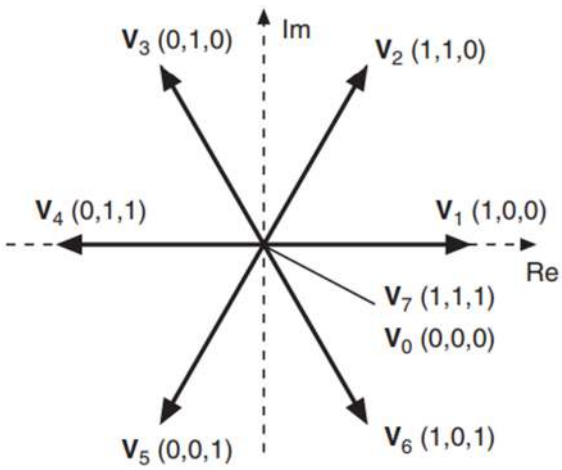


Figure II- 3 : Voltage vectors in the complex plane

In order to reduce the number of calculations for the output current, we can transform the three equations in (II.7) into one equation using (II.10). We obtain:

$$i[k+1] = \left(1 - \frac{RT_s}{L}\right) i[k] + \frac{vT_s}{L} \tag{II.11}$$

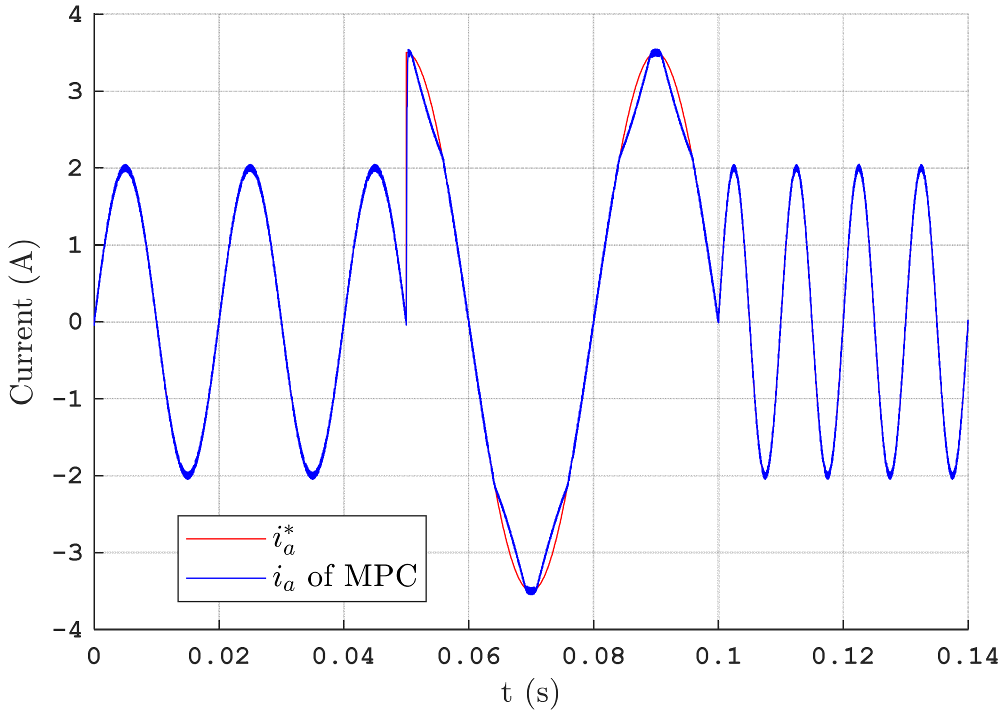
Thus, the cost function (II.8) becomes:

$$J = |i[k+1] - i^*[k+1]| \tag{II.12}$$

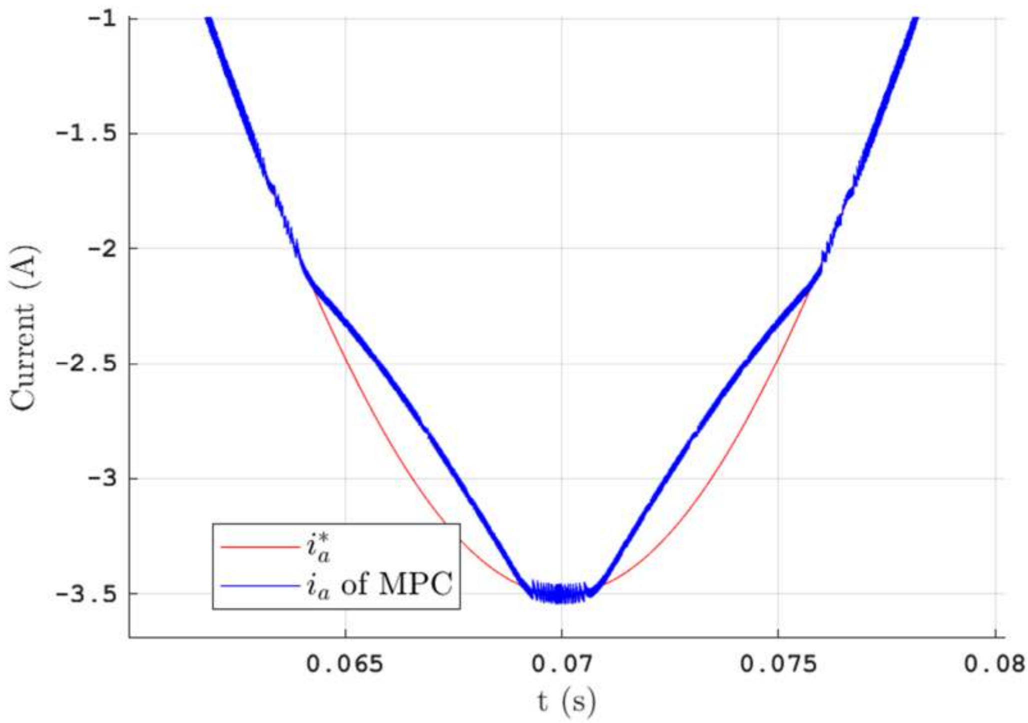
The output voltage vectors of the inverter are stored and selected rather than calculated each sampling period of the algorithm. The calculation of the cost function is a subtraction of two one-dimensional complex variables rather than three-dimensional variables. So, the number of calculations is considerably reduced.

II.3 Simulation Results analysis

In this section we will provide a comprehensive study and evaluation of the proposed control strategy, taking into account different loads under various operating conditions.
To verify the proposed MPCC (Model predictive current control), we used MATLAB (2019b)/SIMULINK software components to implement the SIMULINK model and the simulations results of the system are shown in the figures bellow

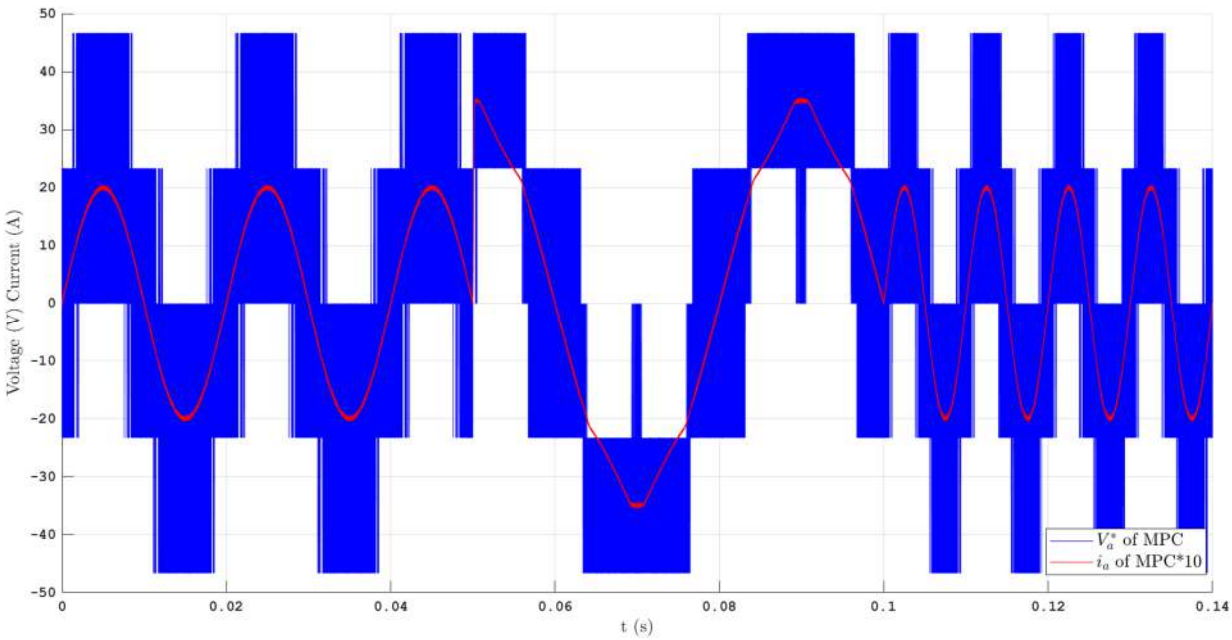


(a)



(b)

Figure II- 4 : Simulation results of current control of a two-level inverter-fed RL load: Reference and output current of phase A and their zoom with MPCC strategy.



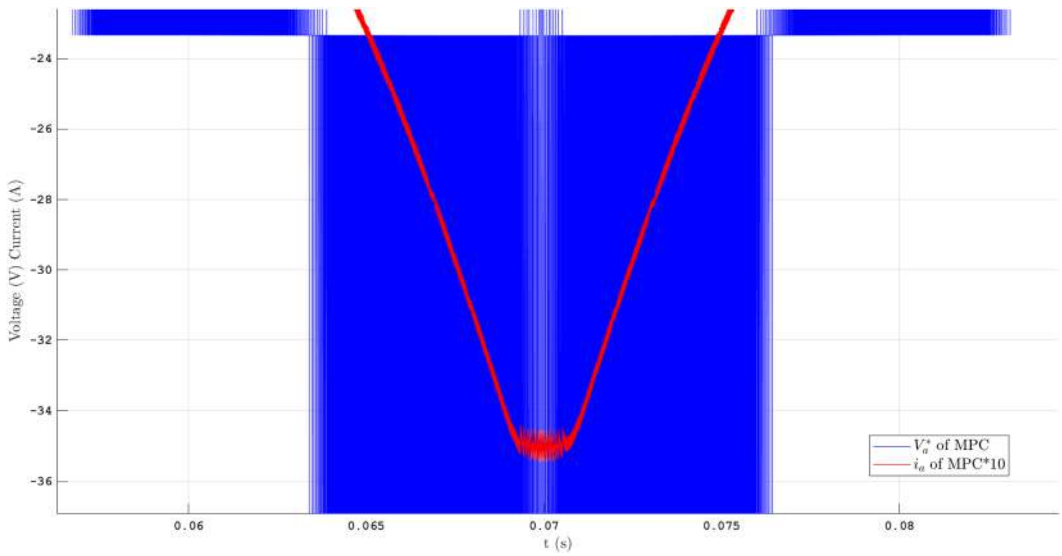
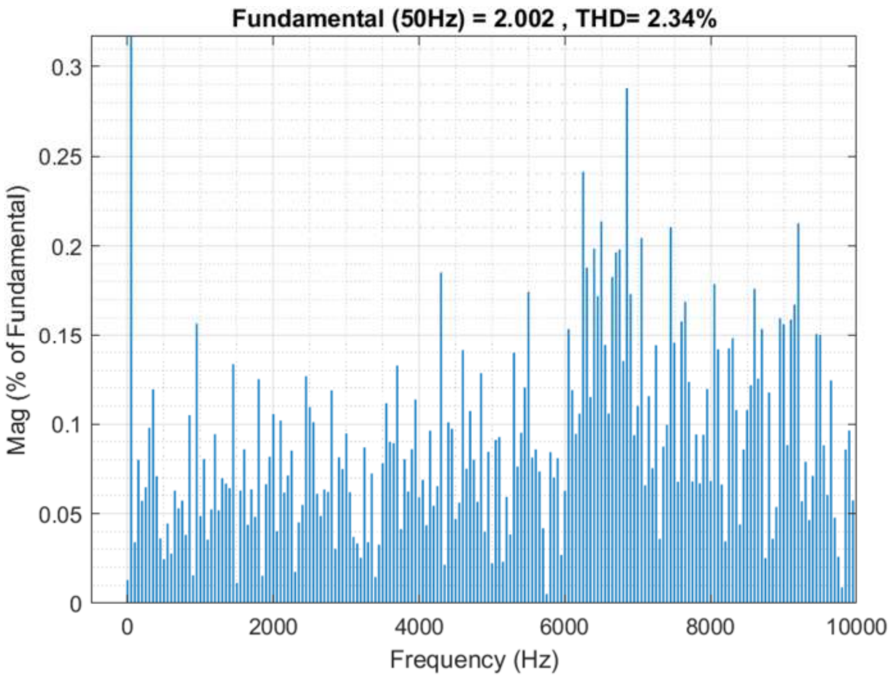


Figure II- 5 : Simulation results of current control of a two-level inverter-fed RL load: Output voltage of the inverter and 10 x the load current of phase A and their zoom with MPCC strategy.



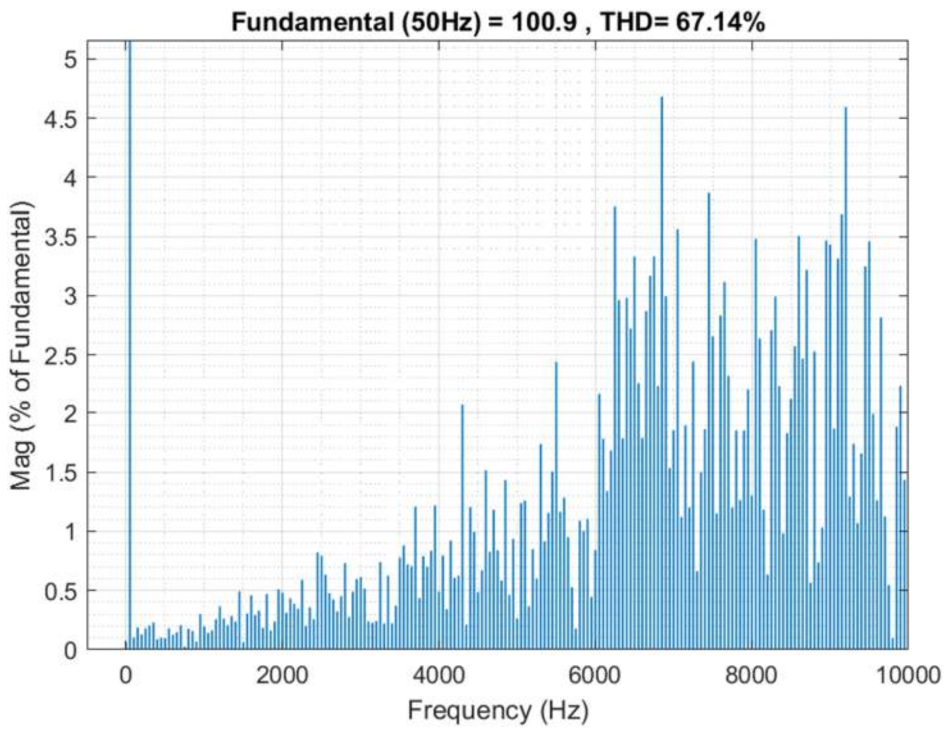


Figure II- 6 : Simulation results of current control of a two-level inverter-fed RL load: Output current and output voltage spectra expressed as percentages of fundamental |I*|=2A and f*=50 Hz with MPCC strategy.

Figure II-4, Figure II-5 and Figure II-6 preent the simulation results of the MPCC of a two-level inverter-fed RL-load

Figure II-4 represents the reference current and the output current with MPCC strategy with zoom, and it shows that for the choisen current reference (magnitude and frequencie), the output current track the reference (magnitude, frequency and phase) in a short response time. The output current oscillate around its reference forming a ripple, or a band, around the reference. The magnitude of these oscillations can be reduced by increasing the sampling frequency, which is not ideal for the power switches and the controller circuit.

Figure II-5 represents the output voltage of the inverter and 10 x the load current of phase A with MPCC strategy. This figure clearly shows that the form of output voltage obtained with MPCC follows the output current form at all the instances.

Figure II-6 represents the output current and output voltage harmonic spectrum of the MPCC expressed as percentages of fundamental magnitude with a fixed reference frequency. This figure shows that the strategy can achieve good THD results.

II.4 Conclusion

In this chapter, the predictive current control strategy was introduced, both the converter and the load have been modelled and a cost function has been expressed. The MPCC working principle was explained in detail.

The control scheme was simulated in MATLAB/Simulink environment for different sampling frequencies and different references but we decided to keep the most relevant result. The load current manages to track its reference and its quality gets better with high sampling frequencies.

The higher sampling frequencies help reduce the ripple of the output current, the error between the reference value and the output value of the load current.

Even though the MPC can work with non-linear loads, it requires at least one derivative or integral in the load model in order to predict the value of the controlled variable.

MPCC of an RL-Load is one of the simplest predictive control schemes, it allows researchers to apply this control to other loads like an induction machine for example.

Chapter three

Artificial neural network based on Model Predictive Current Control of a Three-Phase, Two Level, Inverter-Fed RL-Load

CHAPTER THREE

Introduction

In recent years, model predictive current control (MPC) has been proposed as an interesting alternative for the control of power converters and drives. This control technique uses a model of the system to calculate predictions of the future behavior of the system for a given set of possible actuations for a predefined time horizon[70]. On the other hand, a major drawback of MPC is that it requires the optimization problem to be solved online, which involves a huge amount of real-time calculations. However, different solutions have been introduced in order to address this problem [13].In particular, ANN-based controllers and estimators which have been widely used in identification and control of power converters and motor drives.

This chapter presents a neural network based on MPC scheme for a three-phase, two-level, inverter-fed RL-load. The modeling of the two-level voltage source inverter (2LVSI) and of the load will be presented, the working principle, procedure training will be explained and simulation results will be shown.

In this chapter we present a new control scheme for a two-level converter based on combining MPC and feed-forward ANN, with the aim of getting lower THD and improving the steady and dynamic performance of the system. First, MPCC is used, as an expert in the training phase to generate data required to train the proposed neural network.

Then, once the neural network is fine-tuned, it can be successfully used online for controlling, without the need of using MPCC. The proposed ANN-based control strategy is validated through simulation, using MATLAB/Simulink tools, taking into account different conditions.

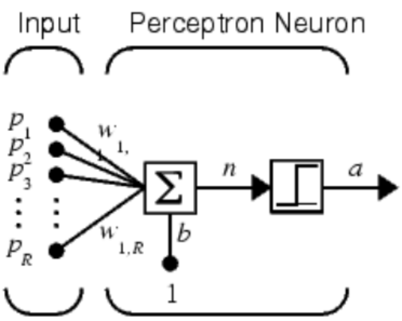
III.1 The artificial Neural Networks architectures

The ANN based on MPCC is absorbed in advantages both neural network and model predictive control, for current control and it undergoes two main steps: (i) we use MPC as an expert or a teacher for generating the data required for training off-line the proposed neural network using standard supervised learning, under full-state observation of the system; (ii) once the off-line training is performed, the trained ANN can successfully control the switching, without the need of using MPC at test time

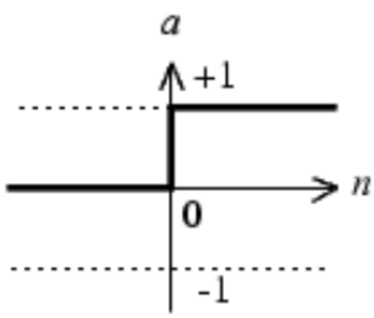
In this chapter, we focus on two different types, perceptron neural network using the hard-limit as active function and feed forward back-propagation which use as activation function Levenberg-Marquardt (trainLm). Though the training data collected from MPC algorithm are the same for both networks, their data processing varies due to the different requires of NN outputs. [13]

III.1.1 Perceptron neural network

The perceptron is a linear combiner that quantizes its output to one of two discrete values. In single-layer perceptron, the input signals p_k are scaled by a set of adjustable weights$w_k$to generate an intermediate output signal$y$, which is then processed by a hard limiter, resulting in the quantized binary output a. This binary output is then compared to the desired response (target), which is also a binary signal, generating an error that is used in a feedback strategy to adapt the weights. The input signals can be binary-valued or they can be drawn according to a continuous distribution. [72]



(a)



(b)

Figure III- 1 : (a) perceptron neural network scheme, (b) the activation function hard-lim

The output unit uses the Hard-limit (threshold) function as an activation function, thus implementing a two-class classification task onto the space {0, 1}

$$a = hardlim(n) \begin{cases} 1 & if\ y > 0 \\ 0 & if\ y < 0 \end{cases}$$

Where: y is the output of the trained ANN.

III.1.2 Artificial Neural Network Fitting (fitnet)

MATLAB R2015a [nnstart] wizard has been used to create and train a network and afterward test the network. Neural network is trained by using Levenberg-Marquardt (trainlm), unless there is not enough memory, in which case scaled conjugate gradient back-propagation (trainscg) will be used. These algorithms display competitive advantages over one another.

Artificial Neural Network Fitting (fitnet) is used for static fitting problems with standard two layer feed forward neural network trained with Levenberg- Marquardt (LM) algorithm, denoted by 'trainlm', works faster when it trains a moderate-sized feed forward neural network that can hold up to several hundred weights [23] and supports the training with validation and test vectors, The data are randomly divided into 70% training, 15% testing and 15 % validation. The training data are used to adjust network weight as per error. The validation data are used for network generalization and to halt training when generalization stops improving. The testing data have no effect on training and it provides an independent measure of network performance during and after training. The hidden layer neurons are increased when network is not performing well after training. The training stops automatically when generalization stops improving as indicated by an increase in the mean square error (MSE) of the validation data samples. [72]

III.2 ANN training procedure

The ANN takes as inputs the measured current$i$, the reference current i^* , all expressed in $\alpha\beta$ coordinates. The real and imaginary parts of these variables are separately fed to the neural network, bringing the total number of input features to four i.e., *inputs* =4. The outputs of the ANN are the three control signals Sa, Sb, Sc.

The training data, which have been collected by MPC, comprises10 experimental conditions; in each experience we choose a specific value of resistance (R= 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 Ω) with different values of current of reference i^*,

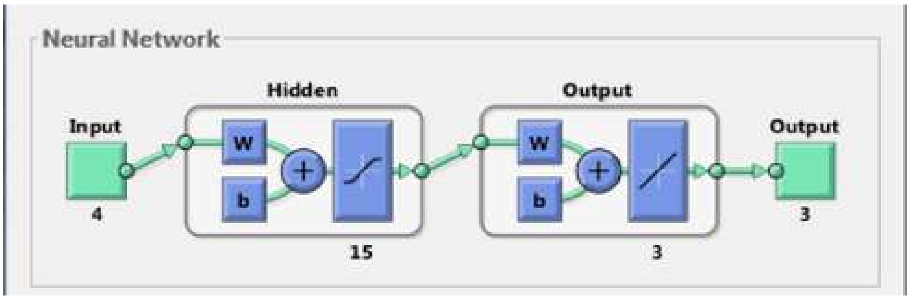


Figure III- 2 : General topology of the 15-neuron hidden layer feed-forward ANN

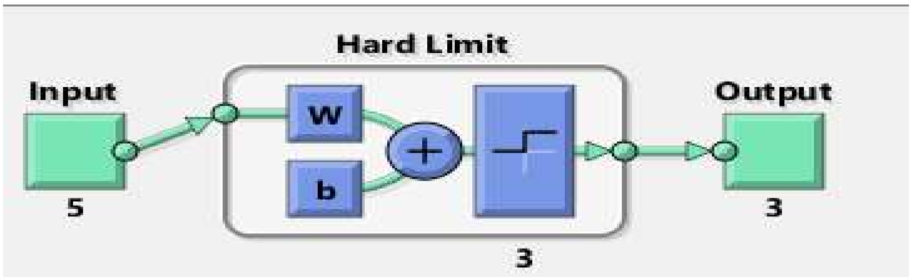


Figure III- 3 : General topology of single layer perceptron neural network

The following table presents the NN training parameters

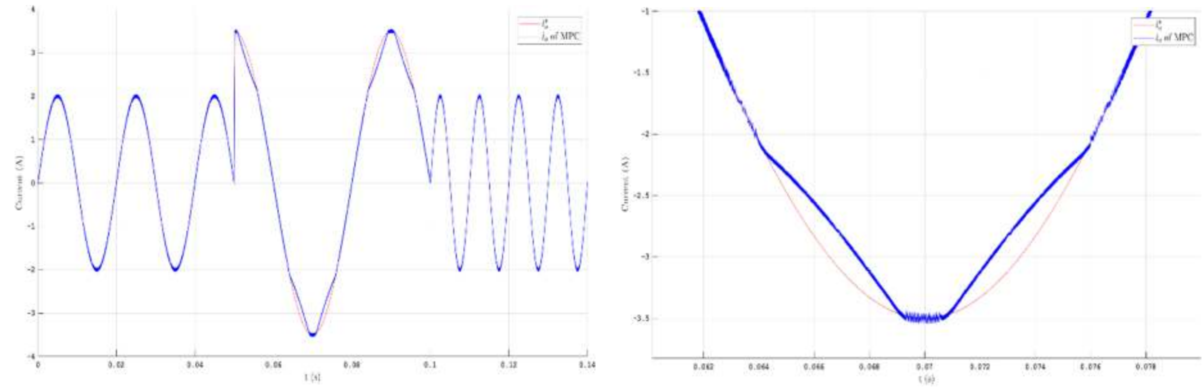
Table II- 3 : the training parameters

	Perceptron	Feed forward back-propagation
Epochs	1	1000
iterations	1	278
Training time	48 mn	27mn
MSE	0.78262	0.058118
regression	-	0.81175
Hidden layers	Single layer	One hidden layer (15 nodes)

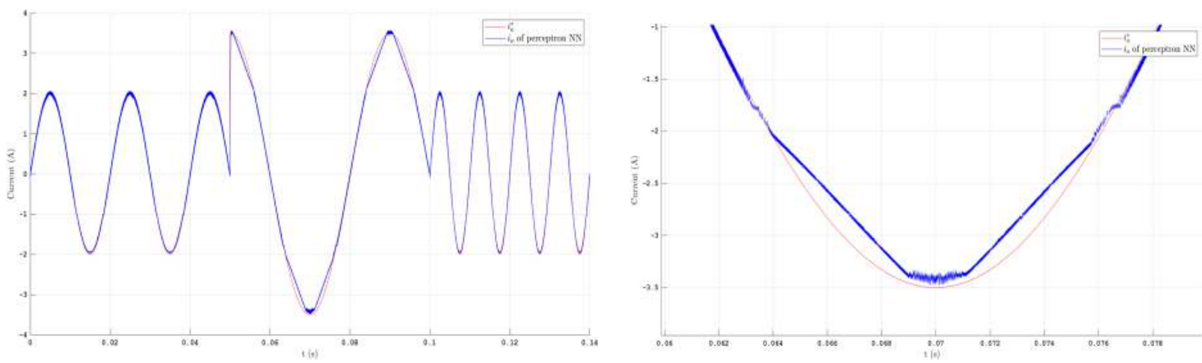
III.3 Simulation Results and analysis

This section provides a comprehensive study and evaluation of the two proposed control strategies, taking into account different loads under various operating conditions.

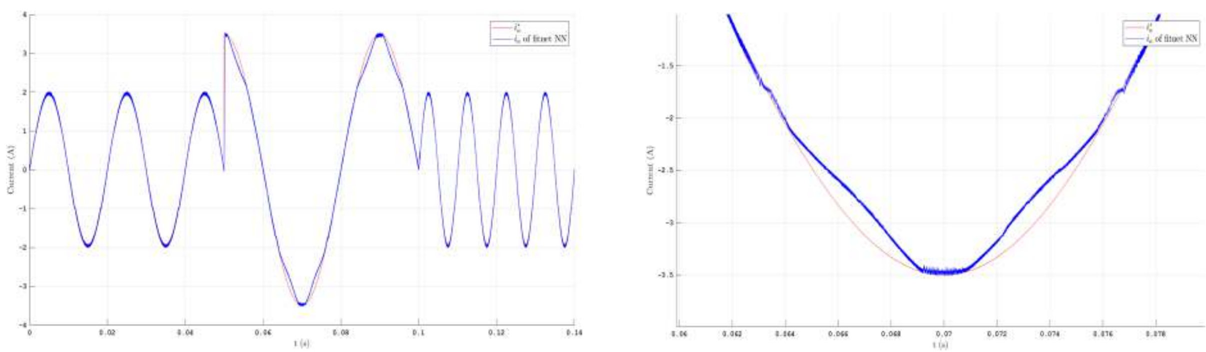
To verify the proposed ANN-based control strategy (model predictive current control) and compare its performance with the conventional MPC, we used MATLAB (R2019b)/SIMULINK software components to implement the SIMULINK model and the simulations results of the system are shown in the figures bellow



(a)

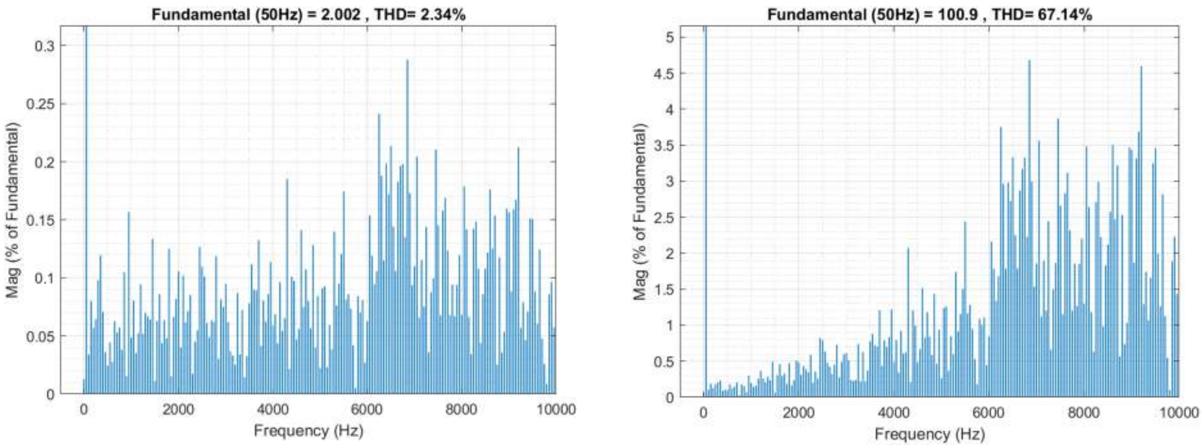


(b)

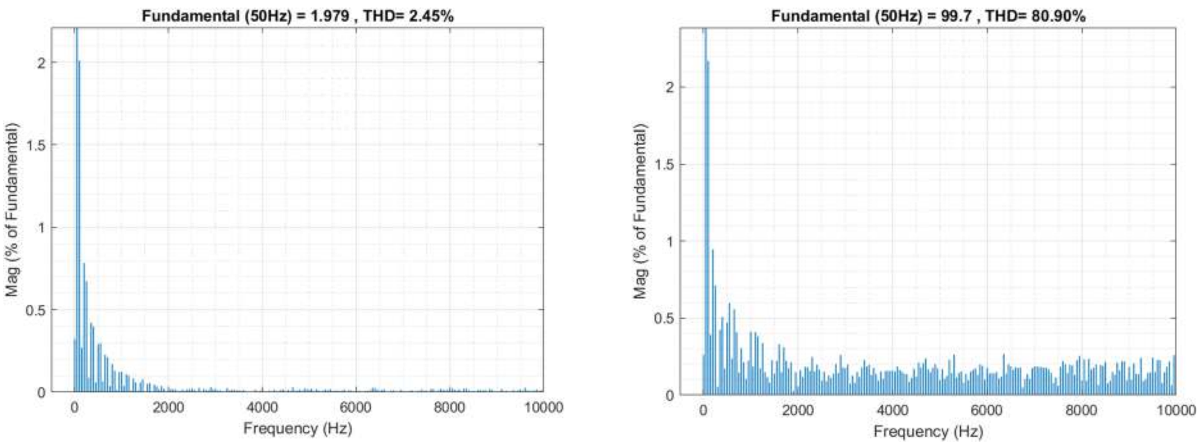


(c)

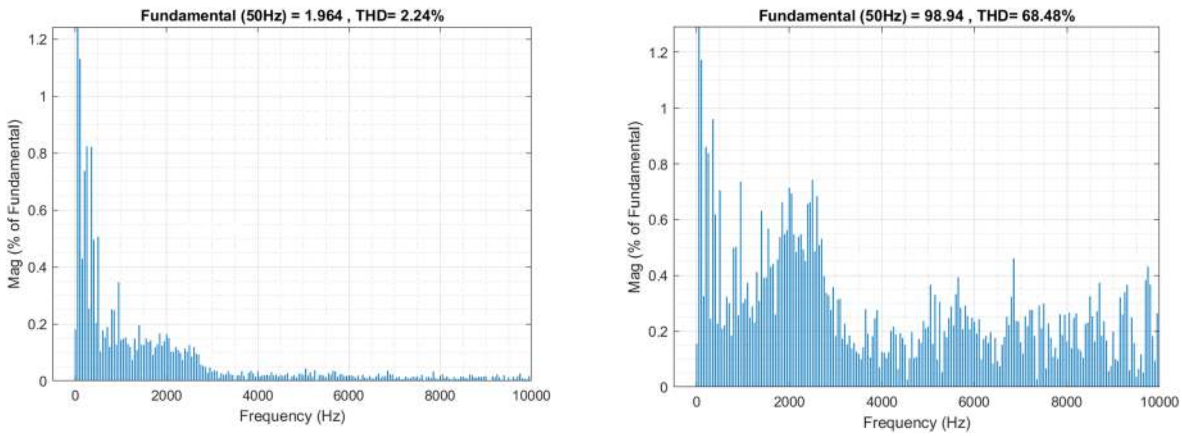
Figure III- 4 : Simulation results of current control of a two-level inverter-fed RL-load: Reference and output current of phase A and their zoom. (a):MPCC, (b):PNN, (c):fitnet



(a)



(b)



(c)

Figure III- 5 : Simulation results of current control of a two level inverter-fed RL-Load: Output current and output voltage spectra expressed as percentages of fundamental magnitude,$|\mathbf{I}^*| = \mathbf{2\ A}$ and $\mathbf{f}^* = \mathbf{50\ Hz}$ with (a) MPC, (b) fitnet, (c) PNN

Figure III-4 shows the simulation steady performance of the MPC controller, PNN, and fitnet controller. For Fig III-4((a), (b), (c)), the outputs currents are controlled to track their references (different magnitudes and frequencies), the output current of MPC oscillates around its reference forming a ripple, or a band, around the reference while in the ANN-controllers almost are superimposed. The output current (2A, 50Hz) The ANN-controllers can track theirs references with fast dynamic response. In addition, both of the ANN-controllers have good wave form current effect compared to the MPC. Also, it can be noticed that current of fitnet is smoother than PNN.

Figure III-5 represents the output current and output voltage harmonic spectrum of the MPC, PNN, and fitnet controllers expressed as percentages of fundamental magnitude with a fixed reference frequency and magnitude. This figure clearly shows that ANN-controllers can achieve good THD results compared to MPC, it can be seen that the output current quality of ANN-based approach is improved significantly, with a current THD of 2.45% for PNN, 2.24% for fitnet compared to 2.34% for MPC.

III.4 Comparison of the three methods

The advantages and disadvantages of the proposed methods are summarized as follow: regarding the computation burden, the ANN-controllers method have the lowest computation, this is the key advantage of the ANN compared to the MPC method. For the control performance, the THD of output current of the fitnet is the best. However, ANN-controllers has a better ability to handle the input variables, which beyond the training data range. The THD of output voltages obtained using MPC are better than that obtained using the ANN-controller.

III.5 Conclusion

In this chapter, a novel control strategy using an artificial neural network control using two methods, to generate a high-quality sinusoidal output current of a three-phase inverter with an RL load has been successfully developed and simulated, under various operating conditions and we tried to keep the most relevant result.

The output current of the inverter is directly controlled, without the need for the mathematical model of the inverter, considering the whole system as a black box. In this work, MPC has been used for two main purposes: (i) generating the data required for the off-line training of the proposed ANN, and (ii) comparing its performance with the proposed ANN-based controller for various conditions. Simulation results, based on a test with different references beyond the training data range, it shows that the proposed ANN-based controllers give better performances than MPC in terms of a lower THD. Fitnet provides a better control performance compared to PNN.

Chapter four

Implementation of MPCC and RNN controllers of a Three-Phase, Two Level, Inverter-Fed RL-Load

CHAPTER FOUR

Introduction

In order to verify the theoretical developments, emphasize the appeal of the MPCC strategy and the ANN control based on MPC. An implementation test has been done in a CDER laboratory.

In this chapter, we will describe our testbench for the implementation of the MPCC and the RNN controllers, and going to present the experimental results at the end.

IV.1 Testbench Description

The test bench is composed of a DC source that can be adjusted by an autotransformer that generates variables AC voltage, this later is then transformed to a DC current be means of diodes and capacitors, the three phases inverter are controlled by a STM32 NUCLEO-F446RE electronic card, the generated PWM signals are amplified using a driver card, the used load is an association in series of a variable resistors and an inductance load, the output current and voltage are then measured using special sensor electronic cards.
Figure IV.1 shows the entire testbench

Figure IV- 1: MPC-RNN testbench

IV.2 Materials and Methods

IV.2.1 Sensors cards

The electrical signal provided from the current sensor is an alternative AC voltage which the peak can reach 15 volts, whereas inputs of the development board STM42F446RE are limited to a positive voltage with only 3.3 volts as a peak. In order to solve this problem, a signal adaption stage is involved, it contains the following elements:

- Reducing the amplitude of measured signals.
- Shifting the measured signals.
- Filtering the measured signals.

IV.2.1.1 Current cards

current cards description is shown in the figure below:

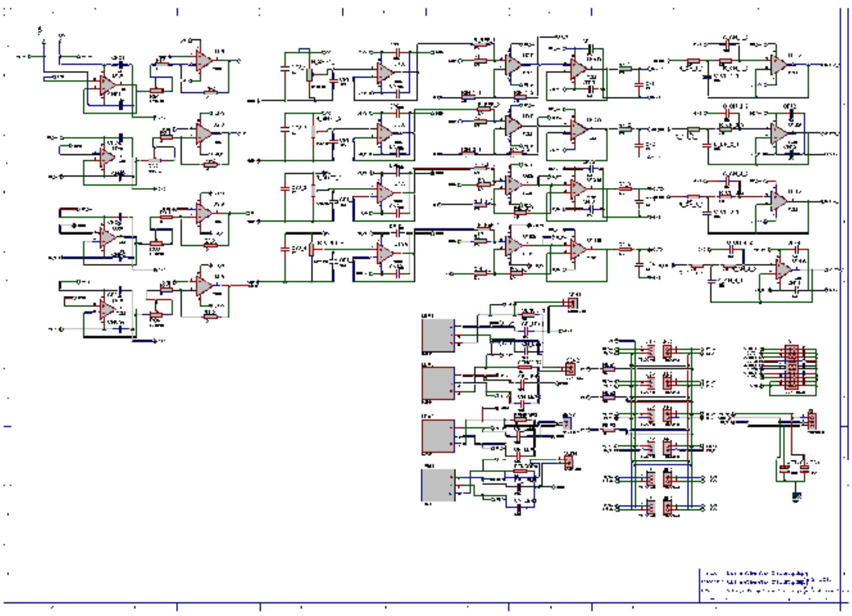


Figure IV- 2 : Current sensor card circuit.

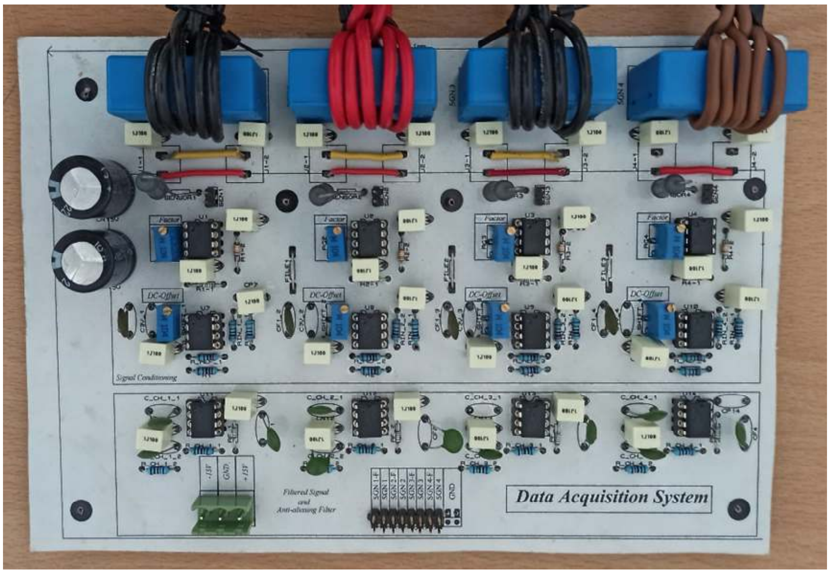


Figure IV- 3 : Current sensor card.

IV.2.1.2 Voltage cards

voltage cards description is shown in the figures below:

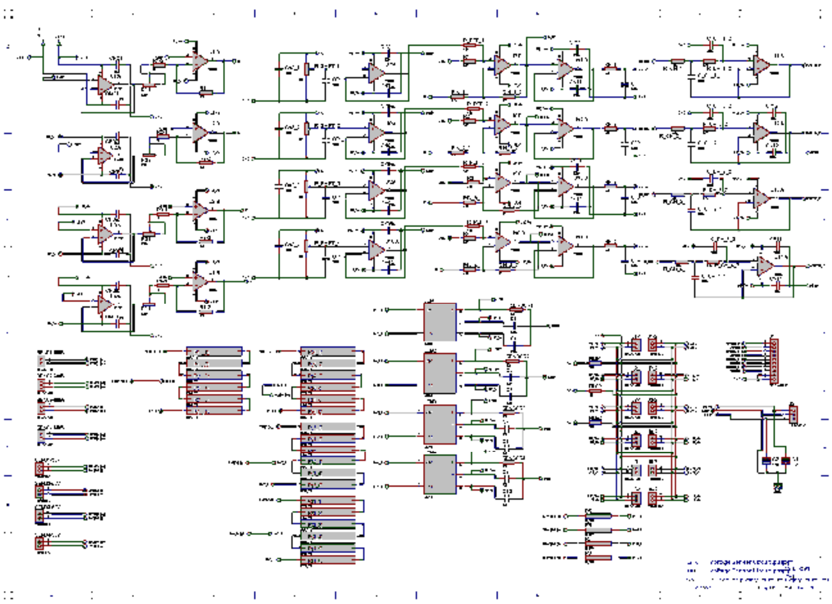


Figure IV- 4 : Voltage sensor card circuit.

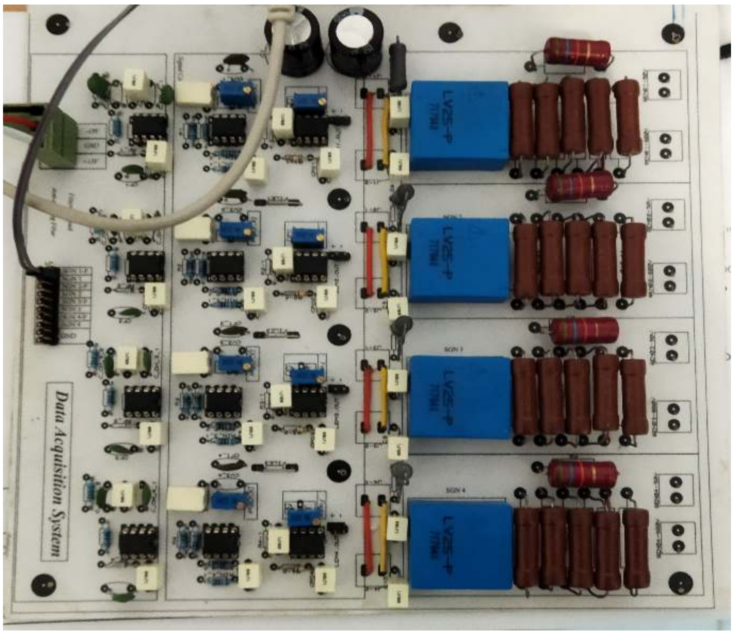


Figure IV- 5 : Voltage sensor card.

IV.2.2 Driver card

Galvanic isolation between the power circuit and the control circuit is ensured by the optocoupler TLP250 (Figure IV-6). An optocoupler is an electronic component used to transmit an electrical signal between circuits without any galvanic contact between them (Figure IV-7).

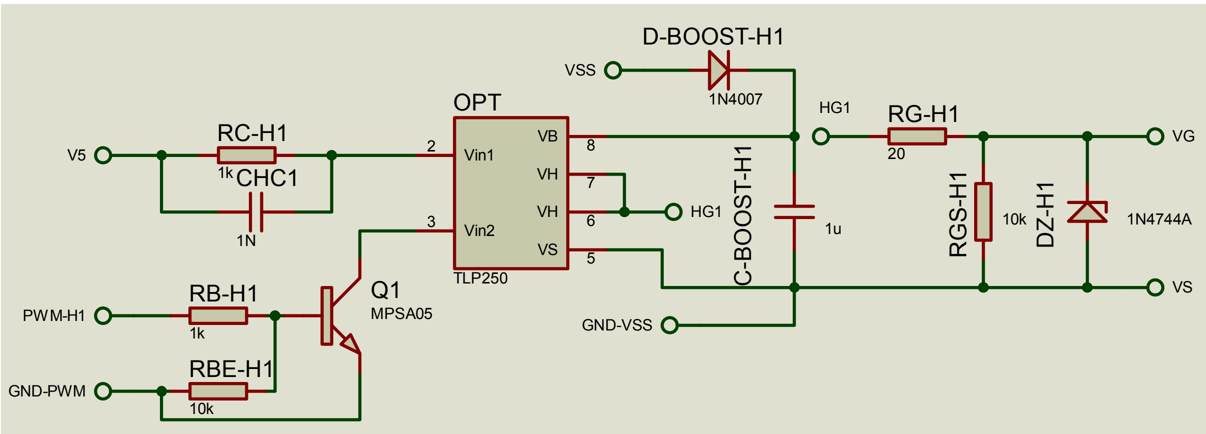


Figure IV- 6 : Circuit scheme of the optocoupler.

The operating principle of TLP 250 is summarized in the following truth table:

Table II- 4: Optocoupler TLP250.6 truth table.

		Tr1	Tr2
LED input	**On**	**On**	**Off**
	Off	**Off**	**On**

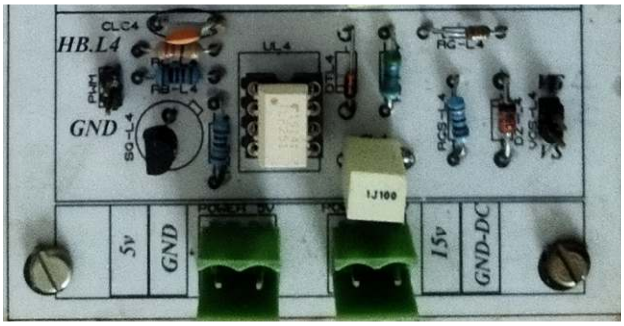


Figure IV- 7 : Optocoupler TLP250.

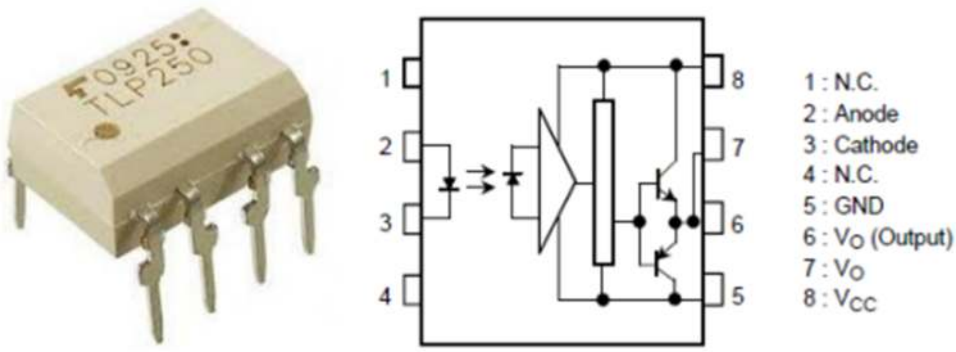


Figure IV- 8 : Symbol scheme of optocoupler TLP250.

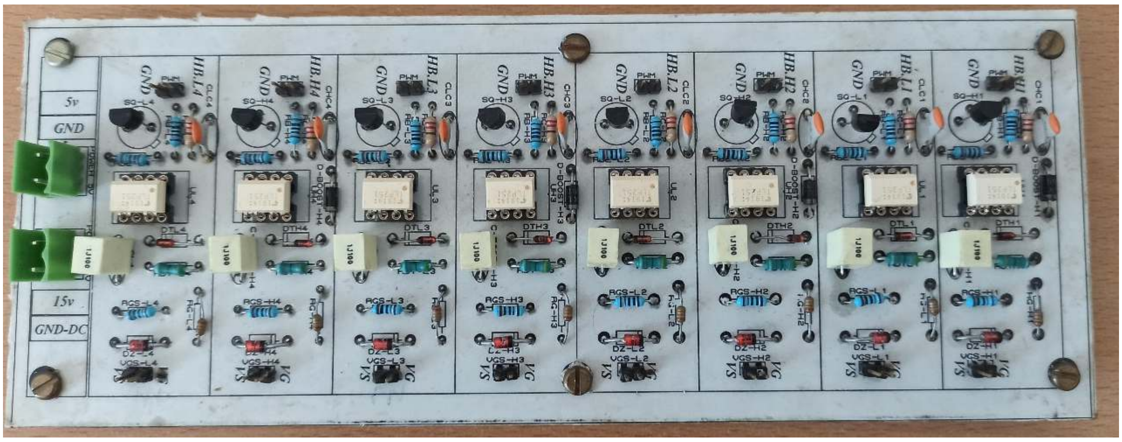


Figure IV- 9 : Driver card.

IV.2.3 Power circuit

IV.2.3.1 The inverter

The inverter used for the test bench is based on the MOSFET IRFP 460 which is capable of supporting a maximum voltage of 500V and a maximum current of 20A, its maximum switching frequency is 1MHz, a protection circuit is added to protect the switches from overheating.

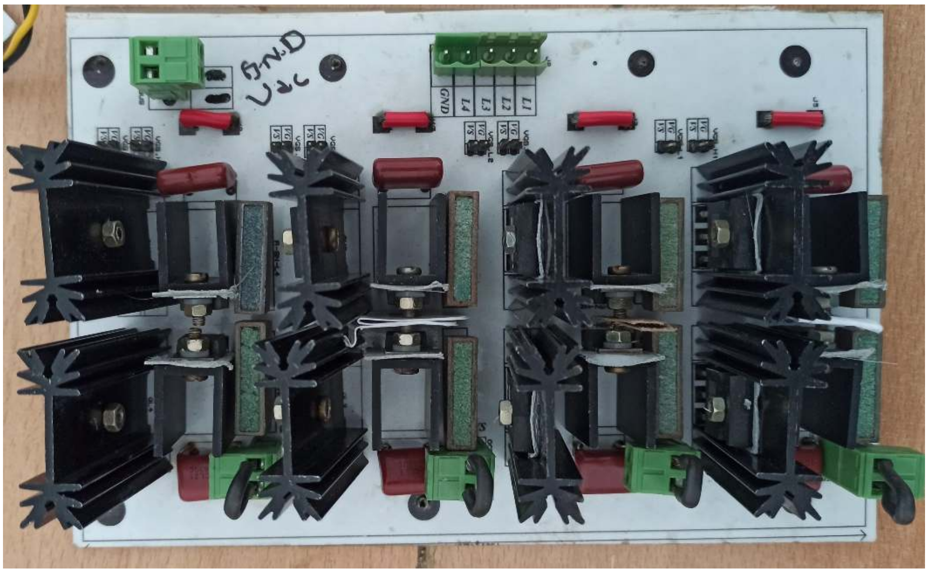


Figure IV- 10 : Inverter circuit.

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IV.2.4 The RL-load

The load is an association in series of a variable resistors and a 3mH inductance load.

Figure IV- 11 : The RL-load.

IV.2.5 Power supply

In order to supply all the circuits and cards used in our testbench we will use two main power supplies. For the sensors cards, we will use 15V DC 2A power supply, and for the driver card, we will use a 15V DC and for the TLP250 optocouplers and a 5V DC supply for the STM32F4 Card.

Figure IV- 12 : 15V LF1502D supply.

For the inverter, we generate a DC voltage source by means of an autotransformer that generates variable AC voltage (from 220V) with a range of 0 to 200%, the generated voltage is transformed to a DC current be means of diodes and capacitors.

Figure IV- 13 : DC source.

IV.2.6 Development card

The development card used for the implementation is the Nucleo STM32F446RE. The STM32 Nucleo-64 board provides an affordable and flexible way for users to try out new concepts and build prototypes by choosing from the various combinations of performance and power consumption features. The STM32 Nucleo-64 board does not require any separate probe as it integrates the ST-LINK debugger/programmer. The STM32 Nucleo-64 board comes with the STM32 comprehensive free software libraries and examples available with the STM32Cube MCU Package.

• Common features:

– STM32 microcontroller in LQFP64 or LQFP48 package

– 1 user LED shared with ARDUINO®

– 1 user and 1 reset push-buttons

– Board connectors:

◦ ARDUINO® Uno V3 expansion connector

◦ ST morpho extension pin headers for full access to all STM32 I/Os

– Flexible power-supply options: ST-LINK USB VBUS or external sources.

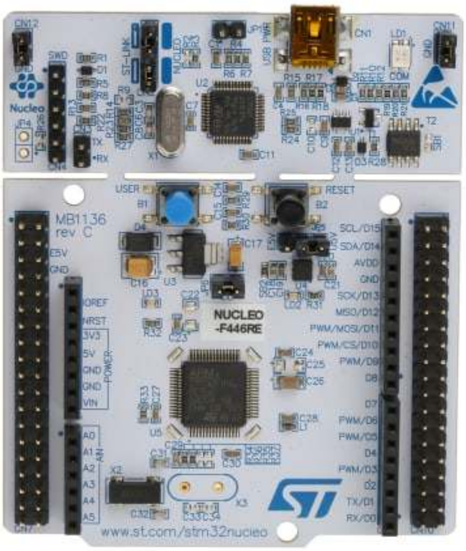

Figure IV- 14 : Development card STM32F446RE

IV.3 Implementation of the program

Implementation test:

In order to test the card and the signals amplitude and frequency we will implement a simple program and observe the results:

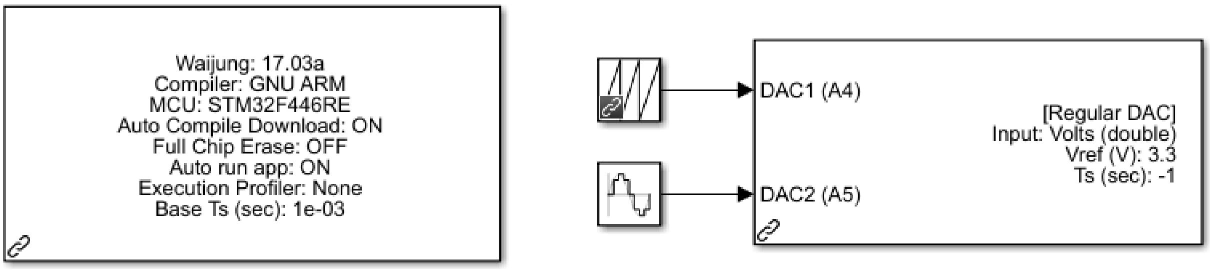

Figure IV- 15 : The model used for test implementation.

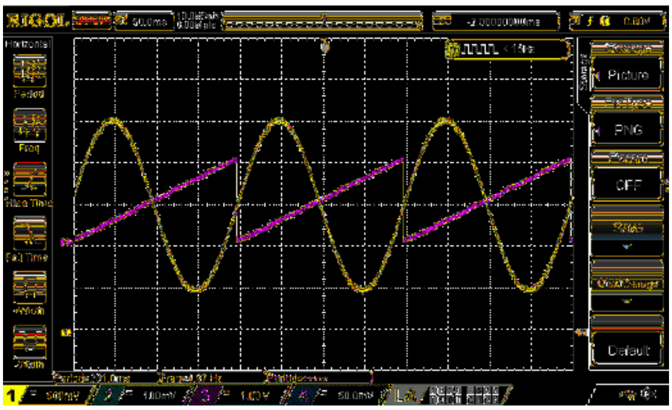

Figure IV- 16 : Signals (sine wave, and sequence generator) test results.

For the implementation, we used Waijung associated with Simulink/Matlab, it is a Simulink Blockset that can be used to easily and automatically generate C code from Matlab/Simulink simulation models for many kinds of microcontrollers (Targets), Waijung has been designed specifically to support STM32F4 family of microcontrollers (STM32F4 Target).

For our application, low frequency was used 40 KHz. The gains in the implementation model are used to adapt the signals returning to the STM32 card.

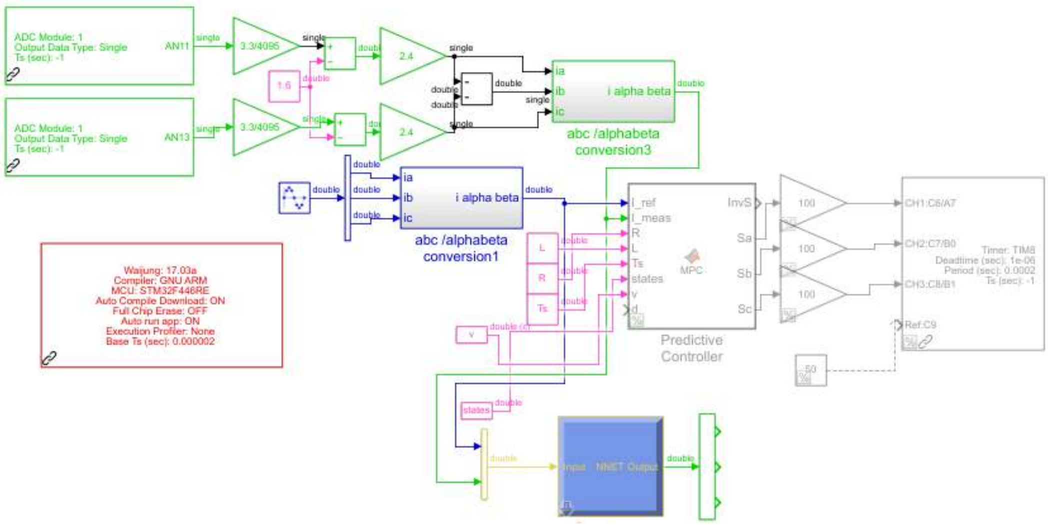

Figure IV- 17 : The model used for real implementation.

Implementation and results

This section provides the obtained implementation results for the proposed control strategies : MPCC and ANN based MPCC.

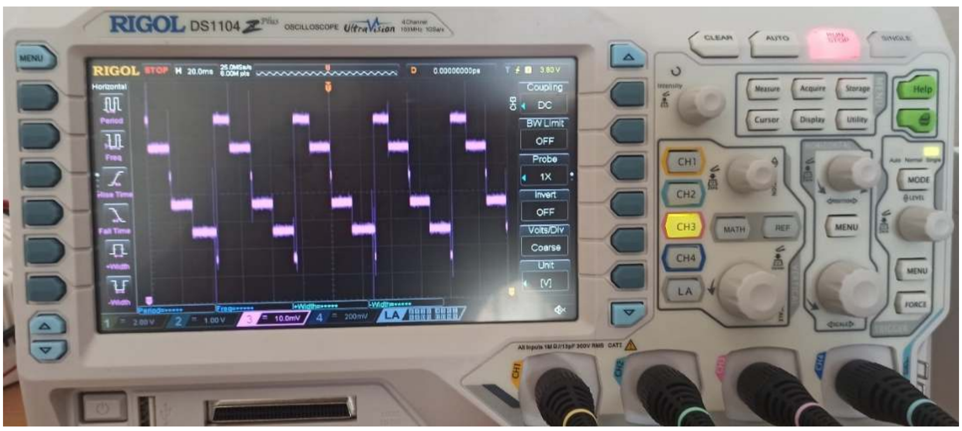

Figure IV- 18 : The cost function signal for MPC controller.

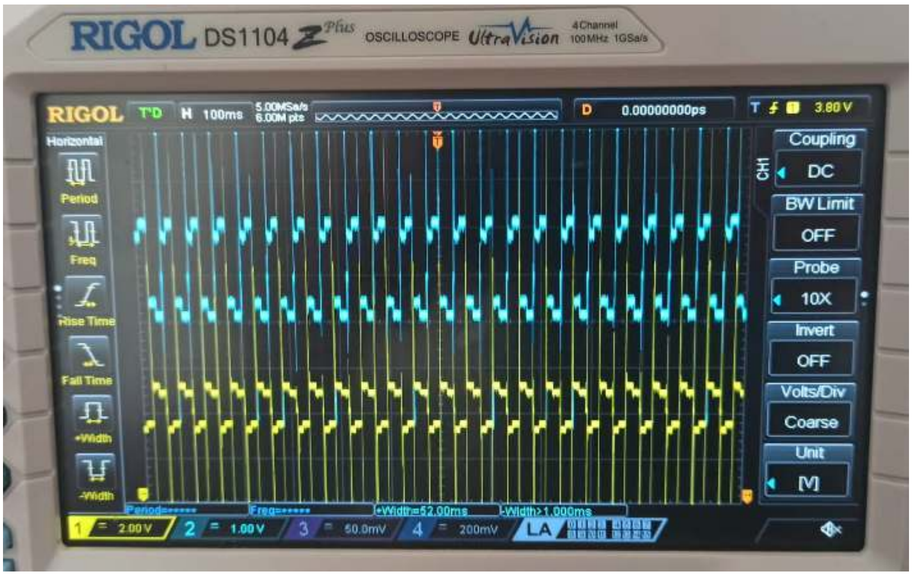

Figure IV- 19 : The output current of phase A and B signals for MPCC strategy.

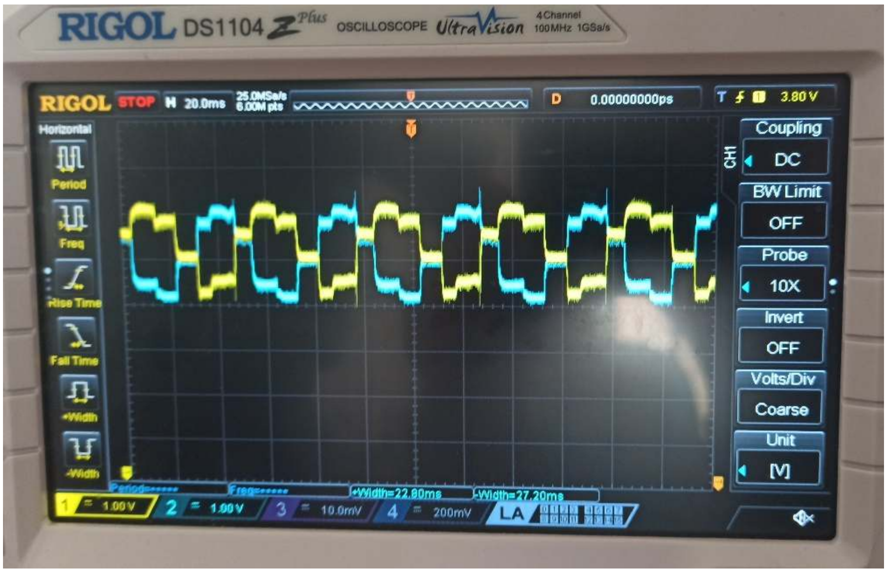

Figure IV- 20 : The output current signals of phase A and B for ANN based MPCC strategy.

Figures from Figure IV-12 to Figure IV-18 present the simulation results MPCC of inverter fed RL load.

Figure IV-18 shows the signal of the cost function for the MPCC strategy on the oscilloscope. As we can see, the cost function is variable which means that the output states of the MPC controller varies too, this shows that the real implementation of MPCC has succeeded and the algorithm works perfectly in the closed loop. The result also shows that the feedback current has been well transmitted to the controller card (STM32).

Figure IV-19 shows the output current signal with the MPCC control on the oscilloscope. We can see that the signal form approximates a sinusoid with measurement noise, it's because of the card capacity in terms of switching frequencies. Also, it is due to the lack of signals filtering of the feedback current.

Figure IV-19 shows the output current signal with the ANN-MPCC (Perceptron NN) control on the oscilloscope. compared to the previous signal, we can see that there is a measurement noise, but the results are better than the MPCC strategy, there are fewer computation, as a result, the card can support the feedback frequencies, and the form of output current signal with this strategy is even closer to a sine wave.

IV.4 Conclusion

The work and the study presented in this chapter have discussed the real implementation of two current control strategies: MPCC and RNN. A test bench was used to test practically the two controller performances. The obtained results show us that the MPCC performances are lower than those of RNN, this is due to the calculation needed for the MPCC, and however, the use of more sophisticated card or the association of the STM32 Nucleo with an FPGA can easily improve the results.

General conclusion

GENERAL CONCLUSION

The MPC suffers from the concern of the relatively low computation efficiency. Therefore, we highlight the methods of performance's improvement of the MPC, the neural network is one of the most promoted solution.

The higher sampling frequencies help reduce the ripple of the output current, the error between the reference value and the output value of the load current.
Even though the MPC can work with non-linear loads, it requires at least one derivative or integral in the load model in order to predict the value of the controlled variable.
MPCC of an RL-Load is one of the simplest predictive control schemes, it allows researchers to apply this control to other loads like an induction machine for example.

When we used the ANN-Based MPCC strategy; the output current of the inverter is directly controlled, without the need for the mathematical model of the inverter, considering the whole system as a black box. In this work, MPC has been used for two main purposes: (i) generating the data required for the off-line training of the proposed ANN, and (ii) comparing its performance with the proposed ANN-based controller for various conditions. Simulation results, based on a test with different references beyond the training data range, it shows that the proposed ANN-based controllers give better performances than MPC in terms of a lower THD. Fitnet provides a better control performance compared to PNN.

The last chapter presents the real implementation of the MPCC and RNN based MPCC strategies and all the different components used in a CDER laboratory for a RL-load fed by an inverter, this implementation took a lot of time and many tests in order to adapt the different cards with the program we want to reach. Fortunately we got very good results despite the difficulty of the experience.

According to the studies conducted in this thesis, the neural network based on predictive control has a great capacity in predicting model, and can appeal attributes of nonlinear identification and control. Also this strategy is able to manage abundant number of data and input variables and get trustworthy predictions.

Neural networks has also disadvantages like the need to be trained and this takes a lot of time mostly in power electronics control strategies because of the very high frequency of the variations. Also, the neural networks quality depends on the amount and the variations of the data with those it is trained.

As a perspective to this work, we plan to:

- Implement the control strategy on a more sophisticated card or the association of the STM32 Nucleo with an FPGA to improve the results.
- Implement the control strategy to control an induction machine.

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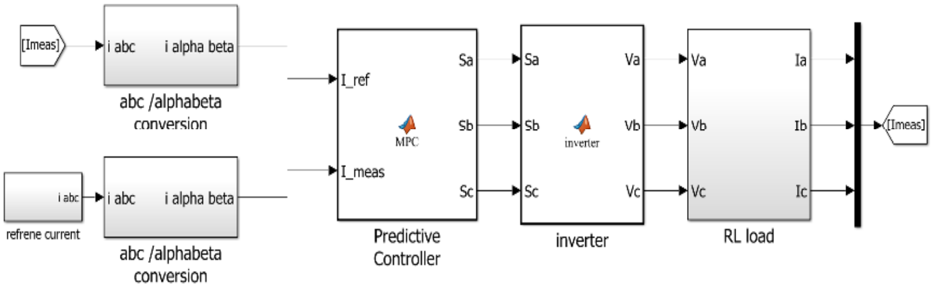
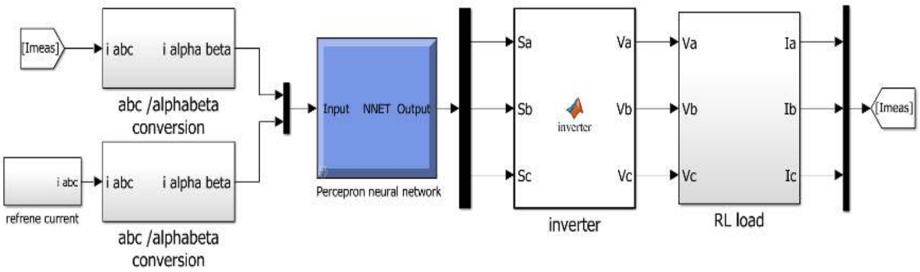
Appendices

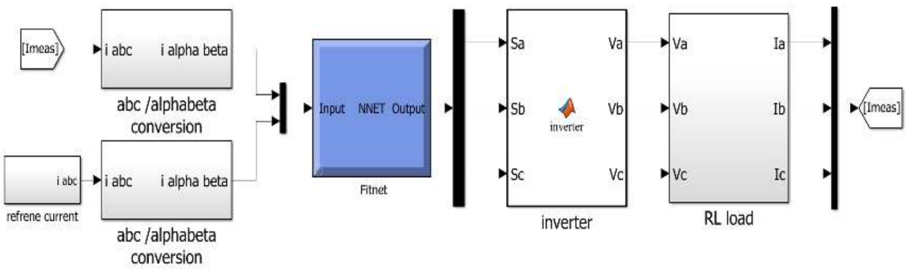
APPENDIX A



(a)



(b)



(c)

Figure A- 1 : Simulink model of a 2 level inverter fed RL load of: (a) MPC, (b) PNN, (c) Fitnet

Parameter	Value
Fixed-step size	5 μs
Solver	ode3
Tasking mode	SingleTasking
Resistance	50 Ω
Inductance	20 mH
DC voltage	300 V

Table A- 1 : Simulation parameters for the MPCC / PNN / Fitnet of an inverter fed RL load

APPENDIX B

Parameter	Value
Resistance	15 Ω
Inductance	3 mH
DC voltage	70 V

Table A- 2 : Real implementation parameters for the MPCC / PNN / Fitnet of an inverter fed RL load