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Thème :

Etat de l'art sur la commande prédictive à base du modèle (MPC) basé sur un réseau neuronalartificiel (ANN)

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ملخص:

الغرض من هذا الموضوع هو وضع توليف ببليوغرافي عن مساهمة شبكات الخلايا العصبية الاصطناعية في تحسين أداء التحكم القائم على النموذج التنبؤي المطبق على المحولات الثابتة.

الكلمات المفتاحية: التحكم التنبؤي القائم على النموذج،الشبكة العصيونيةالاصطناعية، والذكاء الاصطناعي

Abstact

The purpose of this topic is to make a bibliographical synthesis on the contribution of artificial neuron networks (ANN) for the improvement of the performance of predictive model-based control (MPC) applied on static converters.

Keywords: model-based predictive control (MPC), artificial neuron network (ANN), artificial intelligence.

Resumé

Le but de ce sujet est de faire une synthèse bibliographique sur l'apport desréseaux de neurone artificiel (ANN) pour l'amélioration des performances de la commande prédictive à base dumodèle (MPC) appliquée sur les convertisseurs statiques.

Mots clés : commande prédictive à base du modèle (MPC), réseau de neurone artificiel (ANN), intelligence artificielle.

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Dedication

I dedicate this project

To my dear parents MOHAMMED and SONIA this is for that look on your faces when I told you the good news , thank you to never stopped, to say prayers for me, to support me , make me happy and believe on me so that I can achieve my goals.

To my lovely brothers, IYED and ABD EL OUED this is for your permanent support, you were in my sides in every hard step

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To all those I love and those who love me

AYA

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State of the art:

Model predictive control
based on neural network

Introduction

In recent decades, control of electrical drives has been widely studied. Linear methods like proportional-integral (PI) controllers using pulse width modulation (PWM) and nonlinear methods such as hysteresis control have been fully documented in the literature and dominate high performance industrial applications [1, 2]. The most widely used linear strategy in medium and low power electrical drives is field-oriented control (FOC) [3–4], in which a decoupled torque and flux control is performed by considering an appropriate coordinate frame. A nonlinear hysteresis-based strategy such as direct torque control (DTC) appears as a solution for medium and high power applications [4]. By the end of the 1970s, model predictive control (MPC) was being used in the petrochemical industry [5–6]. The term MPC does not imply a specific control strategy, rather it covers a wide variety of control techniques that make explicit use of a mathematical model of the process and a minimization of an objective function to obtain the optimal control signals [7]. The slow dynamics of chemical processes allow long sample periods, providing enough time to solve the online optimization problem. Nowadays, the use of digital signal processors (DSP) and the development of powerful and fast microprocessors have made it possible to use MPC in the power electronics field. The continuously increasing computational power of some common hardware platforms for Power Electronics applications. The first ideas about applying MPC to power converters surfaced in the 1980s [8,9]. The main concept is based on calculating the system's future behavior to compute optimal values for the actuating variables.

I.1 FSC-MPC in power electronics and drives

Due to the broad range of MPC methods [10, 11], the MPC techniques applied to power electronics have been classified into two main categories: Classical MPC and finite control set MPC (FCS-MPC) or Finite-State MPC (FS-MPC) or direct MPC (DMPC) [11]. In the first type e.g., [12] and [11], the control variable is usually the converter output voltage, in the form of a duty cycle that varies continuously between its minimum and maximum magnitude, while an open-loop receding horizon optimization problem is solved at every sampling step to calculate this voltage. On the other hand, the second type, FCS-MPC, uses the inherent discrete nature of the power converter to solve the optimization problem.

Here, the discrete-time model of the system is evaluated for every possible actuation sequence up to the prediction horizon$\boldsymbol{Np}$. Then, the outcomes of these predictions are compared to the reference to select an actuation sequence that best fits the control objectives. Several works have reported the use of this technique on power converters such as the two-level voltage source inverter (2L-VSI) [13], three-level neutral-point-clamped (3LNPC) [14], cascade H-bridge inverter (CHB) [15], flying capacitor inverter (FCI) [16], and matrix converters (MC) [17], whereas the use on electrical drives fed by 2L-VSI and 3L-NPC has been reported in [18–19] and [20,21] respectively. Each application and converter topology has its own control objectives but uses basically the same general control formulation [22]. In drive applications, FCS-MPC can be classified into two main categories according to the length of the prediction horizon: large prediction horizon$\boldsymbol{Np} \geq 2$ and short prediction horizon N p = 1. An example of a large prediction horizon FCS-MPC formulation can be found in [23]. Where a finite state model of a stator current control scheme is presented(PCC). In [24, 21] the same technique is used, but torque and stator flux are controlled.A comprehensive comparison between the steady state performance of short and largeprediction horizon FCS-MPC with respect to FOC using PWM is presented in [25]. The main performance criteria is the compromise between switching losses and stator current (and torque) harmonic distortion achieved by each method. As expected, longer prediction horizons yield better steady state performance than horizon one. However, when larger prediction horizons or more complex converter topologies are considered, the number of calculations grows significantly. The use of only one-step prediction is a less demanding alternative in terms of computational effort and it is chosen in the current work as a benchmark to assess the transient performance of FCS-MPC method against FOC with linear controllers and PWM, [26]. In the recent years, the application of the FCS-MPC in Power Electronics has been tested and proven both theoretically and experimentally. However, the implementation of FCSMPC in the different power converters has given rise to some questions, such as the stability of the control scheme with short and long horizons [27, 28], steady-state error issues [29], weighting factors calculation and the switching frequency operation. Some of these open questions are collected in [30]. A distinctive feature of the FCS-MPC approach is the control flexibility that allows controlling current, voltage, torque, flux and other variables by designing a suitable cost function.

I.2 Model predictive control

In Model-based Predictive Control or Model Predictive Control (MPC), the controller uses the previous and current values to predict the future behavior, it can be computed in a defined prediction horizon. The optimum switching state is selected according to the minimization of a cost function. This scheme can be implemented by considering the inverter control in the algorithm, otherwise a modulator is needed (Classical MPC or continuous control-set MPC or Explicit MPC).

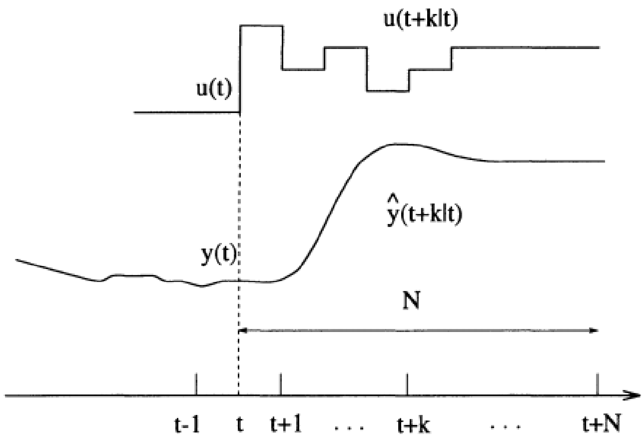

Figure I- 1 : Working principle of MPC

I.2.1 Continuous control-set model predictive control

The total response of the system is computed by summing the natural and forced response. This addition is calculated until the so-called prediction horizon Np is reached. Then, the optimization is carried out by minimizing the cost function for control action variable. The selection of the structure of the cost function depends on the variables which are controlledand their references. Linear and quadratic cost functions are usually selected with the corresponding weighting factors, which may penalize the reference tracking with respect to the control effort. In theory, MPC is able to approximate the performance over an infinite prediction horizon. Unfortunately, the constrained optimization problem needs to be solved online to find a controller output. It has computational complexity, which increases with the prediction horizon. As a consequence, the optimization horizon allows to trade off performance versus online computational effort

I.2.2 Finite control-set model predictive control

FCS-MPC is based on the discrete nature of the converter. In FCS-MPC, the optimal control input among a finite set of control actions, the viable combination of the switching states, are chosen [31]. Due to the advantages of not requiring a modulation strategy and simplicity, FCS-MPC is extensively adopted in many applications, such as control of power electronic converters [32–33].

I.3 Cost function

The most common terms in a cost function are the ones that represent a variable following a reference. Some examples are current control, torque control, power control. These terms can be expressed in a general way as the error between the predicted variable and its reference

I.3.1 MPC's Elements

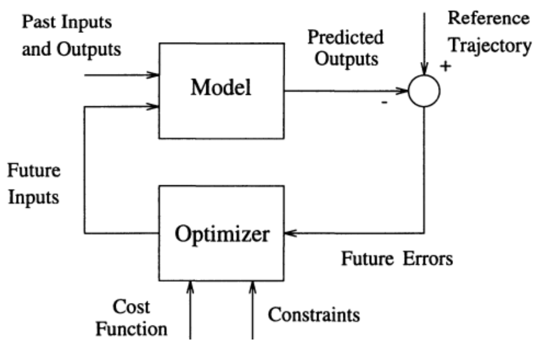

Figure I- 2 : Basic structure of MPC

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

All this makes the existing MPC algorithms suffer from a major challenge: relatively low computation efficiency [34] and huge amount of real-time calculations [35].

I.4 Optimization algorithm

The minimization of the cost function is performed by an exhaustive search for all feasible converter actuation. The proposed control strategy can be described in the following sequence:

- Step 1 Measurement: Sampling to get measurable state variables $\boldsymbol{x}(k)$.
- Step 2 Apply: Set the optimal actuation $\boldsymbol{u}opt(k)$ found in the previous loop iteration.
- Step 3 Extrapolate: Extrapolate the discrete-time model using $\boldsymbol{u}opt(k)$ to estimate$\Delta\boldsymbol{y}(k+1)$.
- Step 4 Predict: Predict the control variables for every possible actuation vector $\boldsymbol{u}(k+1)$, using $\Delta\boldsymbol{y}(k+1)$ as an initial condition for $\Delta\boldsymbol{y}(k+2)$.
- Step 5 Optimize: Select optimal$\boldsymbol{u}opt$. Return to Step 1.

In drive applications there exist some variableswhich its measurement is a hard or unpractical, e.g., measurement of fluxes in an inductionmachine. For this reason, an estimation step is needed in the algorithm.

I.5 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? [36]

At present, the MPC suffer from many problems, such as the lack of systematic handling of uncertainty. Therefore, it is necessary to improve the predictionaccuracy for mismatched prediction models. The other problem is howto design the cost functions and the weight coefficients [37][38] .One of the other drawback of MPC is that it requires the optimization problem to be solved online

II.1Artificial neural network

ANN is a non-linear statistical data modelling tool mimicking the neural structure of the human brain. NNs are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. ANN is trained to perform a particular function by adjusting the values of the connections (weights) between elements. Each such single element is called a neuron. Neurons are arranged in different layers including input layer, hidden layer(s) and output layer. The number of neurons and layers in an ANN model determine the degree ofcomplexity of the network.

II.2Histories

Non-analytical methods discussed in the thesis consider identified system as a “black box” and identify parameters of the model by using a set of data gatheredfrom system’s input and output. When these methods are used, the structure ofthe model has to be chosen before starting the identification procedure or turnedduring it by a predefined algorithm. The structure of the model significantlydepends on its application. For model based control considered in this work, itshould satisfy the needs of the control algorithm.

The history of developing technical systems based on interconnection of nodes representing mathematical models of biological neurons takes its start from the year 1943 when McCulloch and Pitts proposed a mathematical model of the neurons [39]. This model is called an artificial neuron and is used in the most artificial neural networks based applications until nowadays. This model proposed almost 65 years ago is also a major basic element in systems discussed in this thesis. Learning machine built by Edmonds and Minsky in 1951 can be considered as the first artificial neural network simulator. This neural network learning machine, called SNARC (Stochastic Neural-Analog Reinforcement

Computer), was based on Hebb's ideas [40] replicating mathematically what happens when synaptic transmissions occur in the brain [41]. Nevertheless the real beginning of neural networks (NNs) and NN-based learning the invention of a simple neuron like learning network by Rosenblatt [42] in 1962. This simplest layered fully connected neural network is called perceptron. Today multilayer perceptron is still the most popular and the most widespread neural network structure because of its very good and proofed [43] approximation capabilities.It has to be mentioned that very little research was done in the area until about the 1980s mainly because of high computational complexity of training the networks that are capable of solving difficult problems. However, many of the artificial neural networks in use today are still based on the early advances of the McCulloch-Pitts neuron and the Rosenblatt perceptron. The majority of practical neural network based control applications utilize multilayer perceptron as the structure of the network. Numerous examples and research results can be found in literature demonstrating very good approximation, identification and adaptation abilities of this type of neural networks and their relevance to controlsystems design. Majority of research is pointed to approximation capabilities of neural networks and application of this property in technical systems. At the same time significantly lower attention is paid to the structure of the neural network. During the last 20 years multilayer perceptron has shown its very good approximation capabilities and applicability for solving a lot of complex problems from very different fields and therefore it is too general to be the best in each particular application.

II.3ANN modeling approach

There are many challenges in the building operation of neural networks model, which can besummarized as follows:

- Finding the best neural network type.
- Finding the best training algorithm.
- Finding the best activation function.
- Finding the system order.

- Finding the number of the neurons in the hidden layer.

II.4Model predictive control based on neural network

In the last few decades, there has been a significant evolution of traditional control techniques in parallel with the appearance of modern tools associated with artificial intelligence. It should be noticed that most of classical model-based control methods, including nonlinear ones, require the knowledge of the controlled system by means of set of algebraic and differential equations,. Moreover, complete mathematical models describing the systems are often very complex and their parameters need to be known. In real applications, some parameters may be hard to measure or their identification is very complicated. In order to overcome these problems, it is beneficial to use artificial intelligence techniques, such as neural networks, fuzzy logic and genetic algorithms , which do not need the controlled system models and use expert knowledge or experimental data for controller training [43].

Recently, based on a biological prototype of the human brain, the neural networks have attracted considerable attention for modeling uncertain, nonlinear, and complex systems, owing to their learning and adaptation capabilities [44], [45]. In general, the structures of neural networks can be classified as feed-forward NN and recurrent NN [46]

II.4.1 Overview of neural networks

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.

II.4.1.1 The construction of ANN systems

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). [47]

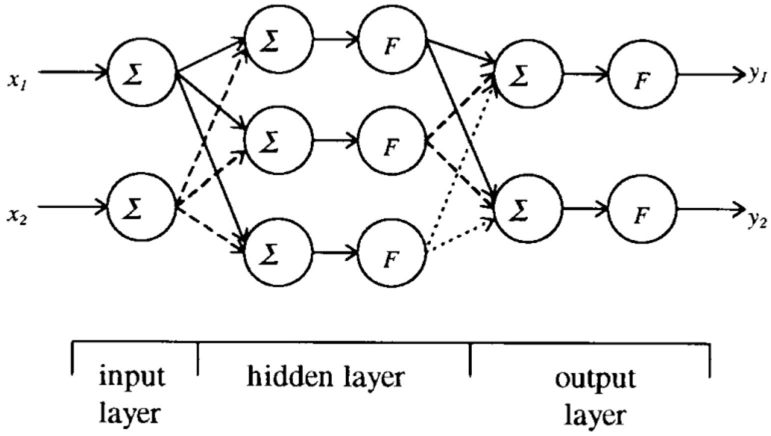

Figure II- 1: A three-layer neural network system

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. [47]

II.4.1.2 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 [47]

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

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 [47]. 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." [48]

II.4.1.3 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 [49].

II.4.1.4 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.[50]

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. [50]

II.4.1.5 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 [51] , 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 [62] 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 [62]

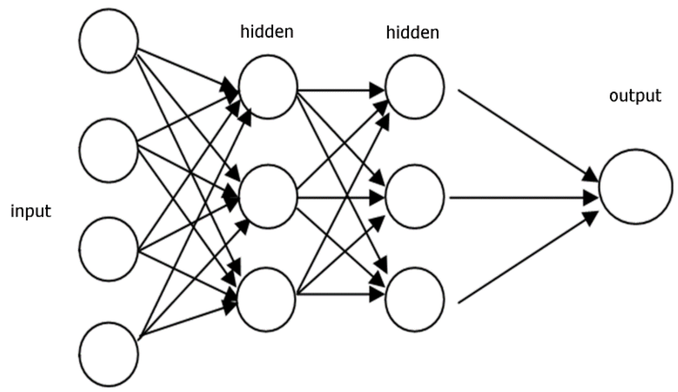

Figure II- 2: The feed-forward neural network

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 [63] 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 [64].Examples of recurrent networks include the Hopfield network [Hopfield, 1982], the Elman network [Elman, 1990] and the Jordan network [Jordan, 1986]. [62]

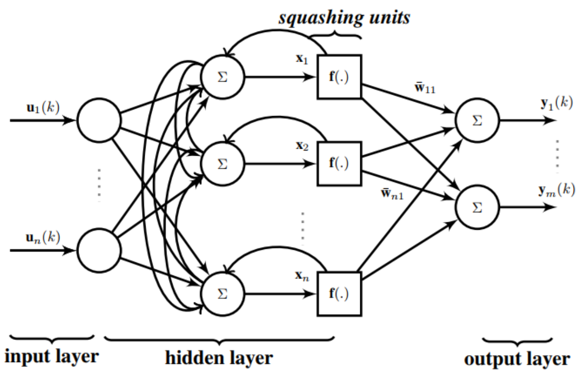

Figure II- 3: Simple recurrent neural network

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 [63]. 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 [64] 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 [65].

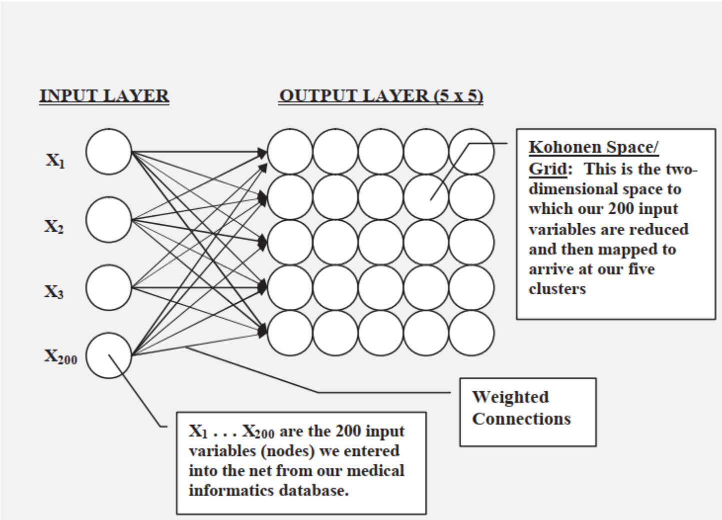

Figure II- 4 : Diagram of a Self-Organizing Map

II.4.2 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.

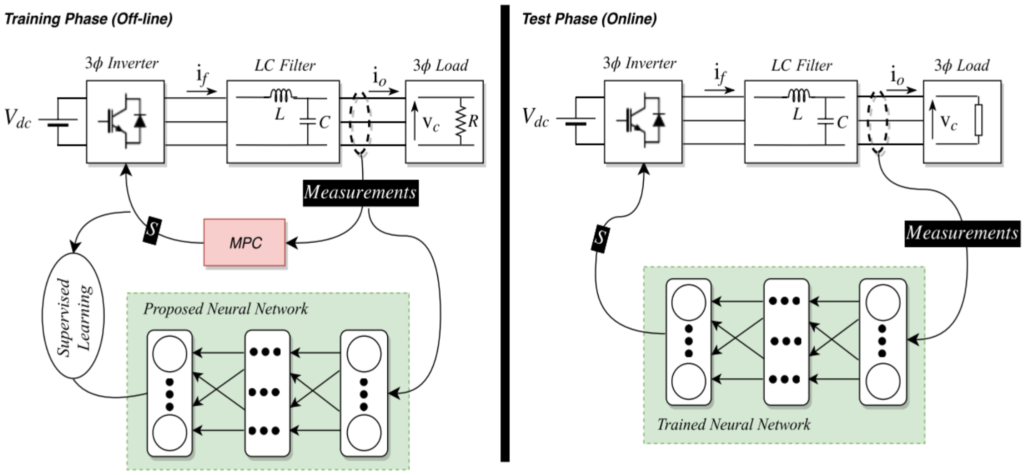

Figure II- 5: An overview of the proposed control strategy

II.5Conclusion

Artificial Intelligence (AI) techniques, particularly the neural networks, are recently having significant impact on power electronics. This thesis explores the perspective of neural network applications in the intelligent control for power electronics circuits.

Neural network based model predictive control for linear and nonlinear systems fed many topologies of power converter (inverter, direct matrix converter, indirect matrix converter…) prove its performance in many terms such as:

Improvement of output current in term lower THD compared to model predictive control, minimization of signals ripples m flux and torque in induction machine

In nowadays neural network take its part in field of electrical engineering particularly on power converter.

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