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***Contribution to Efficiency Enhancement
of Induction Motor Drive using
Artificial Intelligence Techniques***

by

Zineb Rouabah

Electrical Engineer, University of Batna

Master in Electrical Engineering, University of Batna

A thesis submitted for the fulfillment of the degree of
Doctorate of Science in Electrical Engineering

Examining Committee

M.S. NAIT SAID	<i>Professeur</i>	University of Batna	Président
F. ZIDANI	<i>Professor</i>	University of Batna	–Rapporteur–
B. ABELHADI	<i>Professor</i>	University of Batna	Co–Rapporteur–
K. SRAIRI	<i>Professor</i>	University of Biskra	Examineur
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D. KERDOUNE	<i>Lecturer A</i>	University of Constantine	Examiner
S. CHAOUCH	<i>Lecturer A</i>	University of Batna	Examiner

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Résumé

Dans les commandes classiques le flux est maintenu constant à sa valeur nominal hors régime de défluxage constitue un degré de liberté non exploité. Dans la plupart des cas ce degré de liberté est utilisé pour élaborer des stratégies de commande qui minimisent la consommation de l'énergie du moteur tout en respectant les spécifications du couple. Dans ce contexte les techniques d'intelligence artificielles ont été largement exploitées dans le domaine de minimisation des pertes. Parmi ces techniques l'application de la logique floue, les algorithmes génétiques, réseaux de neurones, technique PSO a montrée un degré de performance élevée dans le domaine de l'optimisation énergétique. Le présent travail entre dans ce cadre, où des algorithmes basées sur les techniques intelligentes : à savoir la logique floue et les algorithmes génétiques sont proposés pour optimiser le flux en ligne et par la même améliorer le rendement de l'ensemble motor asynchrone convertisseur statique, en tenant compte des pertes fer et de la saturation dans la machine. Les résultats obtenus attestent de l'efficacité des approches proposées aussi bien pour les faibles charges que pour les charges élevées. La robustesse de ces algorithmes fut aussi testée là aussi les résultats sont assez encourageants.

Mots clés : Moteur asynchrone, Onduleur, Contrôleur Flou , Algorithmes Génétiques Commande vectorielle, Pertes fer.

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Dedication

To my mother memory

To my brother memory

To my father

NOMENCLATURE

- R_s, R_r stator and rotor resistance,
- R_{fs}, R_{fr} stator and rotor iron loss resistance,
- L_s, L_r stator and rotor leakage inductances,
- M magnetizing inductance,
- L_s total stator inductance,
- L_r total rotor inductance,
- σ leakage coefficient,
- σ_r rotor leakage coefficient
- T_r rotor time constant,
- ω motor speed,
- ω_s synchronous speed,
- ω_r
- T_e, T_l electromagnetic and load torques,
- n_p number of pole pairs,
- J motor inertia constant,
- f coefficient of friction,
- v_{sd}, v_{sq} d and q components of the stator voltages,
- i_{sd}, i_{sq} d and q components of the stator currents,
- Ψ_{rd}, Ψ_{rq} d and q components of the rotor flux linkages,
- i_μ magnetizing current,
- PSO Particle Swarm Optimization.

List of Abbreviations

- FOC Field Orientation Control
- LMC Loss Model Controller
- SC Search Controller
- GA's Genetic Algorithms
- RCGA Real coded Genetic Algorithms
- FLC Fuzzy Logic Control

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Introduction

The interplay between economic and environmental issues, increasing energy demand and limited resources, has driven efficiency improvement in every aspects of electrical engineering [Bazzi 2010]. More than 50% of the electrical energy produced worldwide is consumed by motors, mainly the three phase induction ones being the most widely used in industry application. The interest in energy saving is one of the major motivational factors in the introduction of variable-speed drives in some industries. Therefore, it is prevalent to encounter the efficiency computation for electric motors whenever variable-speed is considered, [R.Krishnan 2001]

Induction motors (IM) are imposing themselves as a reliable and more economical choice in a wide range of applications. In industry, they represent an important factor of control.

The efficiency of a drive system is a complex function which depends on the type of the machine, the converter topology and the kind of semi conductor power switches and the modulation algorithm.

Furthermore, the control system has an important effect on drive efficiency. A drive system which normally operates at rated flux yields the fastest transient response. Depending on motor size and design, the rated load efficiency may attain 80 - 90% with power factors of 0.7-0.9. However, when the load is reduced, the performances degrade accordingly [Peter Vas 1999].

Power-loss minimization in induction machines has been investigated for over 30 years. The basic idea of efficiency optimisation control of motors is the adjustment of the motor flux go as to achieve a minimum loss and hence a maximum efficiency. Every motor operating point can be attained by different levels of motor flux and, usually, only one flux value among them ensures a minimum electrical loss. Efficiency optimizing controllers search this optimum value for each operating point and impose it to the machine under control. This leads to a maximum efficiency operation a whole load range [Jinchuan. Li ,.2005].

The IM efficiency optimisation of the drives can be realised by different types of loss minimisation strategies. There are basically two methods for efficiency optimization control: off-line and on-line methods. The off-line method calculates the flux of the motor at each operating point by a set of predefined mathematical equations. The resulting flux values for a range of operating points are then stored in a look-up table. During the motor operation,

the flux value, corresponding to the present operating point, is fetched from memory and is applied to the machine as a command variable. This method is fast and can be implemented easily, since the flux values either exist in memory or are calculated using a simple equation. However, it is very difficult, with this method, to take into account system parameter variations caused by factors like magnetic saturation of iron that affects motor reactance or changes in temperature which affects motor resistances [Jinchuan. Li et al 2005].

To overcome these limitations of the off-line method, on-line efficiency optimization control (loss minimization) has been proposed [S.Vaez , 1999], [N.uddin , 2007], [S.Sergaki , 2008].

Review of Previous Works

Loss Minimization of Induction Motor Drives

Many drives operate at light load most of the time. At light loads, operation with rated flux causes excessive iron losses, thus reducing the efficiency of the drive. For these loads, the slip is small and only small rotor current can flow which result in increased magnetizing voltage , in consequent higher magnetizing current [Peter Vas,1999]. Therefore optimum efficiency at light load operation can be obtained by an appropriate selection of the flux.

Although several papers dealing with the subject have been published Among those focused on the importance of saving energy the one of Nola [Nola, 1977] which proposed a power factor controller. He suggested energy could be saved at light load by restoring the balance between no-load losses and load losses. However limitation of this approach (load must be less than 0.45pu) was demonstrated [Lipo , 1983].

The first strategy of the efficiency optimal control was proposed by [Kusko , 1983]; it is based on an analytical model of losses for induction machine scalar control and direct current (DC) machines. An analysis of motor losses was presented and it is shown that for a given speed and load torque losses can be minimized by adjusting input voltage and frequency.

[Kirshen , 1985] proposed an optimal efficiency controller based on the finding of the minimum input power. Thus, by measuring the input power directly to the DC bus and using the vector control, they propose to gradually adjust the flux and torque stator current components until the input power reaches a minimum

*value for a given output power .It is obvious this strategy has the advantage to minimize the whole losses of the system drive and does not require. any knowledge of the model

parameters however it takes a long convergence time and generate torque ripples when flux value changes.

Loss Model Based Controller (LMC)

Among the techniques leading to efficiency improvement, the so called loss-model – based approach (LMC), which consists of computing losses by using the machine model and selecting a flux level that minimizes these losses. It offers the advantage of fast response and no torque ripples. An overview of previous works is given hereafter.

In their work, [Kirshen., 1984] propose, as part of the design of a scalar control, a loss model much more developed introducing into account hysteresis and eddy currents losses by a resistance R_m . They also include in the equivalent circuit of the induction motor the stray losses. Their investigation also shows the importance of magnetic saturation in the loss model, thus making the optimal slip frequency load dependent and limiting the increase in air-gap flux for large loads.

[Kioskederis,1996] calculated the total of iron loss, copper and stray losses and derived the loss model controller to determine the optimal flux that minimizing the total loss of the scalar control of the induction motor drive. [P.Famouri,1991] derived the per unit efficiency of the IM as a function of slip, frequency and losses including the core loss, the copper losses, rotational power losses and power loss crossing the motor air gap. The optimal efficiency can be obtained at any operating torque and speed by calculating the optimal frequency.

In [Garcia., 1994] the authors propose a new version of the work of [Novotny., 1984], but based on vector control. The optimizing efficiency controller proposed by the authors includes a linear loss model but they did an analysis on the efficiency sensitivity to parameter variations. Parameter that has the greatest influence on the energy efficiency of the system was the rotor resistance R_r .

A loss model including magnetic saturation for machines with AC and DC was presented by [Bernal., 2000].

In [Chakraborty, 2003], a hybrid method combining the loss model and the search approach was presented for the indirect vector control of IM to extract the best of both thus improved the speed and the adaptation capability for a possible change in load or parameters variation. However the computations of loss model and input power measurement have to be done in this method which makes the overall control system more complicated.

[S.Lim , 2004], developed a simplified loss model with leakage inductance. In this model loss was represented as a resistance connected to a dependant voltage source, the simulation and experimental results show that the loss calculation based on this simplified model was closer to that of full model of previous works.

[M.Nasir Uddin , 2008] presented an LMC based on induction motor model in d-q coordinates referenced to magnetizing current which leads to no leakage inductance in rotor. The obtained efficiency optimizer controller was implemented in vector control both simulation and experimental results show the effectiveness of the proposed method.

[C.C.De .Wit,1997] presented a procedure to get minimum energy by deriving the steady state values of current and fluxes for the given load and the design the steady state feedback control based on Lyapunov. Experimental results show good torque capability

One of the failing of LMC is that its precision depends on the accuracy of the motor drive and losses modeling. In the loss model development, a compromise between accuracy and complexity has to be found. To find the loss expression from the full model, it is a difficult task; this is why, in the majority of past literature review, motor models are taken with constant parameters which will lead to the LMC performances deterioration once these parameters are not constant anymore. The online estimation of these parameters can be the solution but it can make the whole minimization scheme more complicated to be implemented in real time [S.Vaez-Zadeh , 2005, [Sang Woo Nam,2006], [de Almeida ,2007].

To solve these issues, intelligent methods like Artificial Neural Networks, Fuzzy Logic, Genetic Algorithms, Practical Swarm Optimization (PSO) can be applied as their design does not require an exact mathematical model of the system and, theoretically, they are capable of handling any nonlinearity.

Search Controller (SC)

In [Sul and Park, 1988], a method that maximizes efficiency by means of finding optimal slip was proposed. The technique can be considered as an indirect way to reduce input power.

In [Sousa , 1995], the authors reduced the flux current reference by minimizing input DC bus power by using fuzzy logic nonetheless the torque pulsation is overcoming by feed forward pulsation torque compensation simulation and the experimental results demonstrate that the convergence time was accelerated. However this controller works only in steady state

when a change occurs in load or speed the control must return to a nominal flux configuration which complicates the system implementation. Also [Bose, 1997] present a neuro-fuzzy version of the previous controller.

The work of [Sul, 1988] proposed an alternative approach to research based on the frequency of optimal sliding. The authors show that at a constant speed, performance depends only on the slip frequency, regardless of the load torque. From voltage and stator current, they deduce the slip frequency, torque and power input. Thus, for invariant load dynamic time, they identify the optimal slip frequency of each operating point and placed it in memory. In normal operating mode, the control system has to adjust the frequency of optimal sliding previously identified.

In [G.S.Kim, 1992] the square rotor flux is adjusted until the measured power reached its minimum; the controller depends on rotor resistance and its variations are also taken into account. Three vector control schemes namely rotor flux orientation, stator flux orientation and air gap flux orientation were studied in [O.Ojo, I, 1993] for IM optimization of torque and efficiency and results shown that rotor flux orientation offers best optimal efficiency.

, [Murphy J.M.D, 1982].

LMC and SC Hybrid Strategy

Other researchers have combined the advantages of both techniques by proposing a hybrid strategy which combines fast convergence and robustness.

The developed controller in [S.N.Vulovasic, 2003] ensures to retain good features of both LMC and SC, while eliminating their major drawbacks. Authors used input power to identify on-line the loss function parameters and optimize flux value. Parameters variation sensitivity and slow convergence were eliminated.

In [S.Ghozzi, K, 2004], LMC and SC both were used and compared. The authors concluded that the LMC is more appropriate in Field Oriented Control (FOC) because the flux can be imposed in a short time while the SC vary the flux continuously which produces more torque ripples.

Artificial Intelligence Based Controller

In classical control systems, knowledge of the controlled system (plant) is required in the form of a set of algebraic and differential equations, which analytically relate inputs with

outputs. However, these models, are often complex, rely on many assumptions, contain parameters which are difficult to measure or may change significantly during operations and sometimes such mathematical models cannot be determined. Furthermore, despite the great devoted efforts classical control theory suffers from limitations due to the nature of the controlled (linearity, time invariance etc..) These problems can be overcome by using artificial intelligence- based control techniques relying on human motivated and procedures [Peter Vas, 1999].

There are many artificial intelligence (AI) based controllers applied to IM optimization through control using fuzzy logic (FL) or artificial neural network (ANN), Natureinspired algorithms, (NIA) like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) seem promising because of their social cooperative approach and also because of their ability to adapt themselves in continuously changing environment [C.Thanga Rag, 2009].

In the field of loss minimization, many works were performed in this area some of them are enumerated below:

[D.H.Kim, 2006] proposed a hybrid technique, GA-PSO based vector control of IM for loss minimization as well as torque control.

[L.Vuichard, 2006] presented a fuzzy controller that enables to calculate the optimal flux value leading to efficiency improvement in short time. They use a linear model.

In [Peracaula, 2002], a loss model including saturation was integrated in artificial neural networks (ANN). The response time of the efficiency optimized controller was about 100-120ms.

[E.Poirier, 2001] derived the loss model by using genetic algorithms to find the optimal flux value. The convergence is very fast. The robustness of the algorithm for parameter variation, was demonstrated.

Problem Identification and Thesis Objective

As mentioned earlier, LMC is suitable for field oriented control but lacks of precision and depends on the accuracy of the motor drive and losses modeling.

To find the loss expression from the full model, it is a very hard task. In the most previous works motor model is taken with constant parameters then when they change the LMC

performance deteriorates. It is always a compromise between accuracy and complexity. Thus the objective of this thesis is to investigate the improvement of the system drive by optimizing energetic performance of IM drive. To perform this task intelligent techniques are introduced so as to make the efficiency optimizer controller derived from the loss model independent of or less sensitive to motor parameter change. In this thesis, the AI energy saving of Induction machine is presented. These AI comprises Fuzzy logic and Genetic Algorithms that are investigated and developed for this purpose.

Thesis Structure

After a general introduction to the undertaken work and the presented literature review, the main body of the thesis is structured as follows:

- Chapter one introduces the basic concepts, notation and basic operations for artificial intelligent techniques such as .Fuzzy logic, genetic algorithms and Particle Swarm Optimization that will be needed for efficiency optimization and control.
- Chapter two presents the induction motor model including iron loss and the inverter loss model. The simplified inverter loss model will developed to be integrated in the efficiency optimization algorithm.
- Chapter three expresses losses which are involved in IM and methods used to minimize them. The optimization is carried out by the use of the artificial intelligence methods described in chapter one.
- Chapter four describes the complete drive system including the developments of the loss minimization algorithm. Extensive simulation results for both controller dynamics and loss minimization aspects will be presented.
- At the end, a summary of the contribution of this investigation to energy saving with a general conclusion and proposed complementary future work are presented.

Chapter One

Artificial Intelligence Optimization Techniques

1.1 Introduction

From an engineering perspective, the description of artificial intelligence (AI) may be summarized as: “the study of representation and search through which intelligent activity can be enacted on a mechanical device”. This perspective has dominated the origins and growth of AI. The first modern workshop/conference for AI practitioners was held at Dartmouth College in the summer of 1956, [George F Luger,2005]

According to), [D.A. Linkens, 1996]intelligent control shows high performance control over a wide range of operating conditions(e.g. parameters uncertainties) . It is defined as systems that have the ability to emulate human capabilities (planning, learning and adaptation).

Unlike conventional control, intelligent control uses tow sources of information (learning from process and designer/skilled operator knowledge) to form the corresponding relationship between inputs and outputs. The most widely used intelligent control schemes are fizzy logic control (FLC), artificial neural networks (ANN). These techniques are used in the field of electrical drives for control process, estimation, system identification and optimization problems however genetic algorithms (GA’s) [Eldissouki, 2002] and particle swarm optimization are used to solving optimization problems.

There are two large electrical drive manufactures, which incorporate AI into their drives there are Hitachi and Yaskawa. In addition to this, Texas Instruments (TI) has built a fuzzy controlled induction motor drive using the TMS320C DSP. The main conclusion obtained by TI agrees with results obtained from various fuzzy-control implementations: the development time of the fuzzy-controlled drive is significantly less than the corresponding development time of the drive using classical controllers.SGS Thomson has also built some DC and AC drives incorporating fuzzy logic control, [P.Vas et al, 1996].

In all drives, but especially in electrical vehicles, energy is a crucial factor. However, by using AI it may be possible to improve the efficiency.

This chapter introduces the trends of intelligent control techniques and its application to AC drives for efficiency optimization. The study focuses on fuzzy control, genetic algorithms and PSO technique.

1.2 Artificial Neural Networks

Artificial Neural network (ANN) resembles human brain in learning through training and data storage. They can approximate complicated functions using several layers of neurons structured in a way similar to the human brain; so, ANN acts as a universal approximator. ANN has learning capability and generalization property. Because of its learning capability, ANN is very powerful in control applications where the dynamics of a plant or process control is partially known or the mathematical representation is very complicated. The generalization property is very useful because it allows training of the neural networks with a limited training data set.

Artificial neural network consists of a number of interconnected information-processing elements called neurons. It has certain performance characteristics in common with the biological neural networks, [Bose, 2006]. A neuron can be modeled to perform a mathematical function such as a pure linear function, step function, tan-sigmoid function etc. These neurons can be interconnected to establish a variety of network architecture. The attractive feature of the neural network is that it can be trained to solve complex nonlinear functions with variable parameters, which may not be attainable by conventional mathematical tools, [B.Kosko,1992]

1.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization is an evolutionary computation technique introduced in 1995; its idea is based on simulation of social behavior of animals such as bird flocks or fish schools searching for food. PSO is another form of evolutionary computation it is population-based method, like genetic Algorithm. However, the basic concept is cooperation instead of competition. It is also very similar to GA, but it does not have genetic operators.

In this algorithm, each individual is referred to as a particle and presents a candidate solution to the optimization problem. Unlike other population-based methodologies, every agent moves along its velocity vector, which is updated using two different best experiences; one is the best experience, which a particle has gained itself during the search procedure and the other is the best experience gained by the whole group. Combination of these experiences can provide useful information for each particle to explore new positions in the domain of the problem.

1.3.1. Original PSO Algorithm

The basic PSO algorithm consists of the velocity and position equations

For each particle i , the velocity and the position of particles can be updated by the following equations, [Taher Niknam,2010]:

$$\begin{cases} V_i(k+1) = V_i(k) + rand1i(p_i - x_i(k)) + rand2i(G - x_i(k)) & (1.1) \\ x_i(k+1) = x_i(k) + v_i(k+1) & (1.2) \end{cases}$$

Where i is the index of each particle, k is the discrete time index, $rand1$ and $rand2$ are random numbers between 0 and 1.

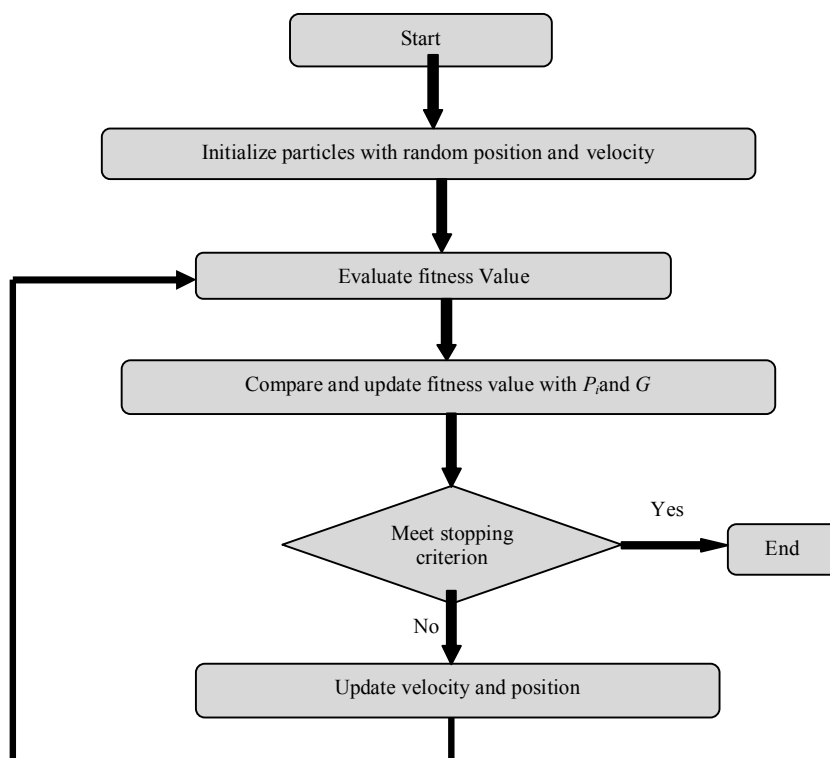
P_i is. The best position found by i th particle, G is the global best particle among the entire population.

The most used PSO algorithm form is including an inertia term and acceleration constants as, [Brian .Brige,2003] :

$$V_i(k+1) = \phi_i(k) V_i(k) + \alpha_1[rand1i(p_i - x_i(k))] + \alpha_2[rand2i(G - x_i(k))] \quad (1.3)$$

ϕ_i is an inertia function and $\alpha_{1,2}$ are acceleration constants.

PSO optimization procedure is established according to the flowchart shown in Figure 1.1..



Fig(1.1). PSO Flowchart

A simple example would be find the minimum of the loss function given in chapter three for a given load $T_l = 25\% T_{IN}$. A particle swarm optimization toolbox developed by [Brian Brige,2003] was used obtained result is shown in Fig (1.2) bellow:

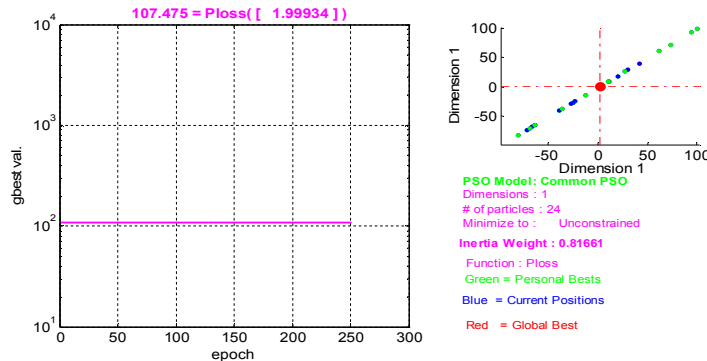


Fig (1.2). Visualization of PSO process

1.4 Fuzzy Logic System

Fuzzy logic systems (FLSs) are else a universal function approximators. The heart of fuzzy logic system is linguistic rule-base, which can be interpreted as the rules of a single “overall” expert, or as the rule of “subexperts” and there is a mechanism (inference mechanism), where all the rules are considered in an appropriate manner to generate the output,[Zadeh,1965],[Mamdani and Assilian,1975],[Lee,1990] and [Kusko,1992]

Fuzzy logic control has found many applications. This is so largely employed because this fuzzy logic control has the capability to control non-linear, uncertain systems even in the case where no mathematical model is available for the controlled system.

The application of fuzzy logic has some advantages:

- When parameters change
- When existing traditional controllers must be augmented or replaced (e.g. to provide self-tuning, to give more flexibility of controller adaptability, etc...).
- If sensor accuracy (or price) is a problem (fuzzy logic can handle imprecise measurements, uncertainties)
- To obtain solutions when solutions are not possible by using other technique.

1.4.1 Conventional and Fuzzy Sets

Fuzzy set theory resembles human reasoning in its use of approximate information and uncertainty to generate decisions. It was specifically designed to mathematically represent uncertainty and vagueness and provide formalized tools for dealing with the imprecision intrinsic to many problems.

Within the framework of classical logic, a proposition is either true or false (1 or 0). to clarify this concept the example bellow is used:

For example, classical logic can easily divide the temperature of a room into two subsets, “less than 18° and 18° or more than 18°. Figure (1.2). (a) Shows the result of this partition. All temperatures less than 18 are then considered as belonging to the set “less than 18”. They assign a value of 1 and all temperatures reaching 18 or more are not considering as belonging to the set “less than 18”. They are assigned a value of 0.

However, human reasoning is often based on knowledge or inaccurate, uncertain or imprecise data. A person placed in a room in which the temperature is either 17.95° or 18.05°, will certainly distinguish between these two temperature values. This person will be able to tell if the piece is “cold “or “hot” without accurate temperature indication.

Fuzzy logic is used to define subsets, such as “cold” or “hot” by introducing the possibility to a value belonging more or less to each of these subsets.

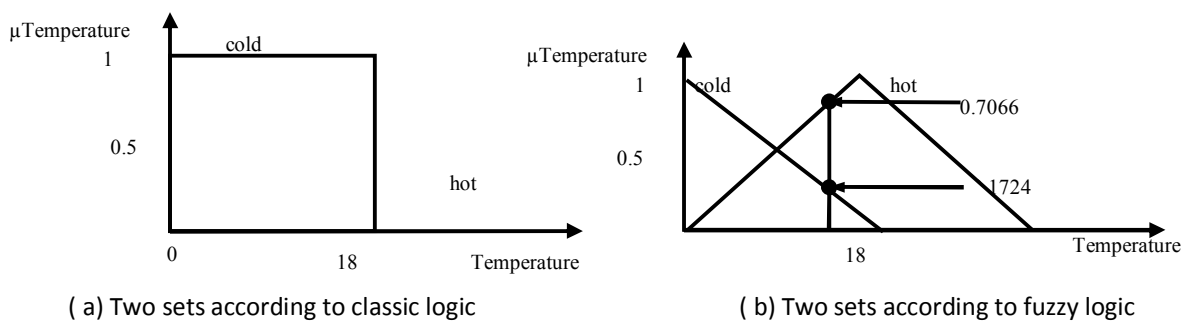


Fig (1.2). Temperature classification of a room in two sets

In fuzzy set theory, the concept of characteristic function is extended into a more generalized form, known as *membership function*: $\mu_A(x): U \rightarrow [0, 1]$. While a characteristic function exists in a two-element set of $\{0, 1\}$, a membership function can take up any value between the unit interval $[0, 1]$. The set which is defined by this extended membership function is called a *fuzzy set*. In contrast, a classical set which is defined by the two-element characteristic function, is called a *crisp set*, [M.N Cirstea et al, 2002]

According to the definition above a fuzzy set from Fig (1.2) can be defined as follows. Let U be a set, called the Universe of Discourse and u be a generic element of U ($u \in U$). A fuzzy set A in a universe of discourse U is a function that maps U into the interval $[0, 1]$. The fuzzy set A is characterized by a membership function (MF) $\mu_A(x)$ that takes values in the interval $[0, 1]$.

1.4.2. Linguistic Variables and Values

Words are constantly used to describe variables in human's daily life. Similarly, words are used in fuzzy rules to formulate control strategies. Referring to the above example, words like "room temperature is hot" can be used to describe the state of a system (in the current case, it is the state of the room). In this example, the words "cold" and "hot" are used to describe the variable "temperature". This means that the words "cold" and "hot" are the values of the fuzzy variable "temperature". Note that the variable "temperature" in its turn, can also take crisp values, such as 18°, 15.6°, 0°, etc.

If a variable is assigned some crisp values, then it can be formulated by a well established mathematical framework. When a variable takes words as its values instead of crisp values, there is no formal framework to formulate it in the classical mathematical theory. The concepts of Linguistic Variable and Value were introduced to provide such a formal framework. According to these concepts, if a variable can take words in natural languages as its values, then that variable is called *Linguistic Variable*. The words that describe the value of that linguistic variable are defined by fuzzy sets in the universe of discourse in which the variable is defined [L.-X. Wang, 1997]. These words are called *Linguistic Values*.

In general a linguistic variable is characterized by (1) a name, (2) a term, and (3) a universe of discourse. For example on Figure 1.1. (b), the variable "temperature" is a linguistic variable with 2 linguistic values, namely "cold" and "hot". The variable "temperature" can be characterized in the universe of discourse $U = [-18^\circ, +18^\circ]$, corresponding to minimum and maximum temperature of the room, respectively. The linguistic values "cold" and "hot" can be characterized by the fuzzy sets described in Figure (1.2. b) or by any other set (depending on the application and the designer's choice).

These definitions show that linguistic variables are the necessary tools to formulate vague (ill-defined) descriptions in natural languages in accurate mathematical terms. They constitute the first step to incorporate human knowledge into engineering systems in a systematic and efficient manner, [L.-X. Wang, 1997].

1.4.3. Membership Functions (MFs)

There are many other choices or shapes of MFs besides the ones described in Figure (1.2). A graphical illustration of typical and commonly used ones in literature is shown in Figure 1.3., [K.M. Passino, 1998]

The simplest and most commonly used MFs are the triangular types due to their simplicity and computation efficiency,[K.M. Passino, 1998],[Bose,2006]. A singleton is a special type of MF that has a value of 1 at one point on the universe of discourse and zero elsewhere. The L-function and sigmoid types are mainly used to represent saturation of variables.

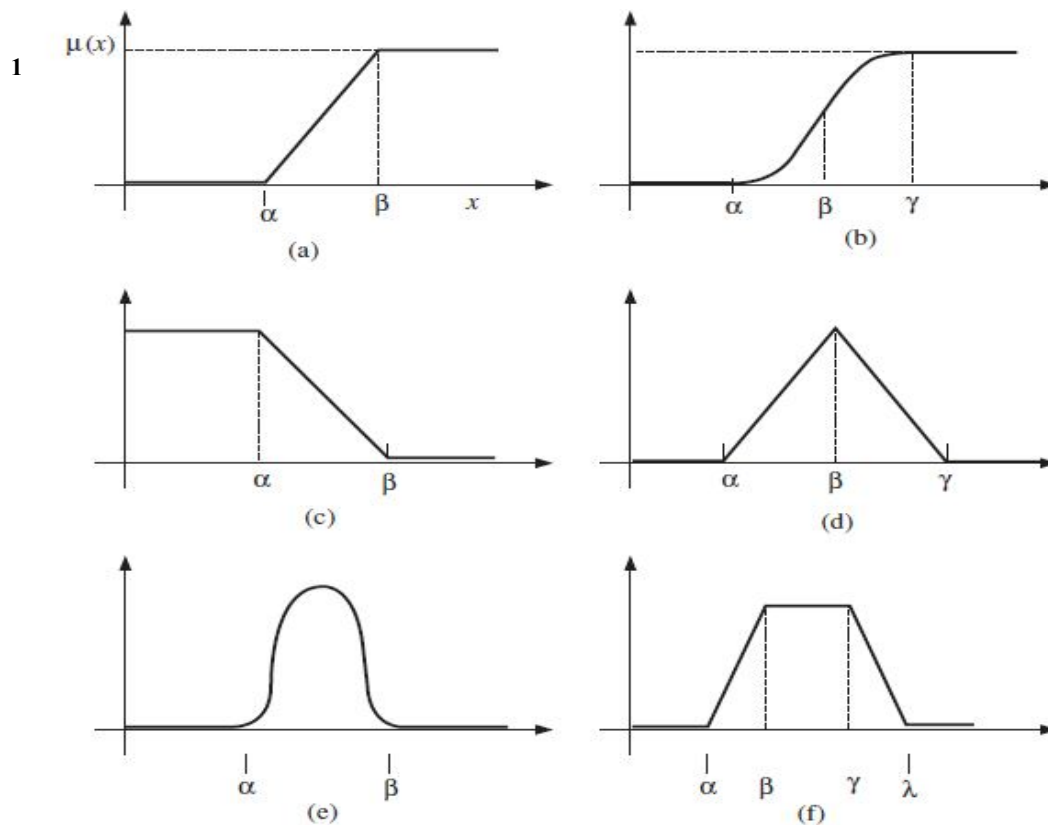


Fig. (1. 3). Typical shapes of MFs (a) ..,(b) sigmoid,(c) L function,(d) Triangular,(e) Gaussian function,(f) Trapezoidal,[M.N Cirstea, 2002]

1.4.4. Fuzzy Rules and Fuzzy Implication

A “fuzzy If-Then- rule” , also known as “ fuzzy rules” , “fuzzy implication” , or “fuzzy conditional statement” assume the form :

If x is A then y is B

Where A and B are linguistic values defined by fuzzy sets on universes of discourse X and Y , respectively. Often “ x is A ” is called antecedent or “premise”, while “ y is B ” is called the “consequence” or “conclusion”.

Examples of fuzzy if-then rules are widespread in our daily linguistic expression, such as the following:

- If pressure is high, then volume is small
- If road is slippery, then driving is dangerous
- If speed is high, then apply the brake is little

The expression “if x is A then y is B ”, is sometimes abbreviated as $A \rightarrow B$

The procedure for assessing these influences is called “*Fuzzy Implication*”. Since fuzzy propositions and relations are expressed by MFs, fuzzy implications also imply MFs as a method of interpretation.

In literature, there are a number of implication methods. The frequently used ones are [BK.Bose 2002], [L.-X. Wang, 1997], [Z. Kovacic, 2006]:

- 1) Zadeh implication,
- 2) Mamdani implication,
- 3) Godel, implication,
- 4) Lukasiewicz implication,
- 5) Sugeno implication,
- 6) Larsen implication, etc

The differences between these methods are summarized in [Ajit.K.mandal.; 2006], [S.N.Sivanandam,2007], [Kwang.H.Lee,2005]. Their mathematical functions indicate that the Mamdani implication is the most suitable for hardware implementation, [K.M. Passino, 1998]. It is also the most commonly used in control system applications.

1.5. Fuzzy Logic Controller (FLC)

Usually a control strategy and a controller itself is synthesized on the base of mathematical models of the object or process under control. The models of an object under control involve quantitative, numeric calculations and commonly are constructed in advance, before realization. Since fuzzy logic control is based on human knowledge and experience, it doesn't need an exact mathematical model, it is an automatic control strategy based on “IF-THEN” rules.

The FLC can be viewed as a step toward a rapprochement between conventional precise mathematical control and human-like decision making.

The principal structure of a fuzzy controller is illustrated in Figure 1.3.. It consists of normalization factors, fuzzification of inputs, inference or rule firing, defuzzification of outputs, and denormalization.

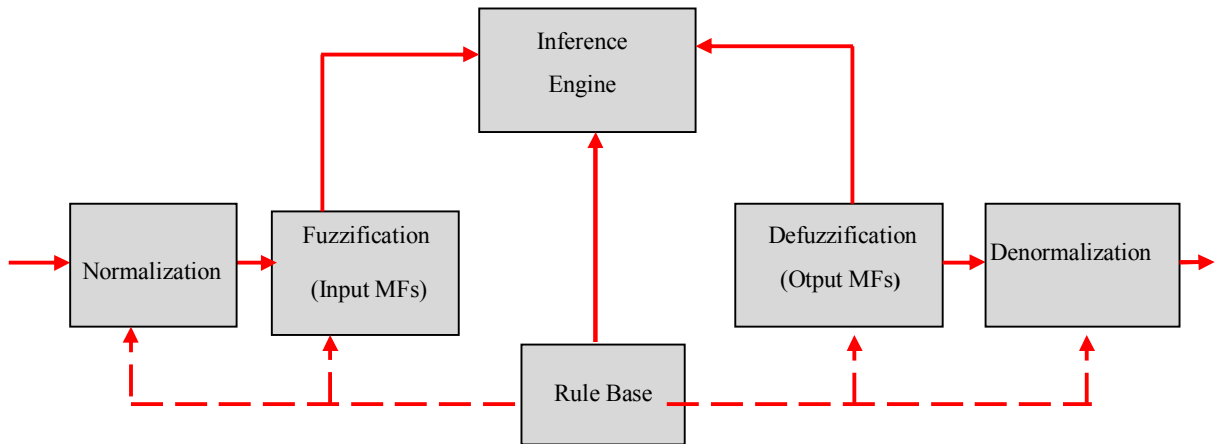


Fig. (1.4). Basic structure of FLC

1.5.1 Steps of Fuzzy Logic Controller Design

- Initially choose the number of inputs/outputs
- Fuzzify the real inputs using appropriate membership functions
- Create the IF THEN rules using AND/OR operator
- Defuzzify the output fuzzy to get the corresponding crisp output

1.5.2. Fuzzification Interface

The fuzzification interface transforms input crisp values into fuzzy values and it involves the following functions, [Kwang H. Lee, 2005].

- Receives the input values
- Transforms the range of values of input variable into corresponding universe of discourse
- Converts input data into suitable linguistic values (fuzzy sets).

1.5.3. Rule Base

Although differential equations are the language of conventional control, the dynamic behavior of a system is characterized by a set of linguistic descriptions in terms of fuzzy rules in FLCs Fuzzy rules serve to describe the quantitative relationship between the input and the output variables in linguistic terms such that, instead of developing a mathematical model that describes a system, a knowledge-based system is used.

Fuzzy rules are the core of the FLC. Generally the dynamic behavior of a fuzzy controller is characterized by a group of fuzzy rules which follows the format:

If antecedents Then consequence.

The antecedents can be joined by union (OR) or by intersection (AND). In the speed control of induction motor for example typical rule reads as:

If “*the speed error*” is positive small (PS) AND “*change in speed error*” is negative small (NS) THEN u is negative small (NS).

1.5.4. Inference Engine

The function of the inference engine provides a way to translate the input of a fuzzy set into the fuzzy output. It determines the extent to which each rule is relevant to the current situations as characterized by inputs. The inference engine is the decision-making logic of an FLC. It has the capability of simulating human decision-making based on fuzzy concepts and inferring fuzzy control actions using fuzzy implication and the rule of inference in FL.

Normally this mechanism consists of set of logic operations.

There are several ways to implement a fuzzy inference: the Mamdani fuzzy reference system and the Sugeno reference system are two commonly used. [Hung T. Nguyen., 2003]

1.5.5. Defuzzification Inference

The result of implication and aggregation steps in the inference engine is a fuzzy output. This output is the union of all the outputs of individual rules that are validated [Bose 2002]. The conversion of this fuzzy output set to a single crisp value (or a set of crisp values) is referred to as *Defuzzification*. Hence, this latter interface generates the output control variables as a numeric value.

Defuzzification can be implemented in different ways, general methods include MOM (mean of maximum), COA (center of area), and COM (center of maximum), [Hung T. Nguyen., 2003], [Bose, 2002].

1.6 Genetic Algorithms

Genetic algorithms (GAs) are global optimization techniques developed by John Holland in 1975. They are perhaps the most widely known type in the family of evolutionary algorithms,[Mitsuo. Gen, 2000]. These algorithms search for solutions to optimization problems by “evolving” better and better solutions. A genetic algorithm begins with a “population” of solutions and then chooses “parents” to reproduce. During reproduction, each parent is copied, and then parents may combine in an analog to natural cross breeding, or the copies may be modified, in an analog to genetic mutation. The new solutions are evaluated and added to the population, and low-quality solutions are deleted from the population to make room for new solutions. As this process of parent selection, copying, crossbreeding, and mutation is repeated, the members of the population tend to get better. When the algorithm is halted, the best member of the current population is taken as the global solution to the problem posed,[Mitsuo.,Gen 2000], [Kwang,Y. Lee,2008];[Goldberg,1989].

There has been widespread interest from the control community in applying the genetic algorithm (GA) to problems in control systems engineering. Compared to traditional search and optimization procedures, such as calculus-based and enumerative strategies, the GA is robust, global and generally more straightforward to apply in situations where there is little or no a priori knowledge about the process to be controlled. As the GA does not require derivative information or a formal initial estimate of the solution region and because of the stochastic nature of the search mechanism, the GA is capable of searching the entire solution space with more likelihood of finding the global optimum.

The process of evolution is based on the following principles:

- Individuals in a population compete for resources and mates.
- The most successful individuals in each generation will have a chance to produce more offspring than those individuals that perform poorly.
- Genes from ‘good’ individuals propagate throughout the population so that two good parents will sometimes produce offspring that are better than either parent. Thus each successive generation will become more suited to their environment.

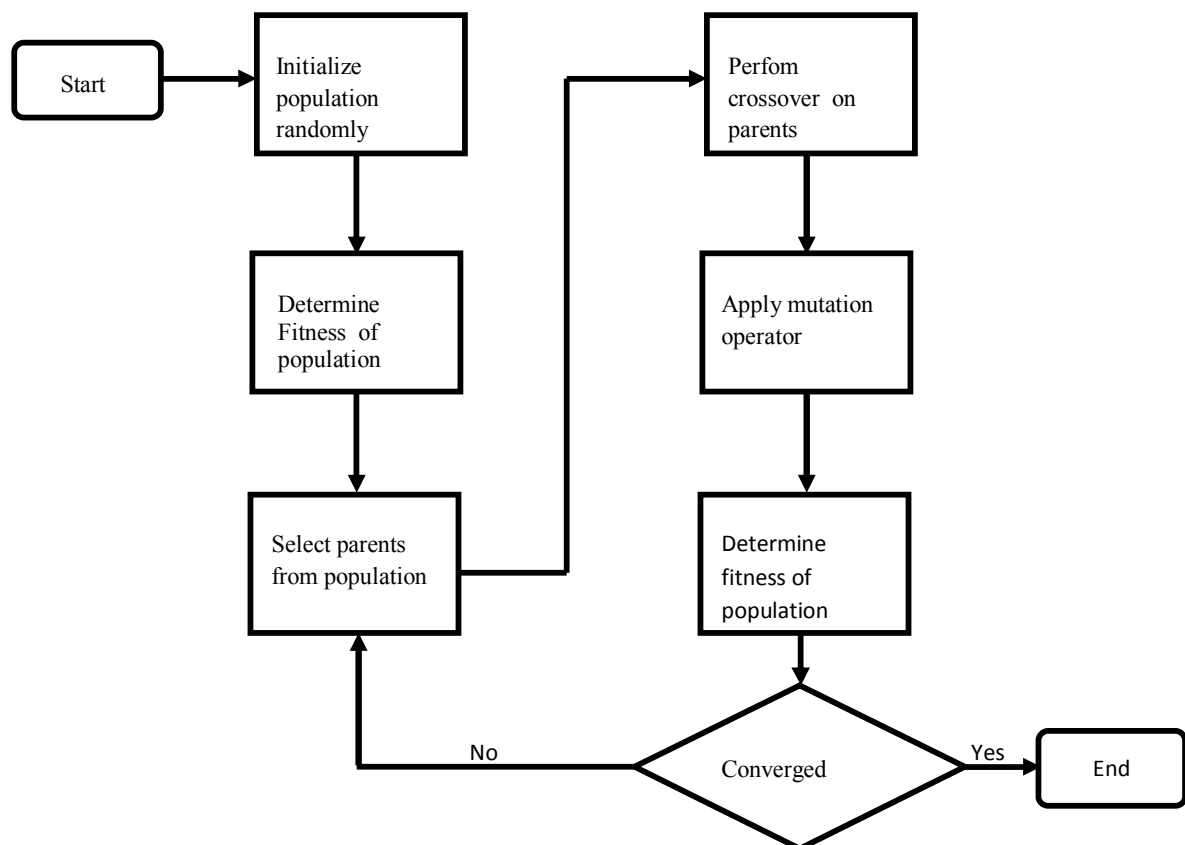
1.6.1 Implementation Details

A population of individuals is maintained within search space for a GA, each representing a possible solution to a given problem. Each individual is coded as a finite length vector of

characters. A fitness value is assigned to each solution representing the ability of an individual to 'compete'. The goal is to produce an individual with the fitness value close to the optimal. By combining information from the chromosomes, selective 'breeding' of individuals is utilized to produce 'offspring' better than the parents. Continuous improvement of average fitness value from generation to generation is achieved by using the genetic operators. The basic genetic operators are:

- Selection: used to achieve the survival of the fittest.
- Crossover: used for mating between individuals.
- Mutation: used to introduce random modifications.

The genetic operators are used in the GAs optimization procedure according to the flowchart given in Figure (1.5).



Fig(1.5). Genetic algorithms flowchart

1.6.1.1. Selection

The selection mechanism favors the individuals with high fitness values. It allows these individuals better chance for reproduction into the next generation while reducing the

reproduction ability of least fitted members of population. Fitness of an individual is usually determined by an objective function.

1.6.1.2. Crossover

The crossover operator divides a population into pairs of individuals and performs recombination of their genes with a certain probability. If one-point crossover is performed, as shown in Figure (1.6)., one position in the individual genetic code is chosen. All gene entries after that position are exchanged among individuals. The newly formed offspring created from this mating are put into the next generation. Recombination can be done at many points, so that multiple portions of good individuals are recombined, this process is likely to create even better individuals. The crossover operator roughly mimics biological recombination between two single-chromosome (haploid) organisms.

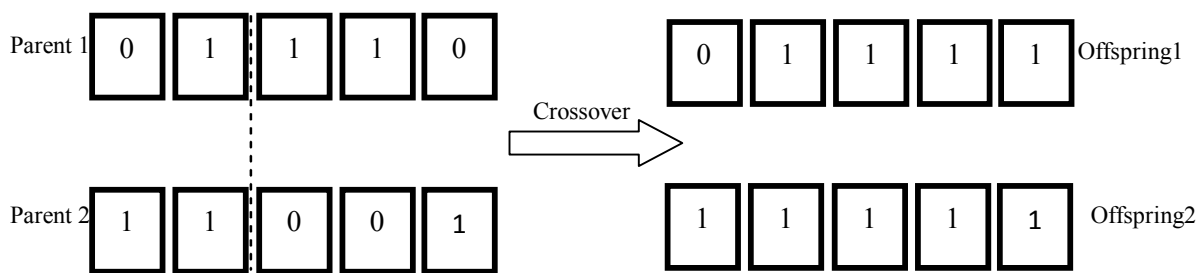


Fig (1.6). One-point crossover example

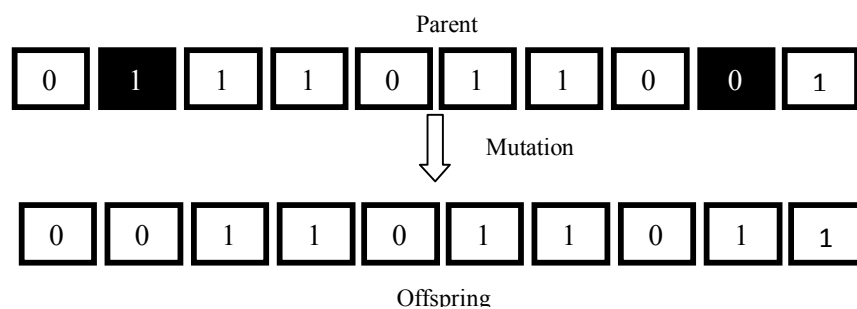
1.6.1.3. Mutation

When using mutation operator a portion of the new individuals will have some of their bits flipped with a predefined probability. In Figure (1.7). Mutation operator is applied to the shaded genes of the parent. The purpose of mutation is to maintain diversity within the population and prevent premature convergence. The usage of this operator allows the search of some regions of the search space which would be otherwise unreachable.

The described operators are basic operators used when the individuals are encoded using binary alphabet. Operators for real valued coding scheme were developed by Michalewicz [xx]. The following operators are defined: uniform mutation, non-uniform mutation, multi-non-uniform mutation, boundary mutation, simple crossover, arithmetic crossover and heuristic crossover.

- Uniform mutation randomly selects one individual and sets it equal to an uniform random number.

- Boundary mutation randomly selects one individual and sets it equal to either its lower or upper bound.
- Non-uniform mutation randomly selects one variable and sets it equal to a non uniform random number.
- Multi-non-uniform mutation operator applies the non-uniform operator to all of the individuals in the current generation.
- Real-valued simple crossover is identical to the binary version.
- Arithmetic crossover produces two complimentary linear combinations of the parents.
- Heuristic crossover produces a linear extrapolation of the two individuals.



Fig(1.7). Mutation example

As an example of application of the two intelligent techniques used in this thesis an optimal fuzzy controller based on GA is developed in next section.

1.7. Induction Motor Speed Regulation

This section will be dedicated to investigate the speed regulation of IM using both techniques focused in this chapter mainly fuzzy logic and genetic algorithms, in the first step an FLC is used to regulate motor speed than its performances are optimized by using GA'.

1.7.1 Speed Control using FLC

The components of the FLC will be introduced by using speed control of induction motor problem. Fig (1.9). depicts the typical response to step consign. One can see there are four zones: A1/ rise, A2/overtake, A3/ **damping** and A4/ steady state regions.

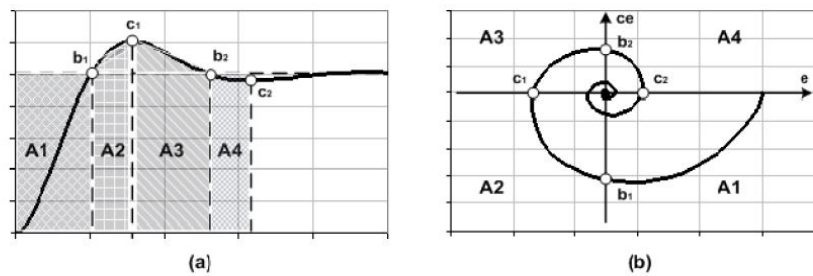


Fig. (1.8). System step response

Most closed-loop speed control systems react to the error ($e(t)$) between the reference speed and the output speed of the motor. When controlling processes, human operators usually compare the actual output of the system with the desired (reference) output and observe the evolution of this difference. This is why in most FLCs, including the controllers proposed in the input variables are the system error, $e(t)$, and the change-in-error, $Ce(t)$, to complete the initial description of the investigated speed control closed loop, let $u(t)$ be the FLC output variable, i.e. the process input signal (which consist of the torque current component namely I_{sq}).

As the first step is the fuzzification hence it:

- (1) Measures the values of the input variables ($e(t)$ and $Ce(t)$) for the presented example,
- (2) Performs a scale mapping of the measured crisp values of the input variables into the universes of discourse of these input variables, and
- (3) Converts the input values into linguistic values compatible with the fuzzy set representation in the rule base. The three operations are performed as follows. Just as ($e(t)$ and/or $Ce(t)$) take on values of, for example 0.2p.u at time instant t , linguistic variables also assume linguistic values at every time instant t . The values that linguistic variables take on over time change dynamically.

Let's suppose, for the presented example, that $e(t)$, $Ce(t)$, and u take on the following values: "Negative Big" or NB, "Negative Small" or NS, "Zero" or Z, "Positive Small" or PS, and "Positive Big" or PB. The meanings of these linguistic values are quantified by their respective MFs. For close-loop speed control, each of the following statement quantifies some of different configurations of the system:

- The statement " $e(t)$ is PB" can represent the situation where the output speed is significantly smaller than its reference.

- The statement “ $e(t)$ is NS” can represent the situation where the output speed is just slightly over the reference, but not too close to it to justify quantifying it as Z and not too far to justify quantifying it as NB.
- The statement “ $e(t)$ is PB” and “ $Ce(t)$ is PS” can represent the situation where the speed is significantly below the reference, but while “ $Ce(t)$ is PS”, the motor speed is away from its reference value.

These statements indicate that in order to fuzzify the dynamics of a process successfully, one must first have a good understanding of the physics of the underlying process. Moreover, the accuracy of the FLC is built on the shape, the number and the distribution of linguistic values or MFs used.

Figure (1.10). Shows the fuzzy sets and the corresponding triangular MF description of each signal. The universe of discourse of all the variables, covering the whole region and all the MFs are asymmetrical because near the origin (steady state), the signal requires more precision. This completes the first step of FLCs according to Figure (1.4)

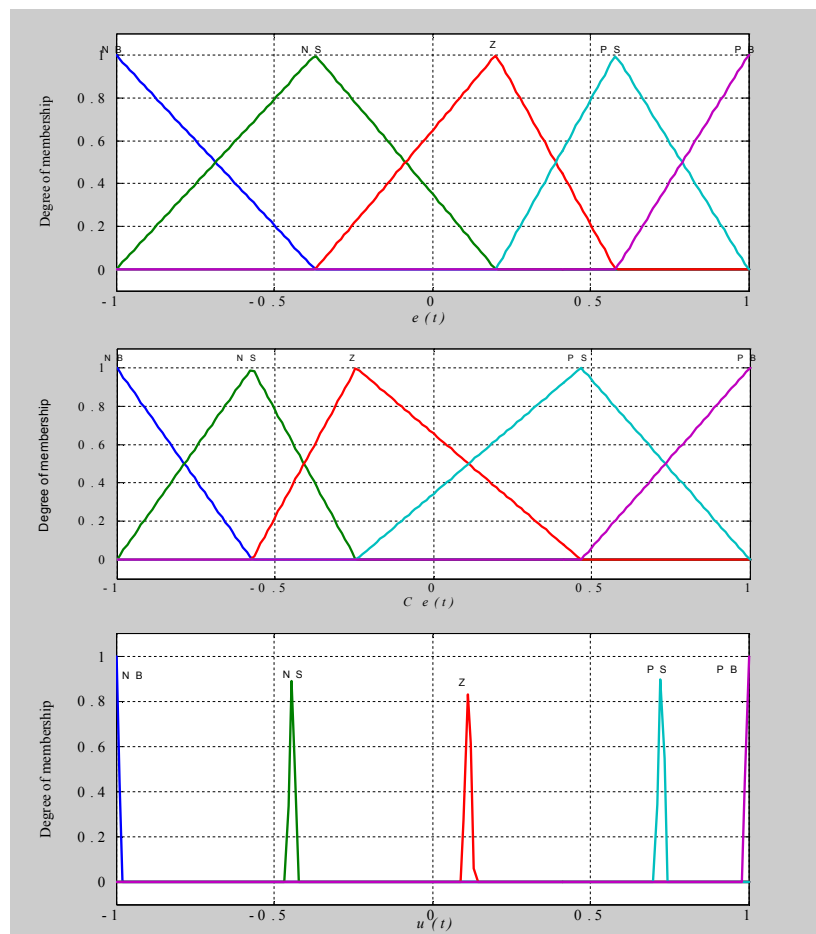


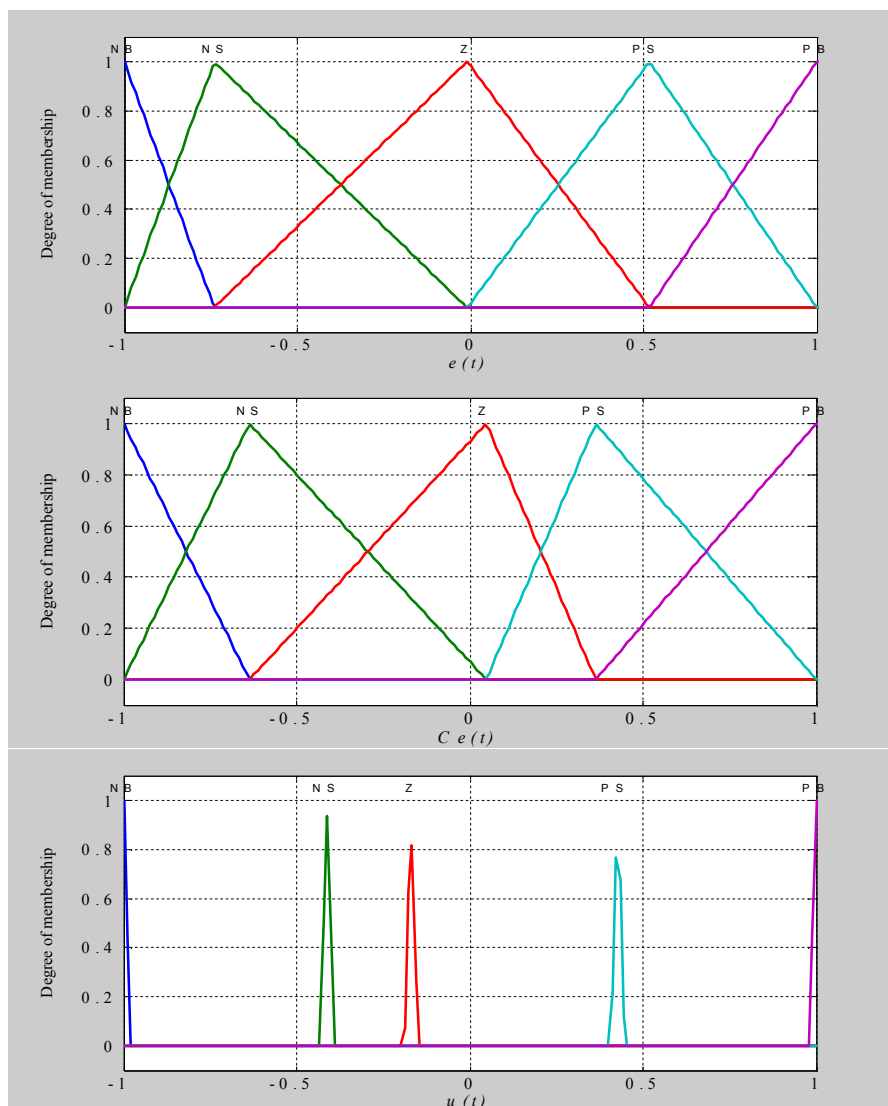
Fig (1.10). Inputs and output MFs of the induction motor speed control

1.7.2 Optimizing an FLC using GA's

Many methods for fuzzy control use genetic algorithms to search the fuzzy controller structure or parameters. However, one of the drawbacks of applying genetic algorithms in optimal fuzzy controller design is a lack of the theoretical knowledge. Each application has a different strategy to represent the fuzzy controller by chromosomes.

In this part; we will be interested by optimizing the MF's of the speed controller used in section 1.3 to achieve this task the fuzzy controller (MF's plus normalization gains) formed the chromosomes while the fitness was the square error of the speed. Genetic operator parameters used probabilities of crossover and mutation are respectively set to 0.8 and 0.005.

Optimized MF's obtained are shown in Figure (1.11). We can see that the MF's intervals are changed compared with those in Figure (1.10).



Fig(1.11). Optimized inputs and output MFs of the induction motor speed control

Figure (1.12). shows the obtained motor speed response for the reference speed of 157rad/s. Thus we can see that the optimized speed controller gives the best response compared to IP and fuzzy controllers. Also it has a very fast perturbation rejection.

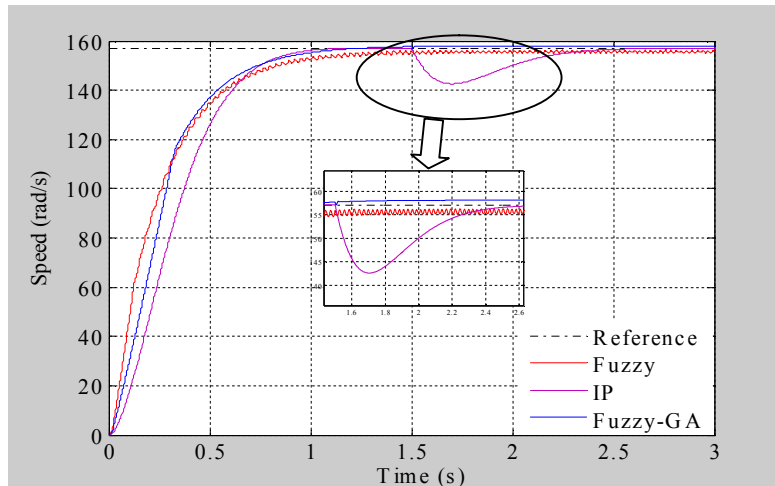


Fig (1.9). Induction motor speed response

1.8. Summary

This chapter has summarized the principles of some artificial intelligent techniques which are used to efficiency drives optimization. Attention has been focused on the two intelligent techniques investigated in this thesis namely fuzzy logic and genetic algorithms. The search of the IM speed response was investigated by both fuzzy logic and genetic algorithms to show the effectiveness of these two techniques.

The investigation of fuzzy logic and genetic algorithms in order to optimize efficiency of the induction motor drive is described throughout the next chapter.

Chapter Two

Motor and Inverter Losses Modeling

2.1 Introduction

Induction motor is the most robust so the most widely used electrical machine, it is used in domestic, commercial and industrial applications. Being very economical, rugged and reliable, induction motors are used extensively and they consume a considerable percentage of the overall production of the electrical energy.

The motor parameters variation is often neglected when estimating motor performance, thus traditionally, the induction motor models are based on constant parameter model; however they do not give full satisfaction when flux level changes or increasing current occur [E.Mendes et al, 1994].

In many applications like electric vehicles it is not only the high performances which are required but also the energy quantities must be optimal such the efficiency thus the flux level must change according to the operating point nevertheless the motor inductances cannot be considered constant. This change must be part of the calculations of the optimal conditions operating, because they have determinant influence on the optimum location and on the energy savings potential, [S.kirschen , 1984].

The induction motor can be connected directly to a standard fixed frequency, fixed voltage three phase power source. Under these conditions, the motor speed and slip will only be determined by the load torque. Power electronic converters are used to produce a variable-frequency supply to AC motors, thereby enabling variable-speed operations.

Power electronic converters have conduction and switching losses in the power devices, in addition to losses in both passive components and the auxiliary cooling systems. Therefore, modeling converters is a constant concern for electrical engineers, where various studies have been conducted in this area.

We can distinguish several approaches designed to represent either the fine development of electrical quantities or their mean values.

For the control of electrical machines, it is unrealistic to use fine representation of switching phenomena because it leads to prohibitive computational time. However in this project, a compromised solution is adopted from [Abrahamsen,2001] simplified model of the converter. This chapter is divided into two parts, the first one presents the mathematical model of the induction motor including iron losses and magnetic saturation, whereas the second one is dedicated to converter losses modeling.

2.2. Induction Motor Model including Saturation and Core Losses

A dynamic modeling of the IM has been widely studied in the literature, by using the famous Park transformation the six equations relating the stator and rotor voltages are reduced to four equations. This transformation is based on a set of hypothesis assumptions, among others symmetrical three phase machine and neglected saturation and iron losses.

The equations of stator and rotor voltages, and also the equation of motion can be used to express the system dynamics.

The magnetic saturation is generally including in the model by modeling the magnetizing inductance as a function of the magnetizing flux or current. Hence, the saturation can be modeled with a rather simple function and the resulting inductance estimate is accurate enough in most cases,[M.Ranta ,2013]

In order to take into account core losses and magnetizing saturation effects, Mendes's and Razek model is used in this work.

In this model the iron losses are represented by an equivalent resistance in series with the magnetizing branch as represented on Fig. (2.1). they are given by the expression; while the saturation is taken into account by the piecewise [Mendes,.1994]:

$$R_{fs} = A \times f_s + B \times f_s^2 \quad (2.1)$$

$$L_s = \begin{cases} 0.6 H & I_s \leq 0.8 A \\ \frac{1.33}{1.44+I_s} H & I_s > 0.8 A \end{cases} \quad (2.2)$$

Where: A and B and f_s are respectively constants and stator current frequency.

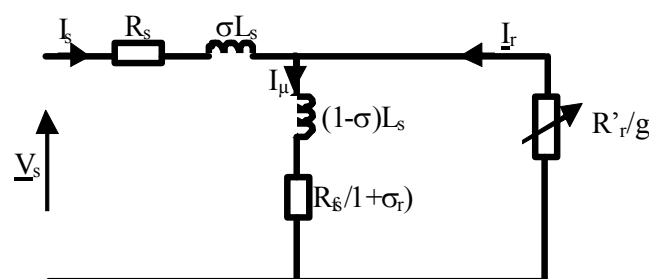


Fig. (2.1) Equivalent circuit of the IM. with series equivalent core losses resistance

The choice of the state vector ($I_s \Phi_r$) allows us to neglect the cross saturation, without great influence on results [Levi,1997] however the α - β model for a three phase IM in the can be written, as, [Z.Rouabah,2003]:

$$\bar{V}_s = \left[R_s + R_{fs} \frac{\sigma_r}{1 + \sigma_r} \right] \bar{i}_s + \frac{d}{dt} \left[\sigma L_s \bar{i}_s + M \frac{\bar{\Phi}_r}{L_r} \right] + R_{fs} \frac{\bar{\Phi}_r}{L_r} \quad (2.3)$$

$$0 = \frac{R_r}{L_r} \left[\bar{\Phi}_r - M \bar{i}_s \right] + \left(\frac{d}{dt} - j\omega \right) \bar{\Phi}_r + R_{fr} \frac{\bar{\Phi}_r}{L_r} + R_{fr} \frac{\sigma_r}{1 + \sigma_r} \bar{i}_s \quad (2.4)$$

Where:

$$R'_s = R_s + R_{fs} \frac{\sigma_r}{\sigma_r + 1}; \quad R'_{fr} = R_{fr} \frac{\sigma_r}{\sigma_r + 1}; \quad T_r = \frac{L_r}{R_r}; \quad \sigma_r = \frac{L_r - M}{M}.$$

The electromagnetic torque is given by:

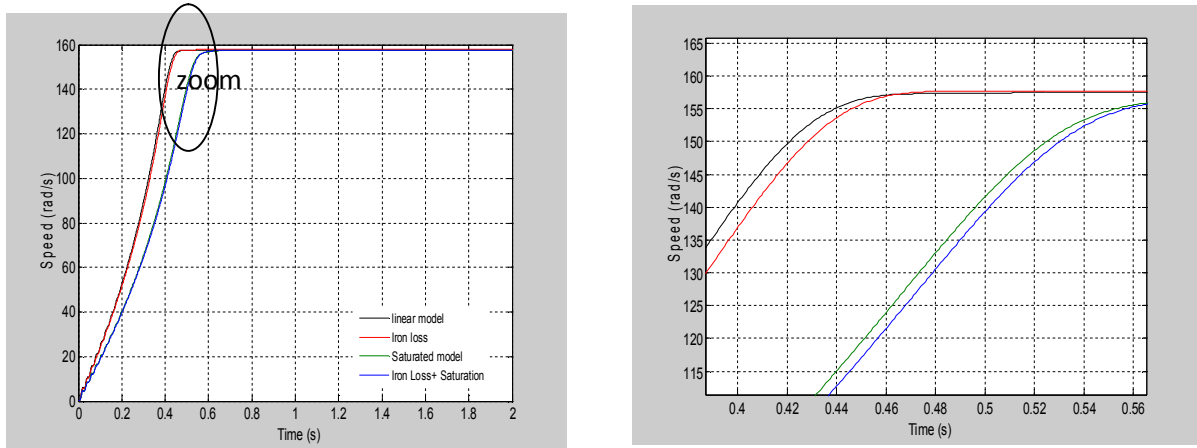
$$C_e = pM \Im m \left[\bar{i}_s (\bar{i}_r e^{j\theta})^* \right] \quad (2.5)$$

The motion equation is given by the equation bellow:

$$T_e - T_l = J \frac{d\omega}{dt} + f\omega \quad (2.6)$$

2.2.1. Simulation of the Motor Model

Simulation was performed using Matlab/simulink, for no load starting at nominal speed, obtained results are given bellow:

**Fig. (2.2)** Speed evolution

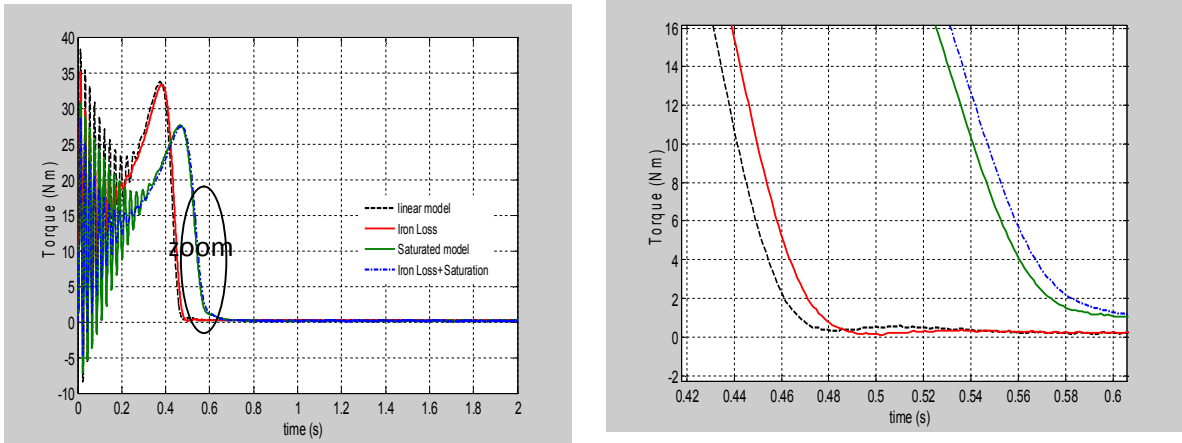


Fig. (2.3) Torque evolution

One can see on the above figures the influence of saturation on the torque which is subdued compared with the linear model however the speed rise time is greater than the linear model.

Figure(2.4) shows the current evolution it is clear that in startup the current value is high nevertheless in steady state this value decreases .

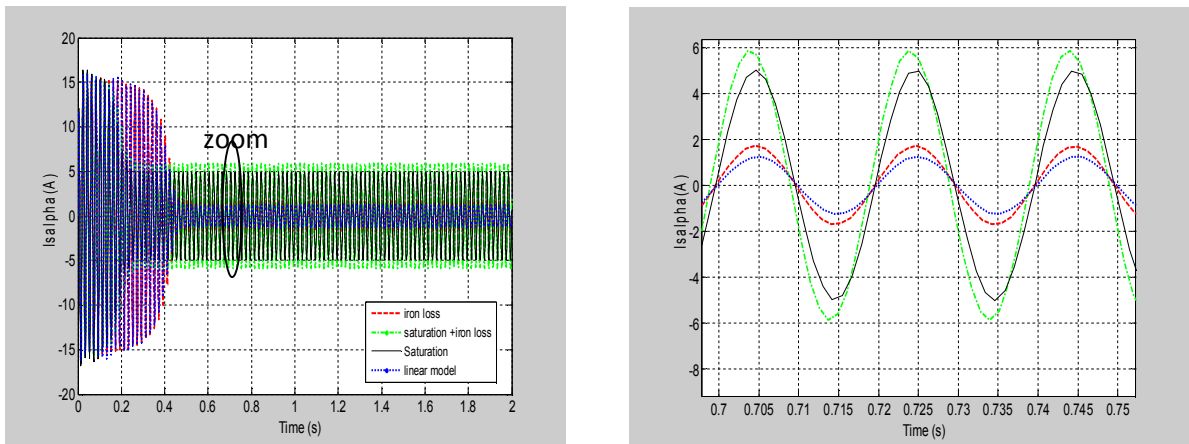


Fig. (2.4) Current evolution

2.3. Inverter Model

The inverter used here consists of three legs, each having two transistor switch and two diodes

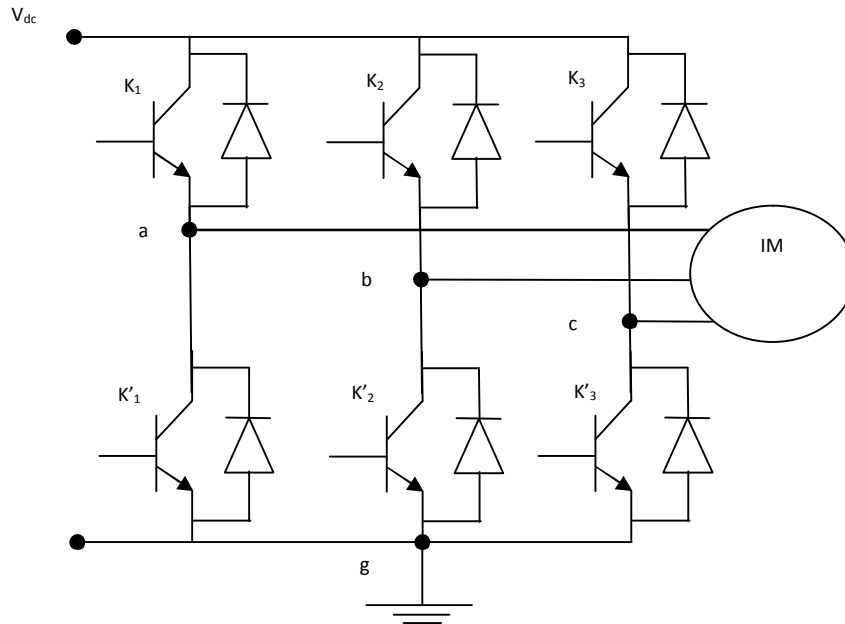


Fig. (2.5) Three Phase Inverter

We assume that the switches are ideal and admit only two states (on and off)

The basic operation of the three phase inverter can be explained by considering the single inverter leg. For example turning on switch K_1 and turning off switch K'_1 would establish V_{dc} across terminal 'a' and 'g' therefore $u_{ag}=V_{dc}$. On the other hand turning off K_1 and turning on switch K'_1 would apply zero across 'a' and 'g' $u_{ag}=0$.

Since the on/off states of the power switches in one inverter leg are always opposite without considering dead time, each inverter leg can be in either one of two states.

Assuming that the motor winding are star connected with n neutral point the relationship between the inverter leg voltages V_{abgc} and motor phase V_{abcn} voltages can be written as:

$$\begin{aligned} V_{ag} &= V_{an} + V_{ng} \\ V_{bg} &= V_{bn} + V_{ng} \\ V_{cg} &= V_{cn} + V_{ng} \end{aligned} \quad (2.9)$$

As the system V_{abcn} is balanced, it follows:

$$V_{an} + V_{bn} + V_{cn} = 0 \quad (2.10)$$

Adding the equations (2.8) we get:

$$V_{ng} = \frac{1}{3}(V_{ag} + V_{bg} + V_{cg}) \quad (2.11)$$

Therefore, substituting equation (2.11) in equations (2.9), it results:

$$\begin{aligned} V_{an} &= \frac{2}{3}V_{ag} - \frac{1}{3}V_{bg} - \frac{1}{3}V_{cg} \\ V_{bn} &= -\frac{1}{3}V_{ag} + \frac{2}{3}V_{bg} - \frac{1}{3}V_{cg} \\ V_{cn} &= -\frac{1}{3}V_{ag} - \frac{1}{3}V_{bg} + \frac{2}{3}V_{cg} \end{aligned} \quad (2.12)$$

Thus the inverter can be modeled by the following matrix:

$$C = \frac{1}{3} \times \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \quad (2.13)$$

2.4. Pulse Width Modulation (PWM)

There are many PWM techniques proposed in the literature, well known ones are sinusoidal PWM, hysteresis band current PWM, and space vector modulation (SVM). In this thesis only the sinusoidal PWM strategy is considered.

Sinusoidal PWM technique is very popular in industrial inverters, it consists of comparing isosceles triangle carrier wave of frequency f_{sw} with the fundamental frequency f sinusoidal modeling wave, and the intersection points determine the switching points of the electronic devices, [Bose, 2002].

2.5. Inverter Losses

An inverter transistor has three states on (conductive), off (non conductive) and commutation state (switching from on to off and inversely). In the open state there is no current flowing therefore no losses, thus the inverter has two types of losses conducting losses and switching losses [Abrahamensen,2000],[Peron,2009]. Conduction losses are produced when the switch is in the on state, however switching losses appear when switch is turned on and off,[Josep Pou,2011]

2.5.1 Inverter Conduction Losses

For power semiconductors conduction losses are often calculated by inserting a voltage “V” representing voltage drop and a resistor “r” representing the current dependency in series, [Uwe Drogenik ,2005],[Josep.Pou,2011]

When transistor of the inverter drives a current I_c , the voltage V_{CE} at its terminals is low but non zero it leads to conduction losses which are directly calculated by the intensity of the current I_c and the V_{CE-SAT} characteristic of transistor.

The diode respectively the transistor on-state voltages can be characterized by dynamical resistance and a constant drop voltage however it can be modeled by [Blaabjerg,1992], [Abrahamsen,2000],[Uwe Drofenik,2005]:

$$V_{on,T} = V_{0T} + r_{0T} \times i_T^{B_{conT}}, \quad V_{on,D} = V_{0D} + r_{0D} \times i_D^{B_{conD}} \quad (2.14)$$

Where: V_{0T} , r_{0T} B_{conT} : constants characterizing the transistor conduction loss.

V_{0D} , r_{0D} B_{conD} : constants characterizing the diode conduction loss.

The instantaneous diode and transistor power losses are then:

$$P_{on,T} = (V_{0T} + r_{0T} \times i_T^{B_{conT}}) \times i_T, \quad P_{on,D} = (V_{0D} + r_{0D} \times i_D^{B_{conD}}) \times i_D \quad (2.15)$$

In practice, these curves can be reduced to a linear expression ($B_{conT,D}=1$), [Perron,2009].

The modulation strategy has no influence on the conduction losses in the inverter. Thus, from the point of view of control, according to [Perron, 2009] it is no possible to reduce the conduction losses in the inverter

2.5.2 Inverter Switching Losses

Switching losses appear during commutation (turn on and turn off) According to [Blaabjerg,1992], it is possible to calculate these losses by means of collector –emitter voltage V_{ce} and collector current I_c mainly because they are related to a type of the used components . These losses can be approximated once the switching energy is measured as a function of load current, [Blaabjerg, 1995], [Abrahamsen,2000],[Perron,2009].

Switching power losses in each device are given by the following relations [Abrahamsen,2000]:

$$\begin{aligned} P_{swon,T} &= f_{sw} \times A_{swonT} \times i_T^{B_{swon}} \\ P_{swoff,T} &= f_{sw} \times A_{swoffT} \times i_T^{B_{swoff}} \\ P_{sw,D} &= f_{sw} \times A_{swD} \times i_{DT}^{B_{swD}} \end{aligned} \quad (2.16)$$

Where:

f_{sw} : switching frequency.

$A_{swon(off)}$, $B_{swon(off)}$: constants characterizing the transistor loss at turn-on(turn-off).

A_{swD} , B_{swD} : constants characterizing the diode loss at turn-off.

The total switching losses are then calculated by adding the equation (2.16). Fig. (2.6) shows the total losses of a 4 kVA inverter used in [Blaabjerg, 1995],

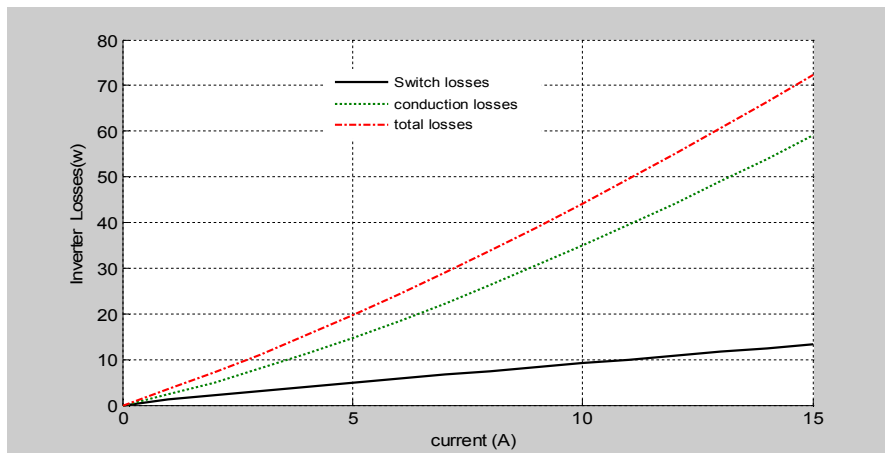


Fig. (2.6) Total inverter losses for one leg

2.6. Simplified Inverter Loss Model

For an energy optimal control strategy where the inverter loss is an integral part of the Algorithm a simplified method is required for real time calculation.

2.6.1 Simplified Model of Conduction Loss

By approximating the on-voltage with linear first order functions as:

$$V_{conD,lin} = V_{0Dlin} + r_{0Dlin} \times i_D, \quad V_{conT,lin} = V_{0Tlin} + r_{0Tlin} \times i_T \quad (2.17)$$

The same procedure is followed for the diode conduction loss calculation. The only difference is that the diode duty cycle used is:

The whole inverter conduction power loss is:

$$P_{con,inv} = 3(P_{conT} + P_{con,D}) \quad (2.18)$$

2.6.2 Simplified Model of Switching Loss

According to [Abrahamsen, 2000] it has been shown that switching losses are proportional to the switching frequency and to the phase current, they are given by:

$$P_{swlin} = 3(K_{sw} \times I_s \times f_{sw}) \quad (2.19)$$

Where K_{sw} is empirically determined constant.

Then the total inverter losses are given by the sum of (2.18) and (2.19) as:

$$P_{loss,inv} = 3(P_{conT} + P_{con,D}) + (K_{sw} \times I_s \times f_{sw}) \quad (2.20)$$

The total inverter loss depends on the following parameters: r , f_{sw} , I_s and ϕ .

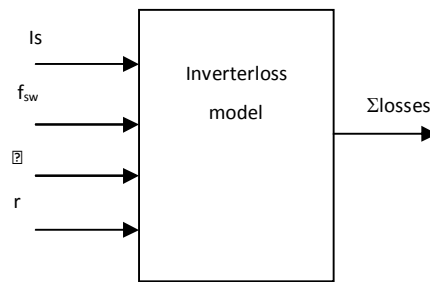


Fig.(2.7) Simplified Inverter Model

2.7. Simulation of Simplified Inverter Model

It is necessary to see the dependence of losses in relation to each of the above parameters to include this model in the energetic optimization. Simulation was performed for:

- I_s varying between 0 and 20 A, $\phi = 30^\circ$ and $r = 0.5$, $f_{sw} = 2\text{KHz}$.
- r varying between 0 and 1; $I_s = 20\text{A}$; $\phi = 30^\circ$; $f_{sw} = 2\text{KHz}$.
- f_{sw} varying from 1 to 10 KHz, $I_s = 20\text{A}$; $\phi = 30^\circ$ and $r = 0.5$.
- ϕ varying from 10 to 80°, $I_s = 10\text{A}$; $f_{sw} = 2\text{KHz}$ and $r = 0.5$.

Obtained results show that the inverter losses are affected by current and as indicated on Figures (2.8) a, b, c and d.

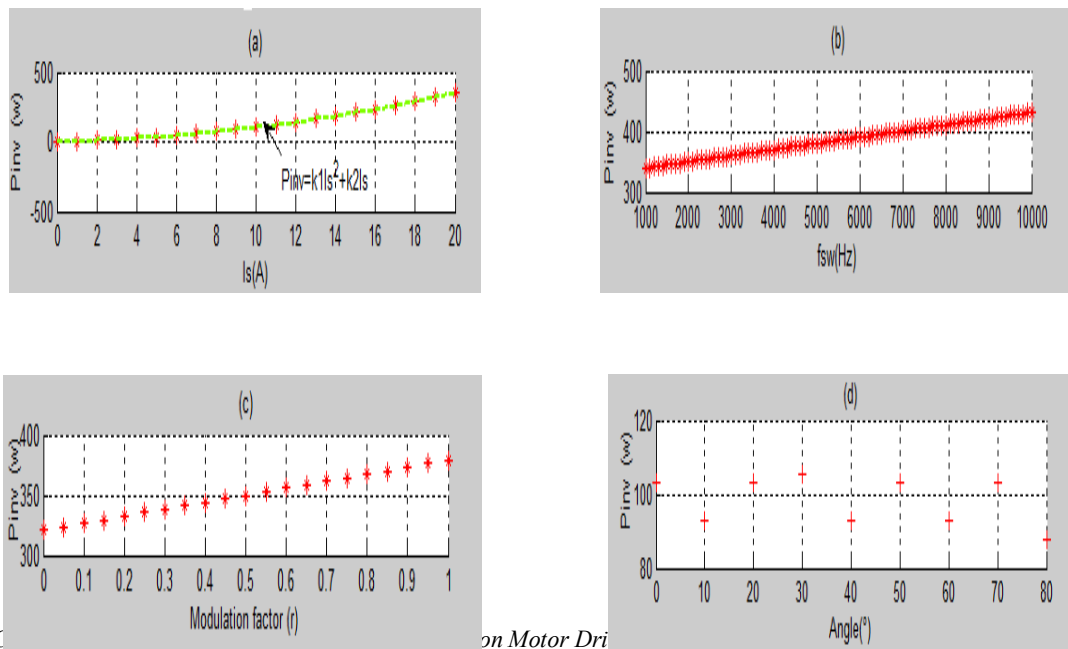


Fig.(2.8) Inverter Losses versus (a) current,(b) switching frequency,(c) modulation index,(d) phase shift

Since the inverter losses highly depends on the current. They can be approximated by a second order polynomial function such as:

$$P_{loss,inv} = k_1 I_s^2 + k_2 I_s \quad (2.21)$$

According to [Branko blanus,2010] among the converter losses comprising those of rectifier and DC link, we find inverter conductive and inverter commutation losses. In fact, the rectifier and DC link inverter losses are proportional to output power, so the overall flux-dependent losses are the inverter losses. They are usually given by:

$$P_{loss,inv} = R_{inv} \times I_s^2 \quad (2.22)$$

Figure (2.9) shows the plot of the approximated function of losses given by (2.21) and (2.22) we can see that the losses curves given by equations (2.20) and (2.21) are coincident.

The values of the coefficients were determined using the Matlab curve fitting toolbox and are successively equals to 0.6849 and 3.8755.

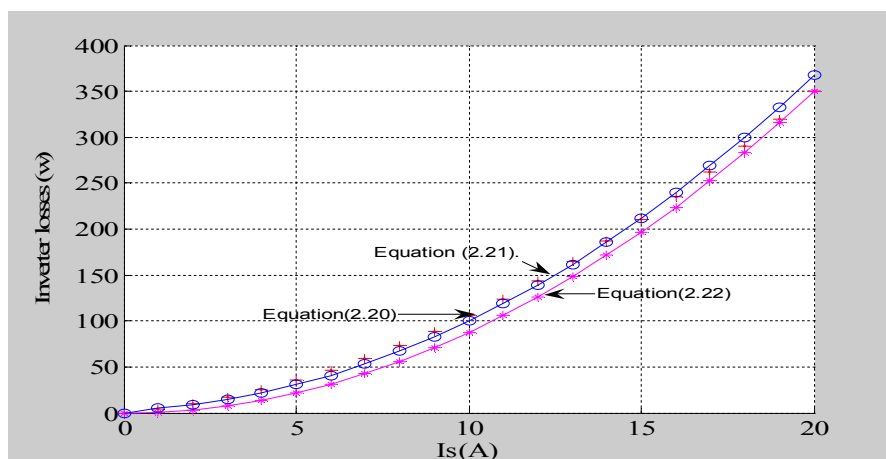


Fig. (2.9) Approximated Inverter Losses function

2.8. Summary

In this chapter the induction motor and converter loss models were highlighted. Commonly used models of induction motors and inverter were also developed. For the purpose of energy optimal control strategy, saturation was introduced in the motor model also a simplified inverter loss model was adopted in this work. To emphasize this model is used in this thesis because it is easy to use and it can be an integral part of the optimization algorithm.

Four simulations were conducted using Matlab/Simulink software in order to verify affecting inverter losses parameters; these parameters are the current (I_s), shift angle (ϕ), switching frequency (f_{sw}), and modulation index (r).

The simulation results show that the inverter losses are mainly influenced by stator current, whereas the other parameters have neglecting effect. Thus the inverter losses were approximated by a second order polynomial function which it comes in agreement with those provided by equation (2.20).

Chapter Three

Efficiency Optimization Approaches of Induction Machine Drive

3.1 Introduction

In this chapter, different types of losses involved in induction motor drives are classified and reviewed in the first section followed, in the second one, by a presentation of the loss model of the motor.

Since the efficiency improvement of the induction motor (IM) is fulfilled by the magnetic flux adjustment, it is very important to take into account the magnetic deviations in the loss model. This is the reason for which the saturated motor model has been introduced. The last part of this chapter is dedicated to the development of proposed losses minimization strategies based simultaneously on genetic algorithms and fuzzy logic methods.

3.2 Losses in Induction Motor Drives

Induction motor drive losses can be divided into grid loss, motor loss and transmission loss. A brief description of these losses is given below [Sang woo Nam, 2006]:

- Grid loss caused by harmonics contents in the input current.
- Converter loss due mainly to switching and conduction losses of the inverter.
- Transmission loss which could probably come from the bad coupled of the load.
- The motor losses comprise resistive losses, core losses, mechanical losses (friction and windage) and stray load losses.

Among the overall motor loss, resistive and core losses are the dominating ones compared to the stray and mechanical losses,[Ranta, 2011]. They also depend on magnetic and electric loading of the machine and therefore controllable. That is why in the current work stray and mechanical losses are neglected. At nominal operating point, the core losses are typically 2-3 times smaller than the copper losses, but they represent the main loss component of highly loaded induction motor drives, [branko blanusa, 2008].

In variable-speed induction motor drives, the losses depend on the flux level of the motor. A large number of loss minimization strategies have been developed for adjusting the flux level

according to the motor load and speed, [Ranta, 2011]. These loss minimization control techniques have been reviewed, in the introduction

Various loss functions have been used for describing the IM losses, [Bazzi, 2010]. Commonly the resistive losses and core losses of the motor are included in the loss model. The core losses are assumed to be proportional to the square of the frequency; this behavior corresponds to eddy-current losses habitually. Also it is possible to include both eddy-current and hysteresis losses in the loss model [Kioskederis, 1996]. If the loss model is sufficiently simple, the optimum flux level can be solved analytically. For more complicated loss models, it is possible to determine the optimum flux level iteratively, [Bazzi, 2010].

This thesis focuses on developing better control technique to reduce motor core loss which is the dominant one in IM drives. Figure 3.1 summarizes the different types of losses in IM drives and shows the possible methods of each loss reduction.

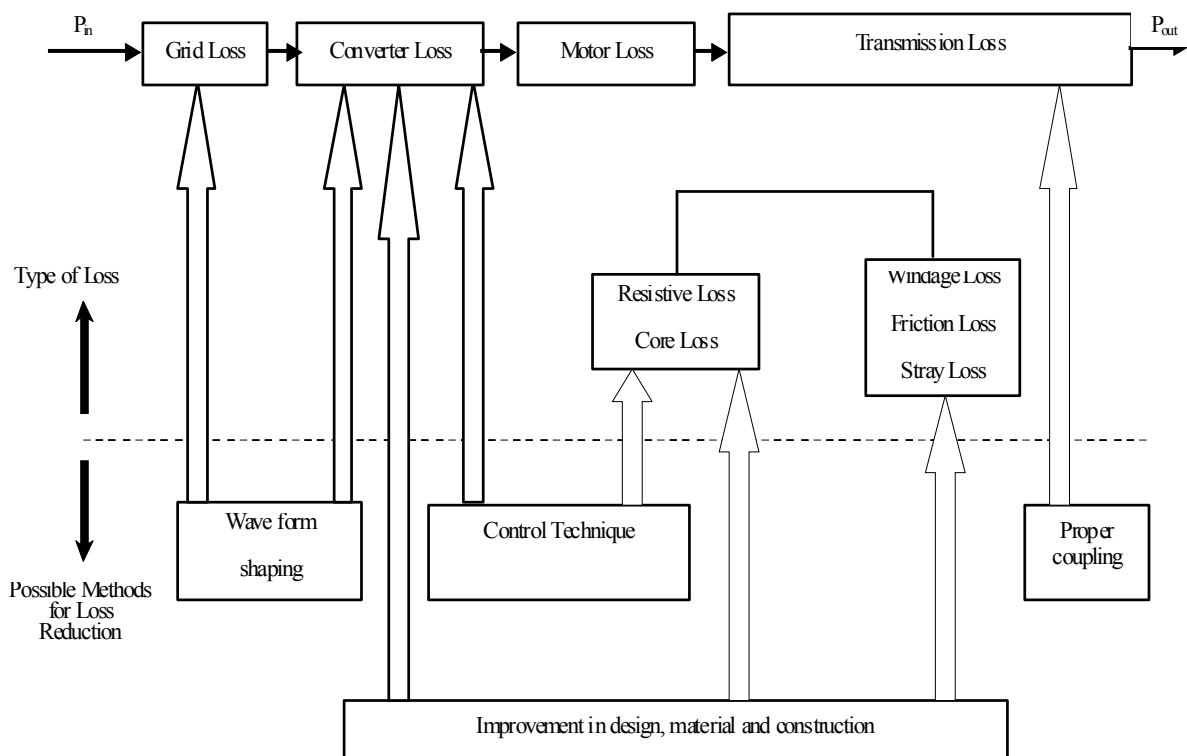


Fig (3.1). Different types of losses in IM drives and possible methods for loss reduction, [sang Woo Nam, 2006]

3.2.1 Motor Losses Model

The d-q model for a three phase IM in the synchronous frame can be written, when selecting the stator currents (i_{sd} , i_{sq}) and the rotor fluxes (Φ_{rd} , Φ_{rq}) as state variables, [Rouabah,2003]:

$$V_{sd} = R'_s i_{sd} + \sigma L_s \frac{di_{sd}}{dt} + \frac{M}{L_r} \frac{d\Phi_{rd}}{dt} - \omega_s \cdot \sigma L_s \cdot i_{sq} + \frac{R_{fs}}{L_r} \cdot \Phi_{rd} - \omega_s \cdot \frac{M}{L_r} \cdot \Phi_{rq} \quad (3.1)$$

$$V_{sq} = R'_s i_{sq} + \sigma L_s \frac{di_{sq}}{dt} + \frac{M}{L_r} \frac{d\Phi_{rq}}{dt} - \omega_s \cdot \sigma L_s \cdot i_{sd} + \frac{R_{fs}}{L_r} \cdot \Phi_{rq} - \omega_s \cdot \frac{M}{L_r} \cdot \Phi_{rd} \quad (3.2)$$

$$V_{rd} = \left(R'_{fr} - \frac{M}{T_r} \right) i_{sd} + \left(\frac{R_r + R_{fr}}{L_r} \right) \cdot \Phi_{rd} - \omega_r \cdot \Phi_{rq} + \frac{d\Phi_{rd}}{dt} \quad (3.3)$$

$$V_{rq} = \left(R'_{fr} - \frac{M}{T_r} \right) i_{sq} + \left(\frac{R_r + R_{fr}}{L_r} \right) \cdot \Phi_{rq} - \omega_r \cdot \Phi_{rd} + \frac{d\Phi_{rq}}{dt} \quad (3.4)$$

Where:

$$R'_s = R_s + R_{fs} \frac{\sigma_r}{\sigma_r + 1}, R'_{fr} = R_{fr} \frac{\sigma_r}{\sigma_r + 1}, T_r = \frac{L_r}{R_r} \text{ and } \sigma_r = \frac{L_r - M}{M}.$$

The total losses of an IM consist of stator and rotor copper losses, core losses P_{fe} and mechanical losses P_m . In the steady state, the stator and rotor copper losses are defined as follows:

$$P_{js} = R_s \left| \vec{i}_s \right|^2 = R_s (i_{sd}^2 + i_{sq}^2) \quad (3.5)$$

$$P_{jr} = R_r \left| \vec{i}_r \right|^2 = \frac{R_r}{(1 + \sigma_r)^2} [(i_{\mu r} - i_{sd})^2 + i_{sq}^2] \quad (3.6)$$

The core losses including eddy current and hysteresis losses are given by:

$$P_{fe} = (k_h \cdot \omega_e \cdot \Phi^2 + k_e \cdot \omega_e^2 \cdot \Phi^2) \quad (3.7)$$

The coefficients of hysteresis and eddy current losses are defined as k_h and k_e respectively. They can be determined from standard no-load test data, [J. M. D. Murphy, 1982].

As a reasonable approximation, the mechanical losses are function of the rotor speed.

$$P_m = k_m \cdot \omega_r^2 \quad (3.8)$$

Where k_m is the mechanical loss coefficient.

As the stator currents i_{sd} and i_{sq} are regulated and the motor is controlled to be field oriented to the rotor flux, according to the following relation:

$$i_{dr} = 0 \text{ and } i_{qr} = \frac{-M}{L_r} \times i_{sq}$$

In steady state, the operating losses of the machine can be expressed from eq. (3.1) to eq. (3.4) as follows:

$$P_{loss} = P_{js} + P_{jr} + P_{fe} + P_m \quad (3.9)$$

The motor torque can be expressed by:

$$T_e = \frac{3}{2} p \frac{M}{L_r} \Phi_r i_{sq} \quad (3.10)$$

By neglecting the mechanical losses and substituting (3.5),(3.6) and (3.7) into (3.9), the operating losses of the machine become:

$$P_{loss,motor} = (R_s + R_{js}) \cdot i_{\mu}^2 + \left(R_s + \frac{R_r}{(1+\sigma_r)^2} \right) \times \left(\frac{T_e}{p(1-\sigma)L_s i_{\mu}} \right)^2 \quad (3.11)$$

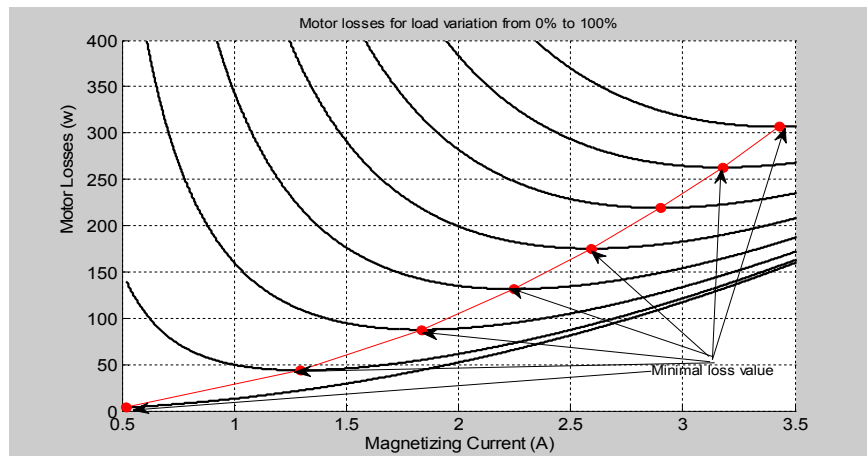
As seen on chapter two inverter losses can be approximated by a second order polynomial function given by equation (2.21) The drive losses which they will be minimized are thus:

$$P_{loss} = P_{loss,motor} + P_{loss,inv} \quad (3.12)$$

3.2.2 Loss Minimization

Equation (3.11) gives the expression of IM losses in vector control drive system.

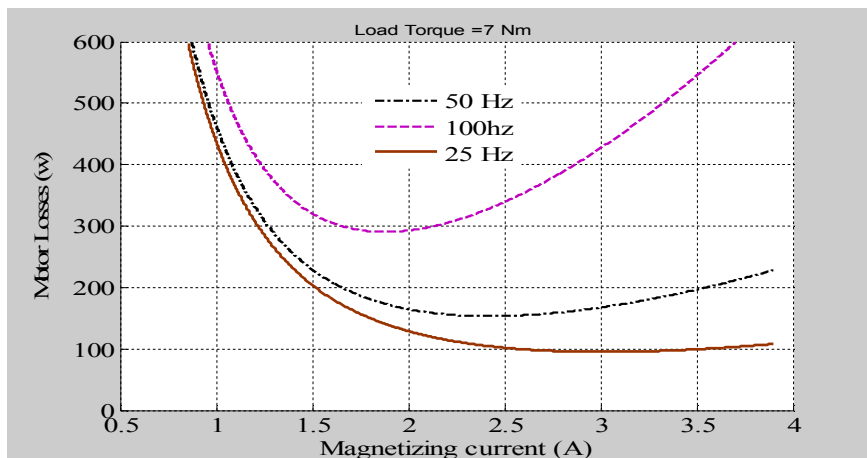
Figure 3.2 depicts the relationship between the motor losses and the magnetizing current (rotor flux) under various loads. It is very clearly that there is a minimum magnetizing current value for each load. The relationship between the total losses and the magnetizing current (rotor flux) under various speeds is also illustrated in Figure 3.3 These figures demonstrate that the total losses may obviously be kept to their lowest values. In these conditions, the highest efficiency can be ensured by tuning the rotor flux or the magnetizing current.



Fig(3.2). Motor losses versus magnetizing current at nominal speed

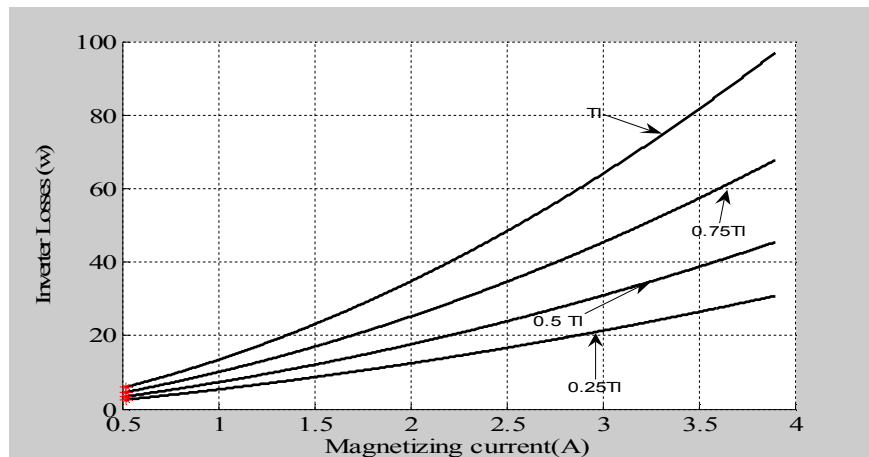
Then we can conclude that the philosophy of the controller efficiency optimization aims to make the motor working at variable flux which leads to efficient conversion of the electrical power within the motor drive. This can be accomplished by finding the optimal value of the magnetizing current that satisfies the criterion below:

$$\frac{\partial P_{loss}}{\partial i_{\mu}}=0 \tag{3.13}$$



Fig(3.3).Motor losses versus magnetizing current at nominal load torque

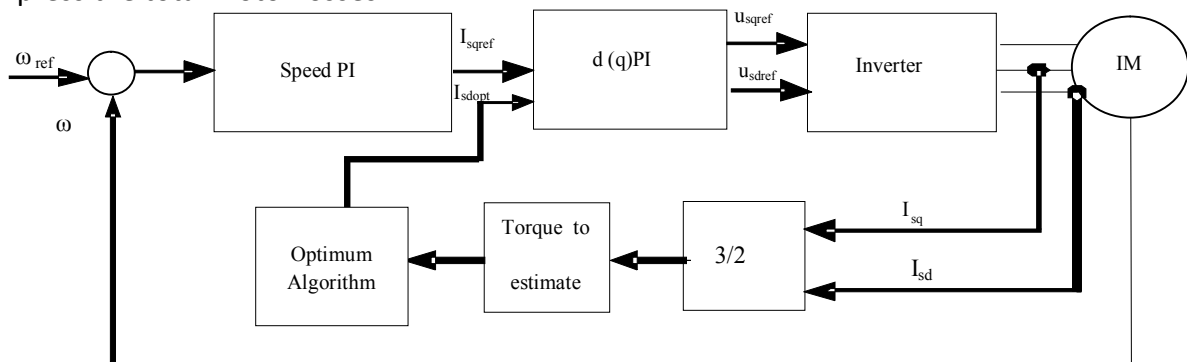
Figure (3.4) shows inverter losses versus magnetizing current (flux) for several load torques. Compared to the motor losses these losses are lowest they are around 4-5% of the motor losses.



Fig(3.4).Inverter losses versus magnetizing current (* minimal loss points)

3.3 Proposed Loss Minimizing Strategies

A simplified block diagram of the proposed efficiency optimization control system is depicted in Figure 3.5. It is implemented in classical indirect rotor flux oriented control (IFOC). In this scheme, two phase currents and the rotor speed are measured in order to calculate the electromagnetic torque and the magnetizing current (i_{μ}) which enables us to express the total motor losses.



Fig(3.5). Block diagram of the Optimization Control System

To get the best optimal solution of equation (3.12) we use fuzzy logic as first approach and then genetic algorithms as a second one with binary and real coding as described in the next subsections.

3.3.1 Fuzzy Logic approach

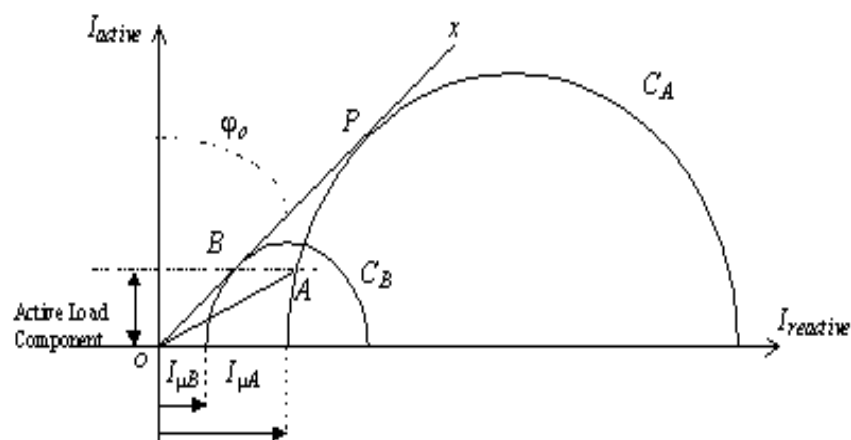
It can be noticed from the losses expressions given by equations (3.10) and (3.11), that the losses are non linear function, also the efficiency control should follow known rules, these reasons permit the application of fuzzy logic to realize an optimal efficiency control, [Bose, 2002]

Two fuzzy approaches are proposed in this section: the first one is based on the calculus of the optimal value of magnetizing current which leads to optimal efficiency, and the second approach is based on the estimation of the K_{opt} which permits the calculus of the optimal magnetizing current too.

3.3.1.1 First Fuzzy Approach

The philosophy of the efficiency optimization controller aims at minimizing the rotor flux by adjusting the magnetizing current component with respect to the torque current one, [Roua, 2008]. According to [M.S. Nait Said 1999], as the flux decreases, the iron losses drop while copper losses rise. Consequently, such flux decrease yields a reduction of the converter input dc link power.

The optimization principle is illustrated by Figure (3.6) which presents the induction motor circle diagram. In fact, as it appears, the induction motor operating point A has a lower power factor (low efficiency) that can be improved by maintaining the same active power, and displacing A to B location (optimal power factor). Under these circumstances, the magnetization current is minimized ($I_{\mu B} < I_{\mu A}$), causing hence a reduction of the stator current. Consequently, this strategy leads to copper losses decrease (i^2t). In this case, losses balance can be approximately achieved leading therefore to a high efficiency level.



Fig(3.6). Losses minimization principle

- **Fuzzy Controller Design**

According to the analysis based on Figure (3.6) two input variables are considered, the torque current component I_{sq} and its variation ΔI_{sq} . The output of the fuzzy controller is the stator current component I_{sdn} , which is calculated to minimize both copper and iron losses. The above inputs and output variation domains are limited and normalized as follows, [Roua,2008]:

$$I_{sqn} = \left| \frac{I_{sq}}{I_{sq\max}} \right| \quad (3.15)$$

$$\Delta I_{sqn} = \left| \frac{\Delta I_{sq}}{\Delta I_{sq\max}} \right| \quad (3.16)$$

$$I_{sdn} = \left| \frac{I_{sd}}{I_{sd\max}} \right| \quad (3.17)$$

Control rules are extracted and summarized in Table 3.1 below, also the membership of the used controller are shown in Figure (3.7):

Table 3.1 Rule matrix for efficiency improvement

ΔI_{sq}	I_{sq}	Z	P
	I_{sd}	Z	P
Z		Z	P
P		P	P

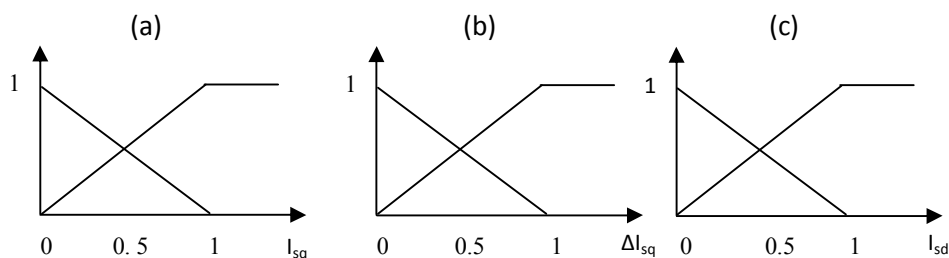


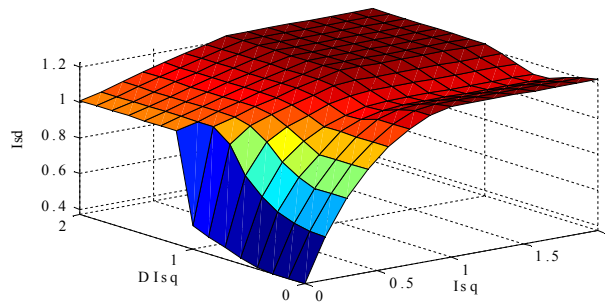
Fig (3.7). Membership distribution (a) input 1, (b) input 2 and (c) output

The linguistic terms are defined as:

Z: Zero

P: Positive

The law mapping is illustrated by Fig(3.8)



Fig(3.8). Optimization control Law Mapping

3. 3.1.2 Second Fuzzy Approach

This second approach is based on the adaptation of the optimal factor K_{opt} , which depends on the motor parameters . Figure (3.9), shows the principle of the proposed fuzzy controller. The stator current magnitude change and the change of the magnetizing current are used as its input variables where the output variable is the K_{opt} change.

The calculation of the derivative of equation (3.13) when neglecting inverter losses leads to:

$$K_{opt} = A / [n_p(1 - \mu) L_s]^{1/2} \tag{3.14}$$

Where : $A = [((R_s + R_r) / (r + 1))^2 + r R_{fs} / (1 + r)] / (R_s + R_{fs})^{1/2}$

The choice of these input variables is made regarding to the variation of K_{opt} versus R_r and R_s , L_s and M as illustrated respectively in Figure (3.10) ,where the influence of magnetizing and stator inductance is clearly shown .

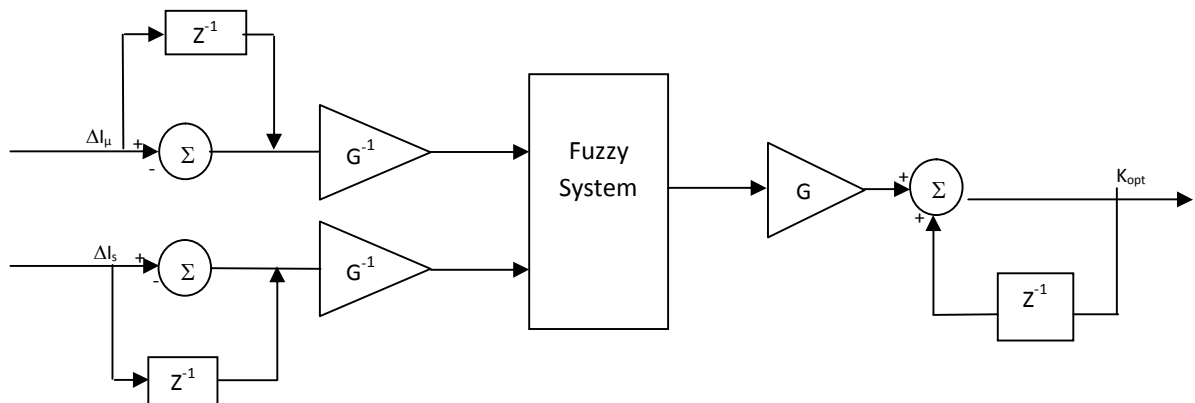


Figure (3.9). The proposed fuzzy controller

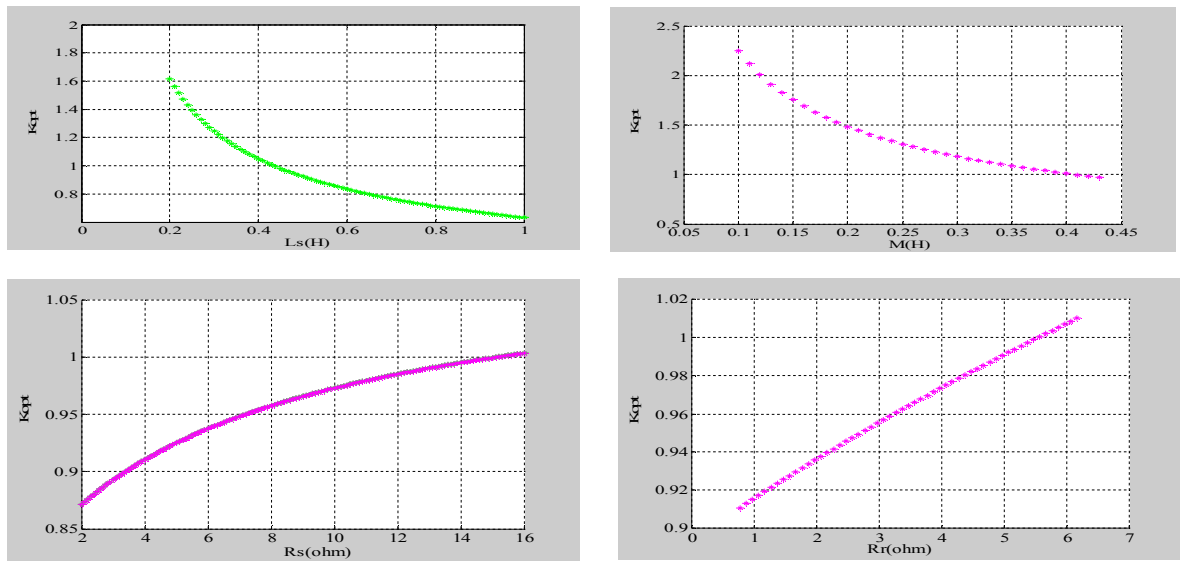


Fig.(3.10) K_{opt} variation versus L_s , M , R_r and R_s

- **Fuzzy Controller Design**

The fuzzy controller is designed to have two fuzzy state variables and one control variable for reaching optimum motor efficiency as presented in Figure(3.11). Each variable is divided into fuzzy segments. The number of these fuzzy segments for each variable is chosen to have maximum control with minimum number of rules. The first variable is the stator current error and the second one is the magnetizing current error.

Both fuzzy inputs are defined as:

$$\Delta I_s = I_s(k) - I_s(k - 1) \quad (3.18)$$

$$\Delta I_\mu = I_\mu(k) - I_\mu(k - 1) \quad (3.19)$$

The universe of discourse of the first input is divided into three overlapping fuzzy sets: Positive Small (PS), Positive Medium (PM) and Positive Big (PB).

The grade of membership distribution is given in Figure (3.11,a) which uses a triangular distribution.

The universe of discourse of the second input is divided into three overlapping fuzzy sets: Negative (N), Zero (Z) and Positive (P). The grade of membership distribution is shown in Figure (3.11, b).

The output variable is the variation of K_{opt} variable. The universe of discourse of this fuzzy variable is divided into seven fuzzy sets. The membership distribution is shown in Figure (3.11,c).

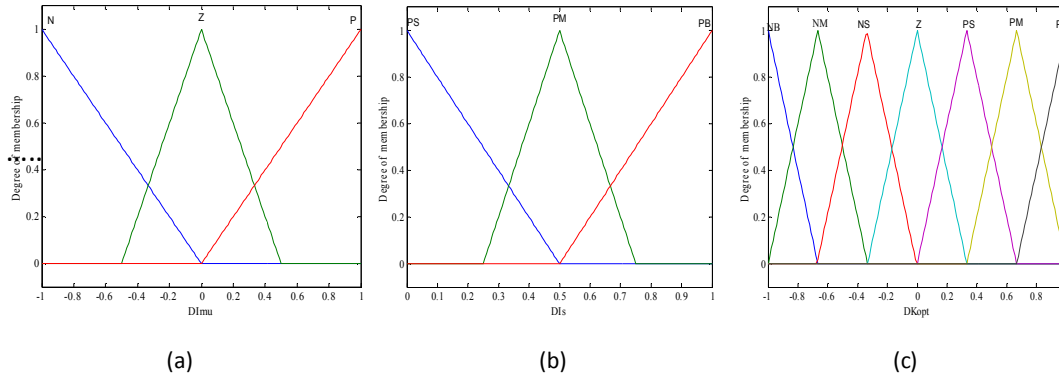


Fig (3.11). The membership distribution,(a) input1, (b) input 2 and (c) output

The adopted inference method is basic and simple and is developed from the maximum operation rule as a fuzzy implementation function, [C.C.Lee, 1990],[Duy C. Huynh,2010].

Table 3.2 contains the corresponding rule table of the designed controller. The mapping of the optimization control law is also shown in Fig (3.12).

Table 3. 2 Rule matrix for K_{opt} adaptation

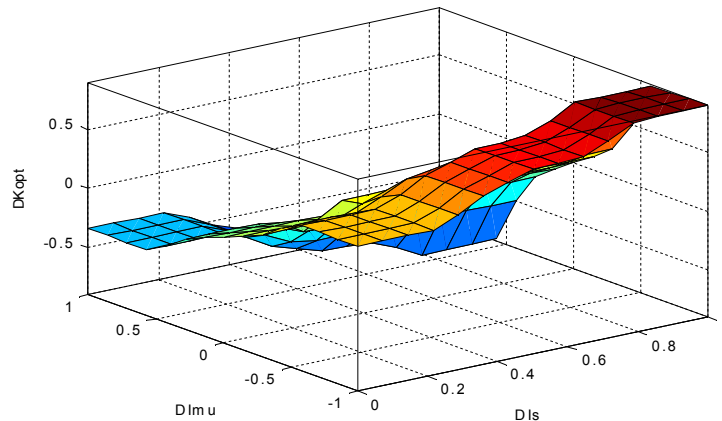
ΔI_s	ΔI_μ	N	Z	P
	ΔK_{opt}			
PS		PS	Z	NS
PM		PM	Z	NM
PB		PB	Z	NB

The linguistic terms are defined as:

Z: Zero P: Positive PS: Positive Small PM: Positive Medium PB: Positive Big.

N: Negative NS: Negative Small NM: Negative Medium NB: Negative Big.

$$K_{opt} = K_{opt}(k - 1) + \Delta K_{opt} \quad (3.20)$$



Fig(3.12). The optimization control law mapping

3.4 Genetic Algorithms Approach

The procedure of loss minimization consists of optimizing the value of the magnetizing current ($I\mu$) for a given load torque so as to minimize the total motor losses in steady state operation. In this section, as in the case of fuzzy logic, two genetic algorithm approaches are proposed.

For the first one an off line optimization was done by using the binary coded genetic algorithms to calculate the optimal current leading to minimum losses. The obtained values are introduced in lookup table and implemented in the control scheme. The corresponding flux optimized value is calculating during the motor operating and is applied as a command variable.

The second approach is an on line optimization. It uses the real coded genetic algorithms (RCGA); these algorithms have many advantages in numerical optimization over binary encoding. Efficiency of the RCGA is increased as there is no need to convert chromosomes to phenotypes before each fitness evaluation, less memory is required and there is no loss in precision by the conversion between binary and real values, [Ki Li She, 2001].

The principle operating structure of genetic algorithms (GAs) block is illustrated by the flow chart of Fig (3.13).

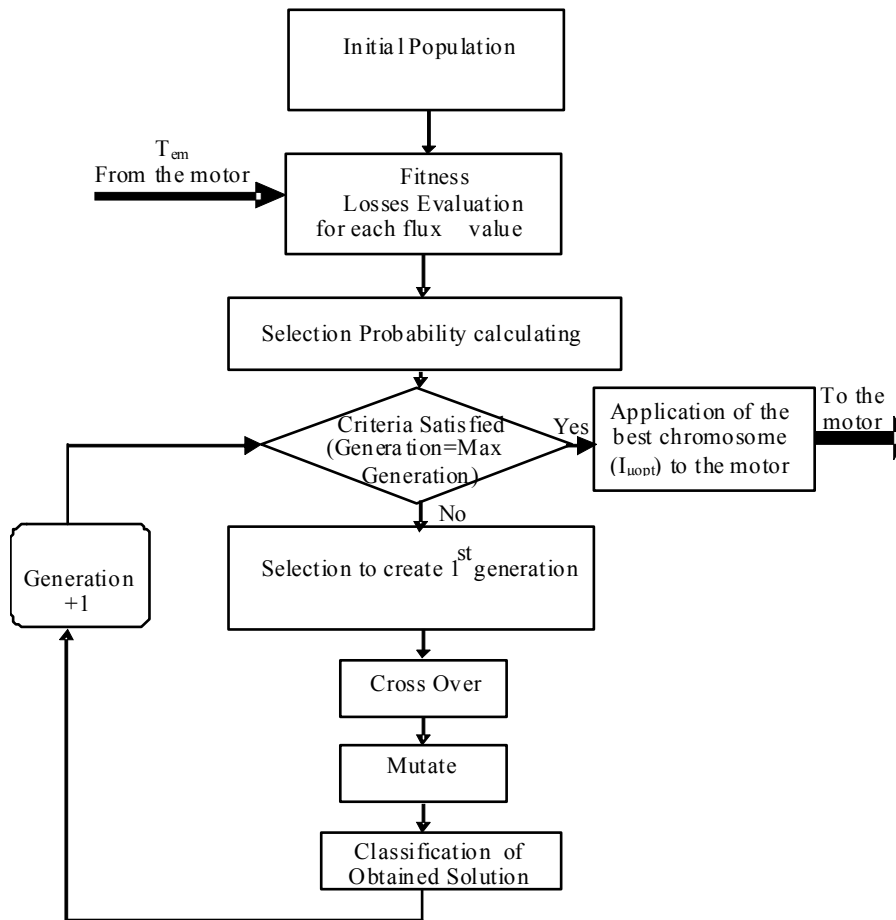


Fig (3.13). Efficiency optimization flowchart by genetic algorithms

3.4.1 Genetic Algorithms Optimization Procedure

This optimization procedure consists of searching the optimum magnetizing current (flux) value for a given load torque by relying on genetic algorithm. The latter is defined as stochastic optimization technique based on the genetic natural evolution mechanism of creative beings, [jnchaun,2005], [Sheble,1995]. Such algorithm is found to be a powerful computational tool in seeking optimums and is considered as the most up-to-date product of artificial intelligence techniques that emulate the mechanics of natural selection and genetics. It explores, with coding parameter set, the workspace by means of mechanism of reproduction, with the target of optimizing the process selection. This mechanism comprises selection, crossover and mutation operations, [Renders J.M, 1995], [Leigh J.R, 2004].

The application of this approach requires the introduction of an objective function which evaluates how good the fitted values of the magnetizing current are. From this function, a fitness that controls the reproduction process is derived.

The criterion to select the best individuals for reproduction is the objective (fitness) function. By proceeding in this way, the objective function adopted for this problem is the IM total losses given by equation (3.13). Each generation is subjected to the crossover and mutation mechanisms. The crossover consists in selecting two parent chromosomes randomly in order to generate two new individuals. The mutation follows crossover and is used to insure that useful genetic data that could have been disregarded during crossover is not permanently lost.

3.4.1.1 Off Line Genetic Algorithms Optimization Procedure

With this procedure, the individuals of the initial GA population are encoded in binary strings where each individual representing a parameter takes 10 bits.

Each generation is subjected to the crossover and mutation mechanisms. The crossover consists in randomly selecting a position along parents string a swapping all binary digits following that position. The mutation follows crossover and works by randomly selecting one string and one bit location, changing that strings bit from 1 to 0 or vice versa.

3.4.1.2 On Line Genetic Algorithms Optimization Procedure

The procedure of real-coded genetic algorithm is outlined as follows:

- 1) Initial generation: the RCGA begins by randomly N individuals inside certain range and forms initial generation.
- 2) Fitness evaluation: every individual's fitness is calculated according to the fitness function expressed by eq. (3.13).
- 3) Reproduction: parent individuals are sorted from big fitness function value to small one, and excellent individuals from the headmost are directly passed to offspring generation and the rest is put in matching pool.
- 4) Crossover and Mutation: those operations are finished in matching pool, and the generated individuals are sent to offspring generation.
- 5) Iteration: the RCGA runs iteratively repeating the actions from 2 to 4 until population convergence condition is met or the maximum number of iterations is reached.

As an example of the

3.5 Results of GA's application

The probabilities of the crossover and mutation are set to 0.8 and 0.01 respectively and for both binary coded and real coded GAs simulation are performed for 30 generation which is choose as stopped criteria.

Figure (3.14) illustrates the optimal values of the magnetizing current (i_μ) for 50% of a rated load for real and coding, while Fig (3.15) shows the optimal evaluation (losses). It can be noticed that the convergence is rapidly achieved for both cases.

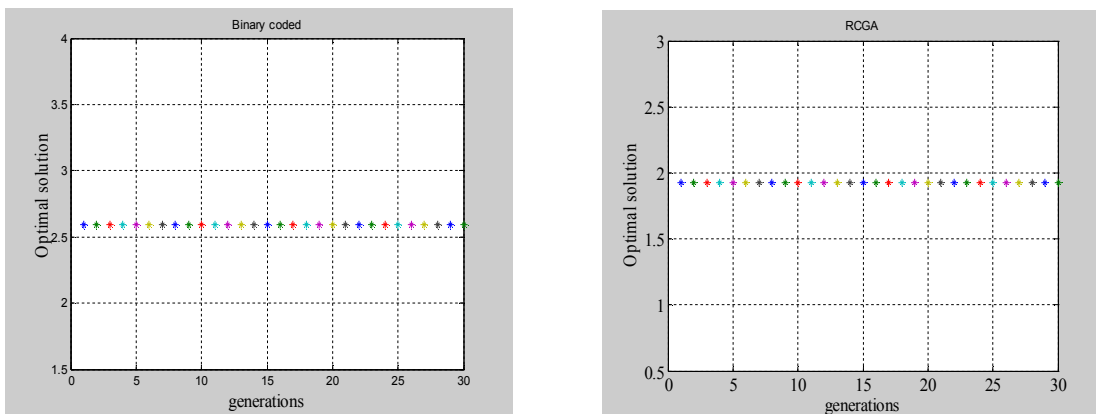


Fig (3.14). Optimal solution obtained by genetic algorithms for $T_L=3.5Nm$

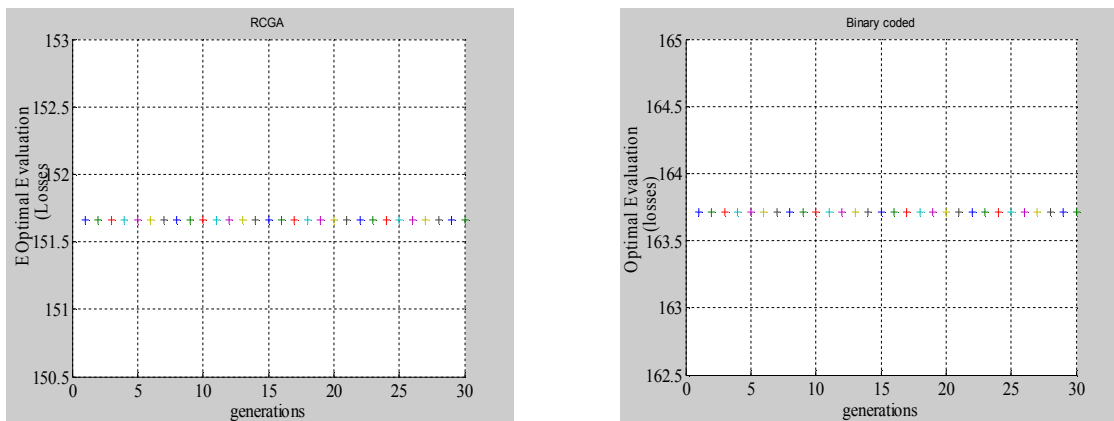


Fig (3.15). Optimal evaluation obtained by genetic algorithms for $T_L=3.5Nm$

3.6 Summary

By focusing on developing a better control technique to improve motor efficiency, this chapter has presented the basic principles of two intelligent optimization techniques based on the loss motor model. The first one is based on fuzzy logic where two online efficiency optimizer algorithms were proposed and the second technique is based on genetic algorithms and both real and binary coding was used for an online and offline calculus of the optimizing magnetizing current. Results, interpretation and validation of the proposed approaches will be presented in the fourth chapter.

Chapter Four

Simulation Results and Discussion

4.1 Introduction

This chapter presents the development of the proposed IM drive system for the simulation study using Matlab/Simulink software. In order to verify the effectiveness of the proposed loss minimization algorithms given in chapter three for efficiency enhancement and their robustness in different dynamic operation. The performances of the proposed algorithms are than compared with traditional field oriented technique. Extensive simulation results on the proposed methods and the complete IM drive are presented.

4.2 Drive System

The proposed control scheme is presented in Figure. (4.1) which show the diagram of the system block using loss minimization algorithm for indirect field orientation of IM. The IM parameters used in the simulation are given in Appendix 1.

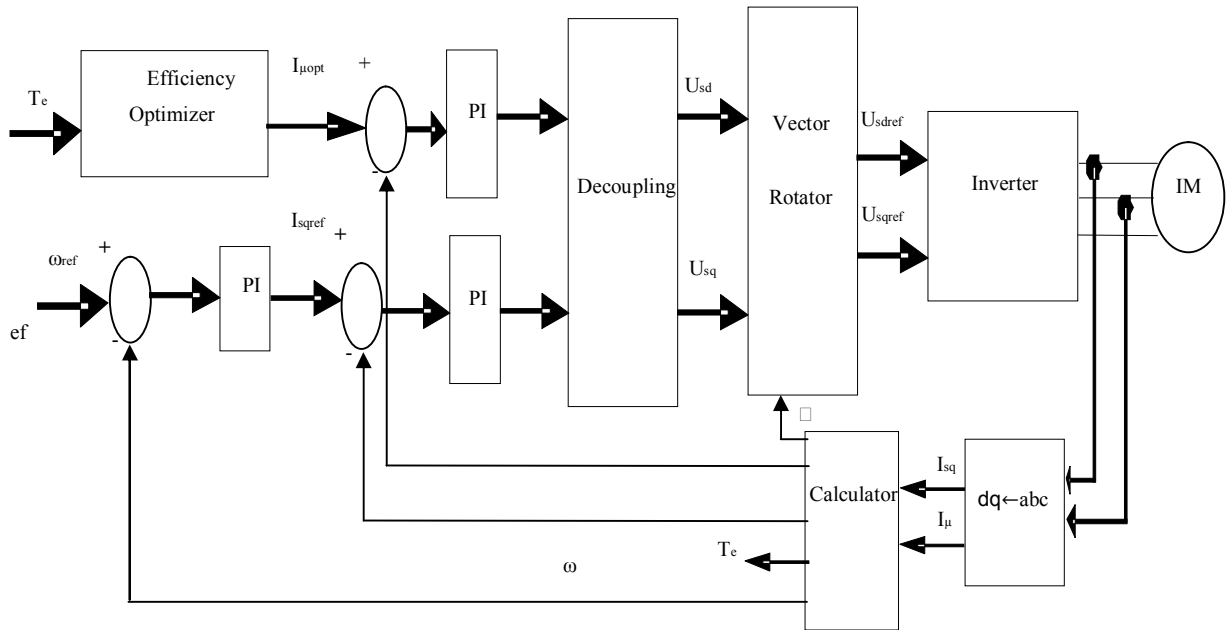


Fig.(4.1). Indirect vector Controlled IM with Efficiency Optimizer

The motor phase currents are fed into the Clarke and Park block, namely abc/dq block. The magnetizing current reference which is the optimal value allowing loss minimization this current is generated based on the solution of equation (3.13). This latter indicates that the flux (magnetizing current) must vary with the torque which is the optimizer input. The command voltages are applied to the inverter via the inverse Clark and Park transformations. These voltages will generate the signals that drive the inverter by comparing with high frequency Pulse Width Modulation (PWM) carrier signal.

4.3 Simulation Results and Discussion

An extensive simulation has been done in order to predict the performances of the loss minimization algorithms without taking into account magnetizing saturation first time. First the performance of the classical FOC has been investigated according to given load profile using a 2 KHz switching frequency. Figure (4.2) shows the torque response it is clear that the motor developed torque follows the load profile.

The speed converges to its reference 157rad/s. without any overshoot, as seen on Figure (4.3). Figure (4.4) shows the fluxes while the Figures (4.5) and (4.6) show losses and efficiency of the drive respectively one can see the poor efficiency when light loads are applied compared to the rated one while the losses are mostly dependant on load torque.

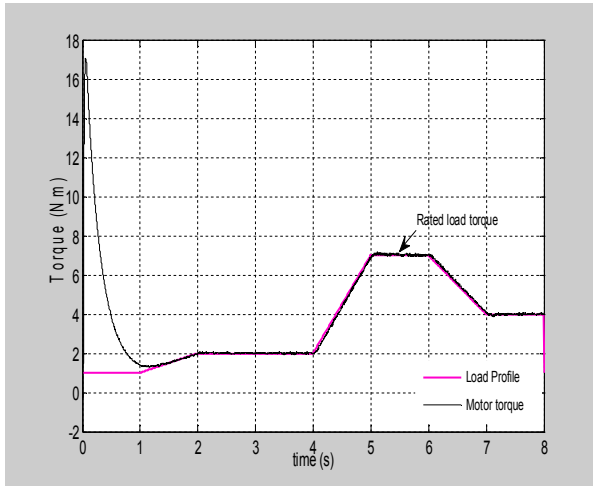


Fig.(4.2) Load Torque Profile and Torque response

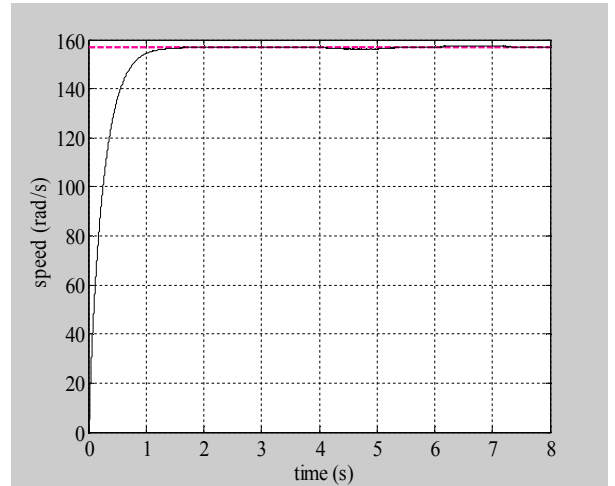


Fig.(4.3) Speed response

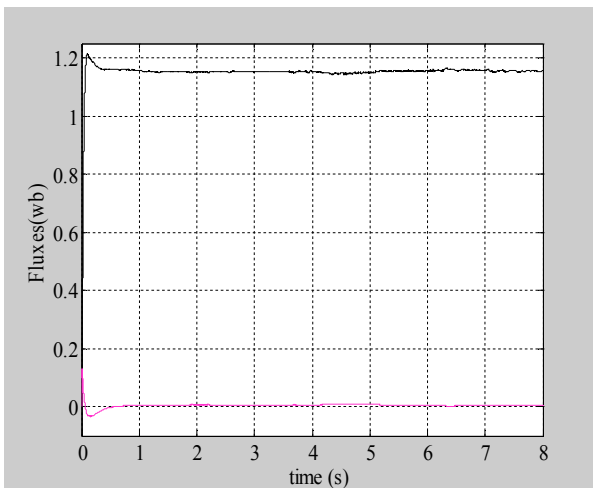


Fig.(4.4) Motor fluxes

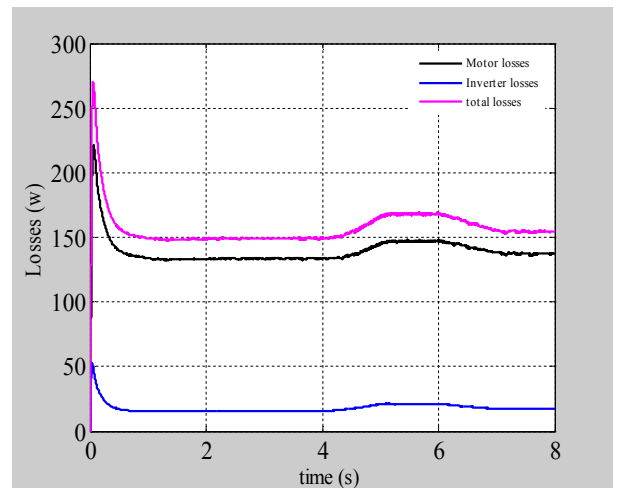


Fig.(4.5) Losses

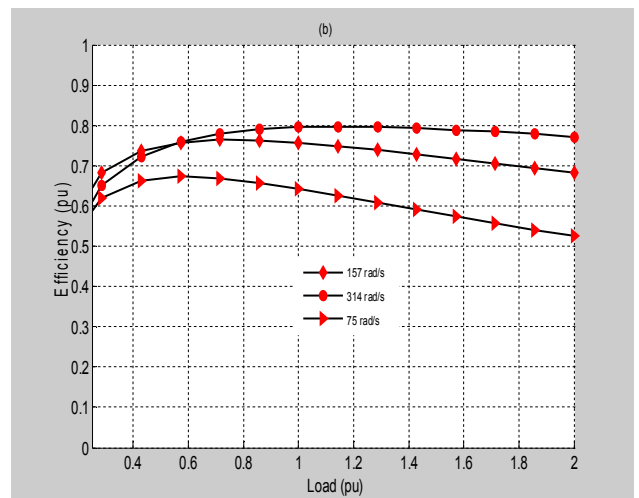
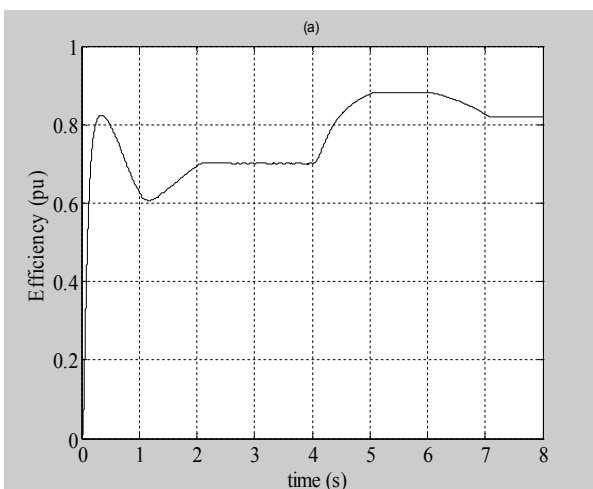


Fig.(4.6) Energetic performance of the drive: (a) Efficiency versus time for rated speed, (b) Motor efficiency versus load

4.3.1 Performance of Fuzzy Logic Approaches

The aim to using the optimization algorithms was to let the motor working at variable flux, also to proof the effectiveness and the robustness of the proposed algorithm the motor drive was tested at different range of speeds highest and lowest than the nominal speed.

The figures bellow show the performances of loss minimization algorithms namely “fuzzy approaches” at rated speed.

When the IM load is varying between 14% and 28% of the rated load for example in the time period 1s to 2 s, the rotor flux reference alters to adapt to the IM load variations as seen on Figure.(4.7). This flux adaptation has a direct influence on the efficiency which is improved. At each operating point, the optimal efficiency is reached when using the optimization algorithm as we can see on Figures. (4.8) and (4.9), the motor efficiency is greatly improved over load range compared with the classical FOC (see Figure.(4.6)).However one can notice that the losses in transient increased for the first fuzzy optimization approach compared to the conventional FOC.

The efficiency improvements are significant at light load torque as it is apparent on the figures the efficiency is increased more than 5% for by the proposed approaches however the first fuzzy approach provides a best efficiency. It can be seen that fuzzy are effective : fast convergence is achieved. Fuzzy efficiency controller work effectively with sudden changes in the operating conditions.

The importance of including inverter loss in energy optimal control is shown here as it is apparent on Figure. (4.9) where the efficiency is reduced about 3-4%.

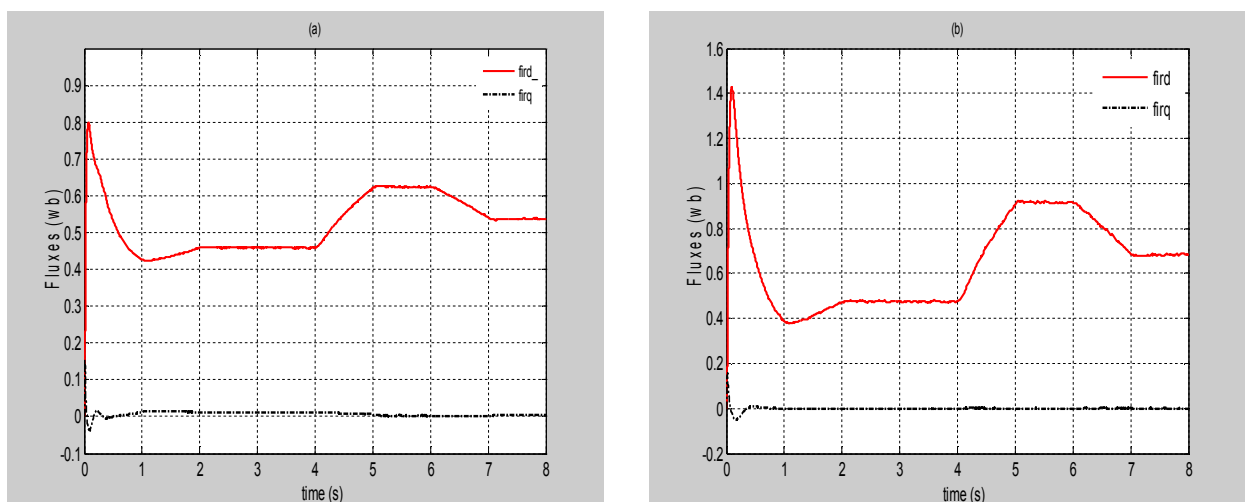


Fig.(4.7) Fluxes of the motor (a) First fuzzy approach ,(b) K_{opt} fuzzy approach

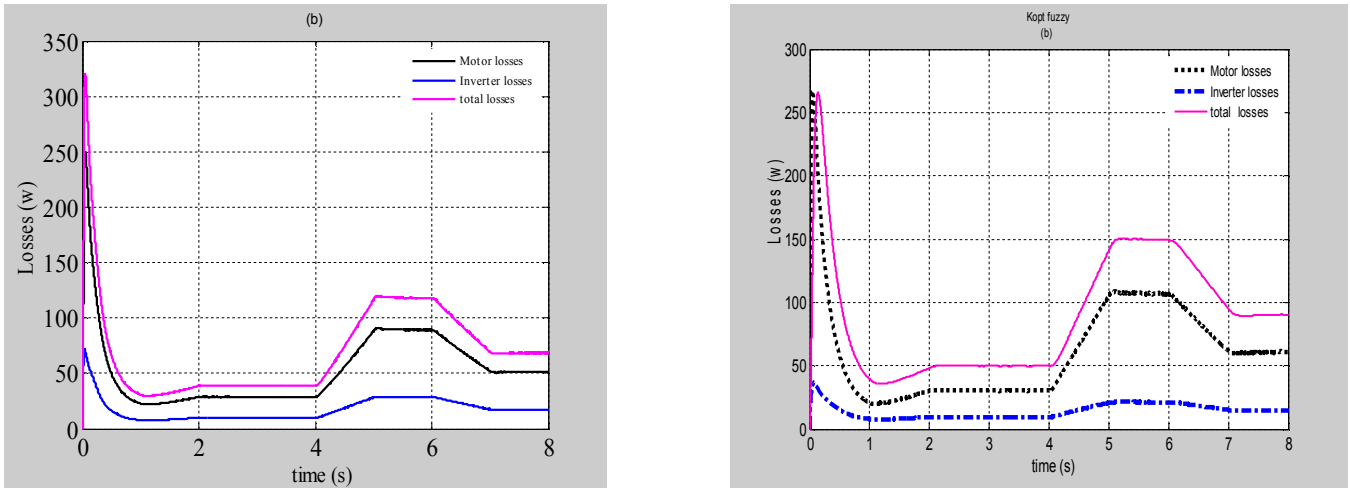


Fig.(4.8) Energetic performance of the drive: Losses (a) first fuzzy approach, (b) K_{opt} fuzzy approach

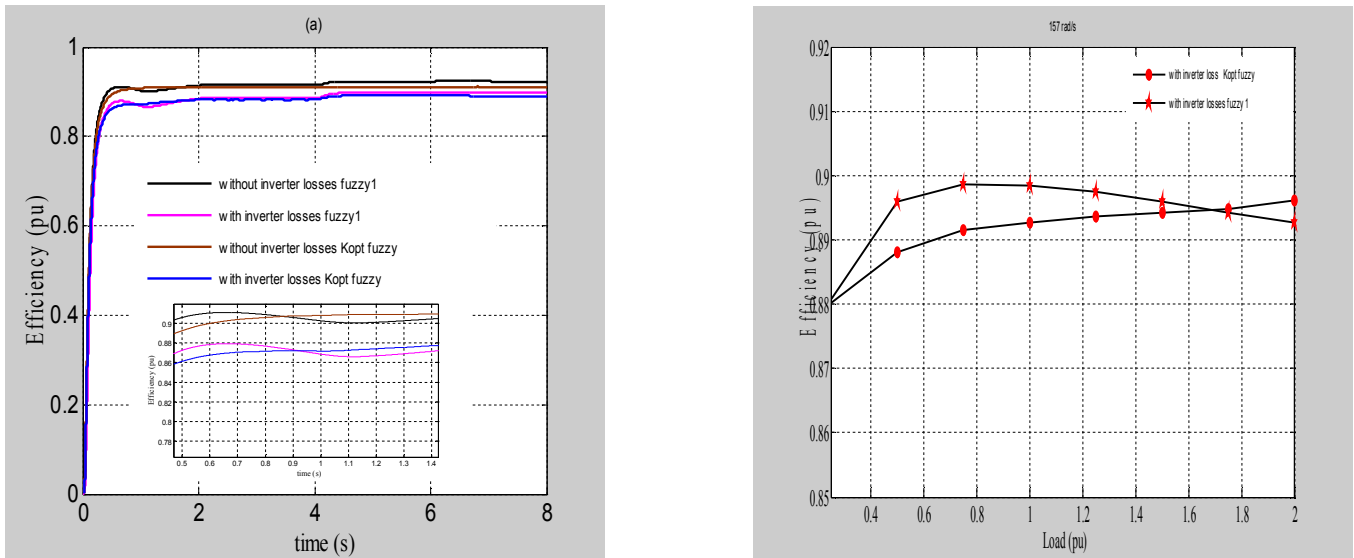


Fig.(4.9) Energetic performance of the drive at rated speed : Efficiency (a) versus time for a given profile load,(b) versus load

In order to fulfill the IM energy saving task robustness by the proposed approaches figures (4.10 a) and (4.10.b) show the efficiency at high (314 rad/s) and lower speed (75 rad/s) respectively. Also in this case it can be noticed the great improvement in efficiency over low load range compared with the classical FOC especially with first fuzzy approach. The motor efficiency is lowest with the inverter because of the harmonic motor loss with the PWM voltages [Abrahamsen,2000].

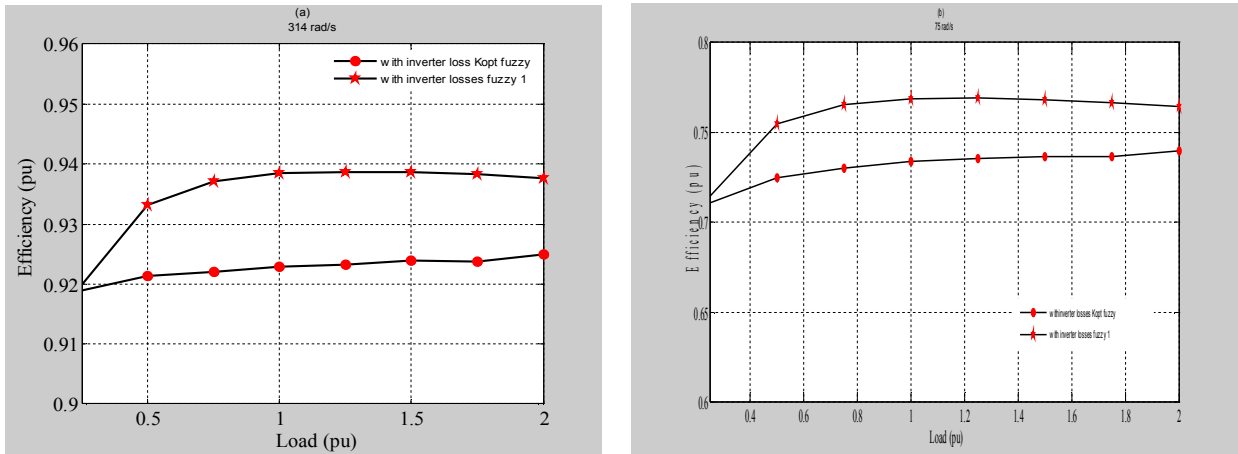


Fig.(4.10) Efficiency Comparison for : high Speed (a)and low Speed (b)

4.3.2 Performance of Genetic Algorithms Approaches

Using the same load profile simulation results given by GA’s approach are presented on figures bellow.

Figure (4.11) shows the fluxes variation according to the control law it is pursuing the load profile, while Figure (4.12) shows losses. One can see the increasing of losses in transient when they are greatly reduced in steady state. The reduction seen on the losses are of course reflected into the efficiency curves on Figures 4.13 (a) ,(b) and (c) where we can see the great efficiency enhancement for rated, high and low speed.

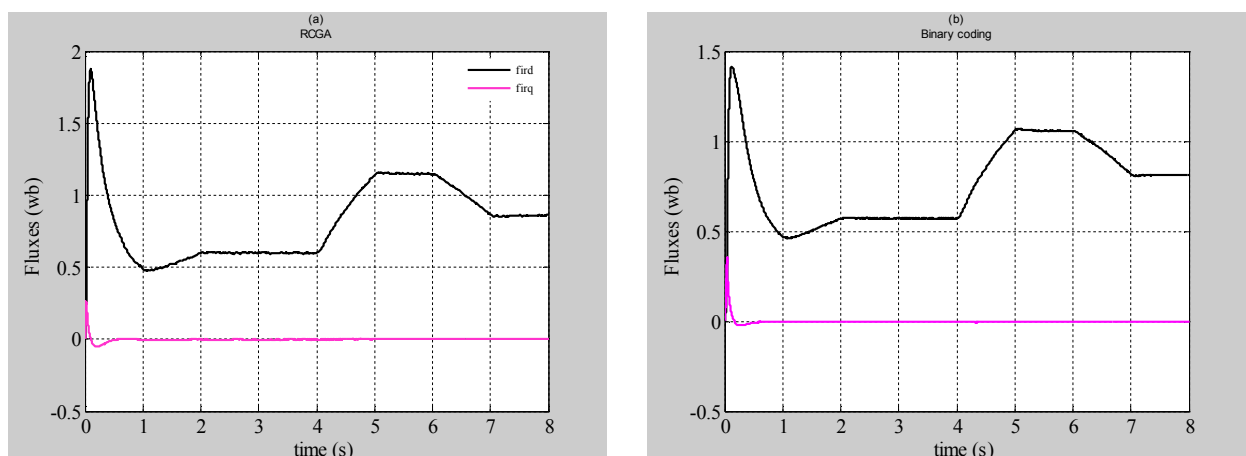


Fig.(4.11) Fluxes of the motor (a) RCGA approach, (b) off line BCGA

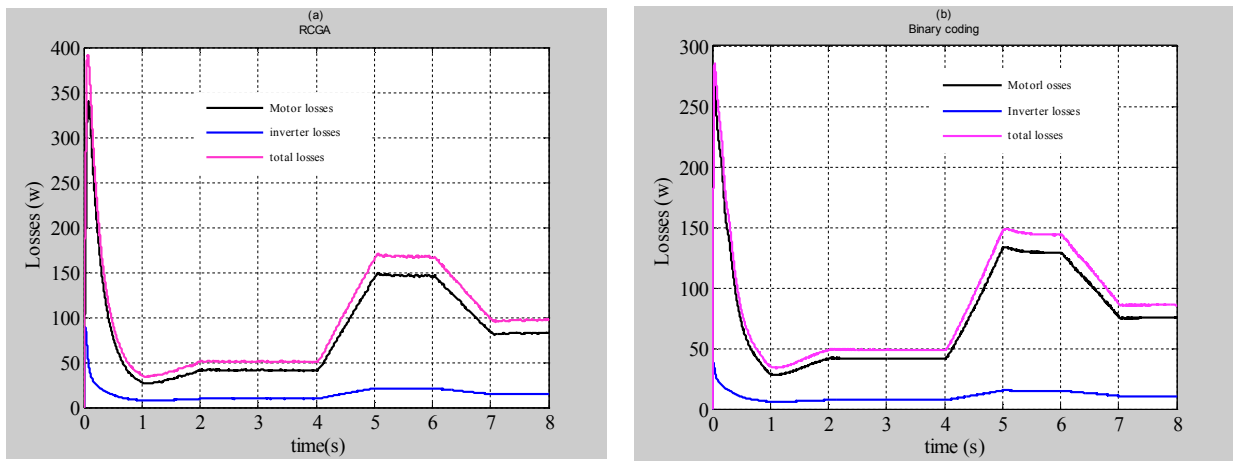


Fig.(4.12) Energetic performance of the drive: Losses (a) RCGA approach, (b) off line BCGGA

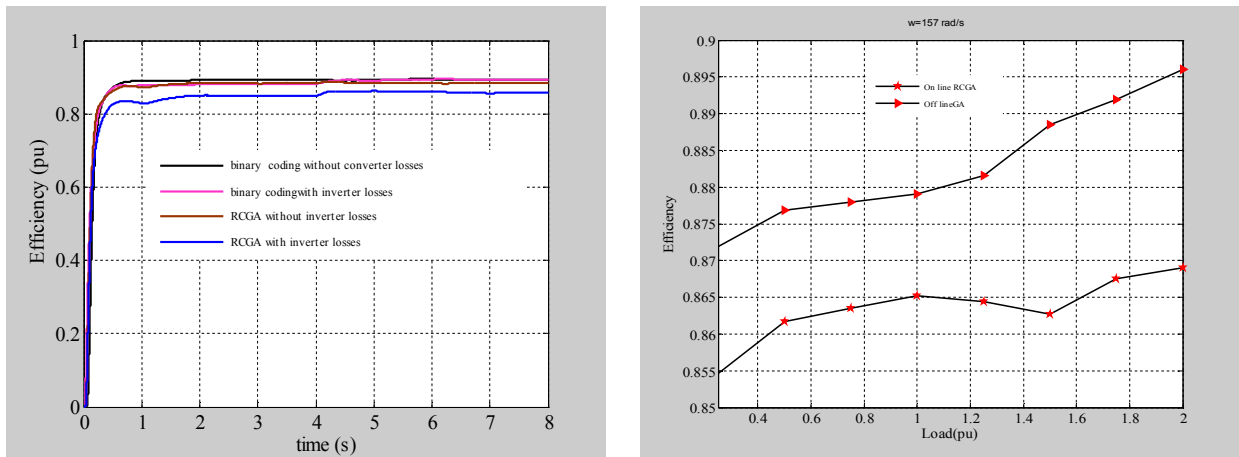


Fig.(4.13) Energetic performance of the drive at nominal speed: Efficiency (a) versus time for a given profile load, (b) versus load

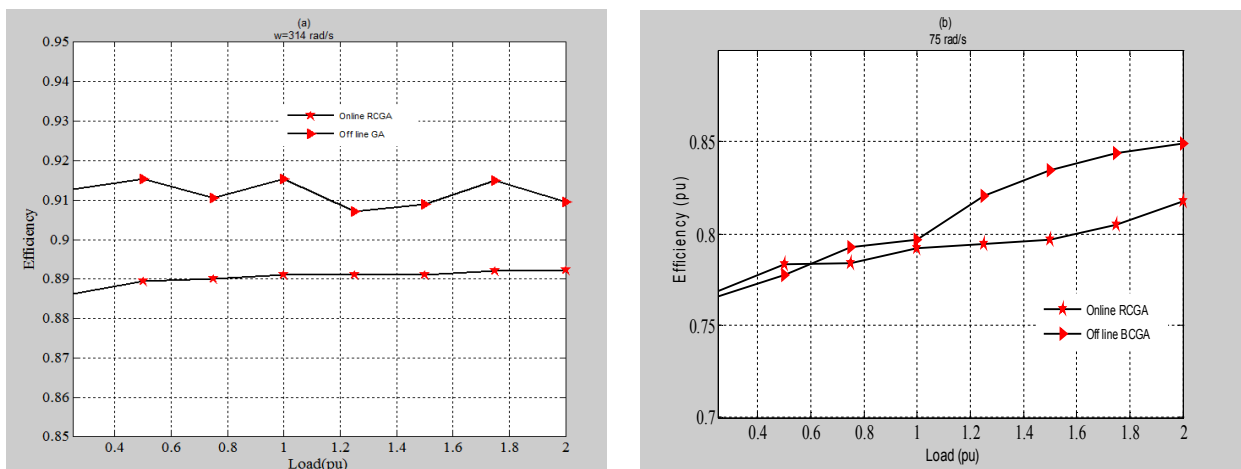


Fig.(4.14) Energetic performance of the drive: Losses (a) High speed , (b) Low speed

These results demonstrate that the proposed methods save more energy than the conventional.

However the losses of the drive are reduced in the steady state while in the transient they are significantly increased relatively to the classical FOC. In the second fuzzy approach mainly called fuzzy K_{opt} this leads us to use the optimizing controller only when steady state is reached and from starting up.

Steady state efficiency optimizer controller is activated when the system reaches steady state and it is determined when the speed error maintains a particular value for a predetermined period of time as presented on Figure (4.15).

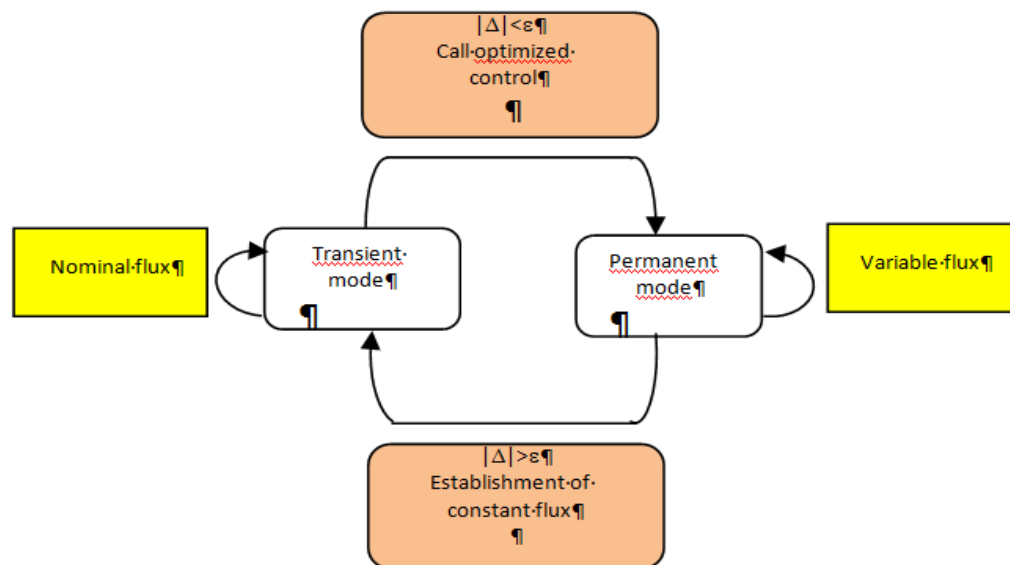


Fig.(4.15) Transit between transient and permanent mode

4.4 Effect of Parametric variation on Performance of the Efficiency Optimization

Motor parameters vary depending on operation conditions, affecting by the way the drive performance. As the efficiency optimization algorithm depends on these parameters in this section investigation of the parameters which critically affect such control is doing.

For a given load torque, the efficiency of the IM drive can be expressed as:

$$\eta = \frac{P_{out}}{P_{in}} \quad (4.1)$$

where:

$$p_{out} = T_e \times \omega_r \quad \text{and} \quad p_{in} = V_{sd} \times I_{sd} + V_{sq} \times I_{sq}$$

In terms of the equivalent circuit parameters the efficiency is given by:

$$P_{in} = P_{out} + M \times \left(\frac{A}{M} + \frac{R_{fs}}{L_r} \right) I_{\mu}^2 + \frac{A}{R_r \left(\frac{L_r^2}{M^2} \right)} \times \frac{T_e^2}{M^2 I_{\mu}^2} + \frac{R_r \times T_e^2}{M^2 I_{\mu}^2} \quad (4.2)$$

$$\text{Where: } A = \frac{R_s + R_{fs} \sigma_r}{(1 + \sigma_r)}$$

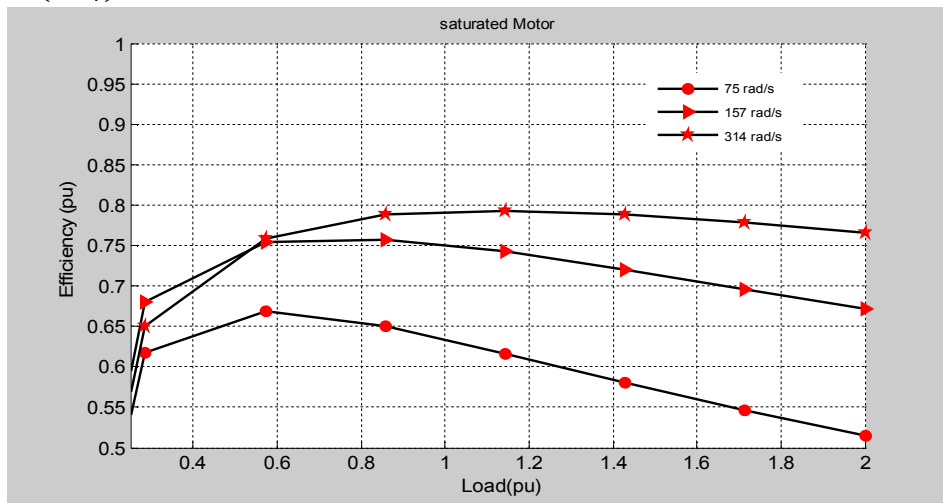


Fig. (4.16) Saturated Motor Efficiency

Figure (4.16) shows the motor efficiency while Figure (4.17) shows the parameters variation effects on the efficiency under rated speed.

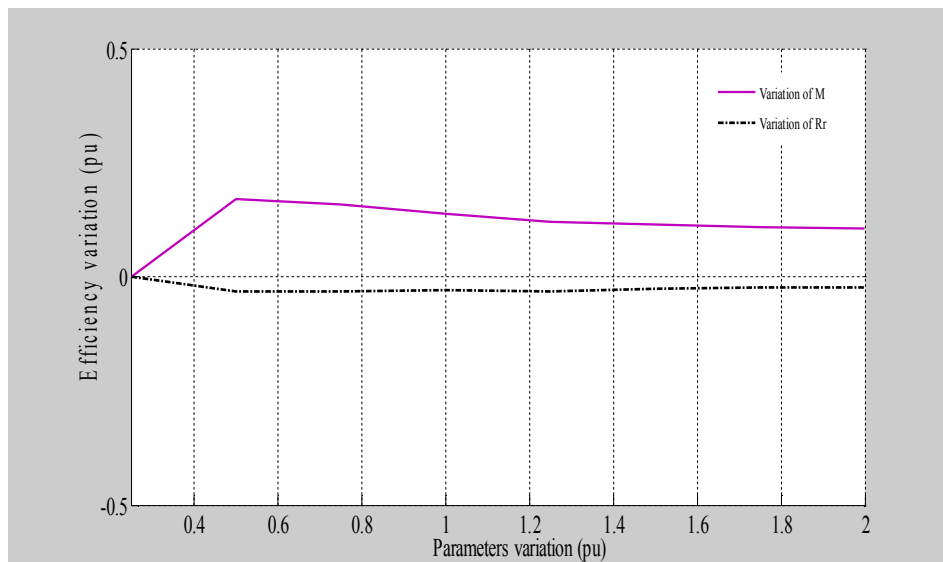


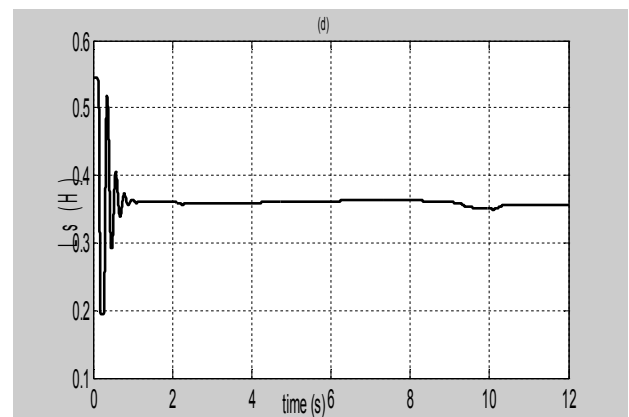
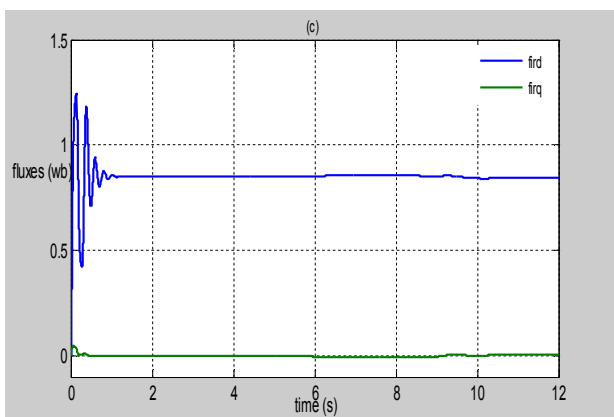
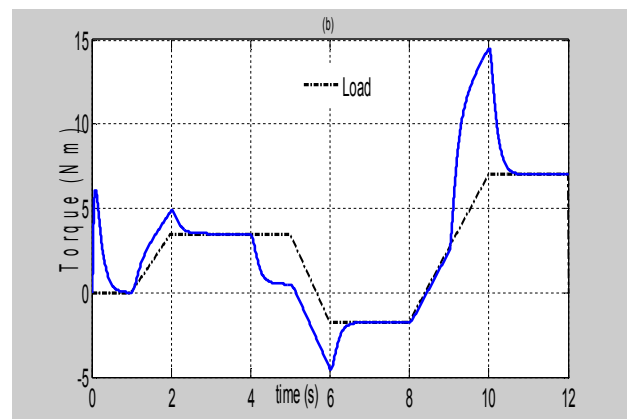
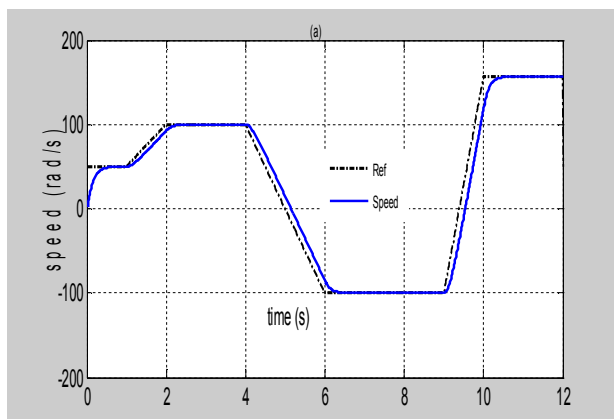
Fig.(4.17) Efficiency variation with Parametric Variation

In the next section the effect of saturation and rotor resistance variation on the efficiency optimization will be focused

4.4 1. Magnetic Saturation Effect

Usually the control algorithm used in vector control is derived from constant parameter induction motor model. Unfortunately, the machine parameters are subject to variation due to temperature changes and saturation, as a consequence mismatch between actual parameters and those used in the control occurs leading to detuned operation of the drive, [Levi, 1990]. To overcome to this detuning Several works including magnetic saturation in control algorithms can found in literature [levi 1990, 2000], [Vas,1998], [Lorenz 1990],[Novatnak , 1990],[Drago Dolinar , 2010].

In this work the inductances variation is taken into account by using the equation (2.2), also to overcome to the orientation detuning the inductances variation is including in the control algorithm . obtained results are shown on figures bellow first for the case without energetic optimization according to a given working profile.



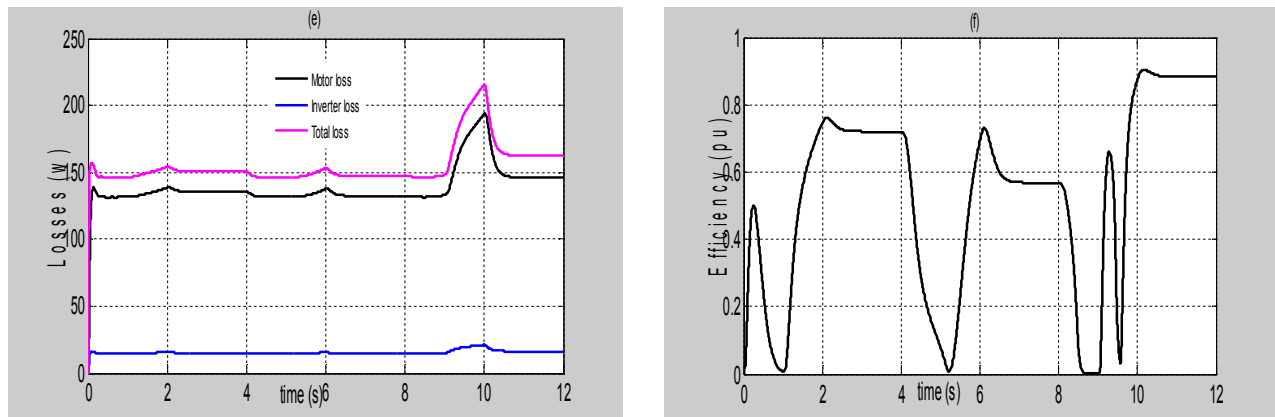


Fig.(4.18) Performances of saturated IM , (a) Speed, (b) Torque, (c) Fluxes, (d) Stator inductance, (e) Losses and (f) Efficiency

One can see the motor speed tracks the commanded speed and load; in addition the flux follows the inductance evolution, it can be noticed also that the field orientation is maintained

Energetic optimization performance of the proposed approaches are presented in the next section

4.4 2. Efficiency Optimization of saturated IM

To enhance the drive efficiency one needs to use a control algorithm that takes into account the variation of the magnetizing inductance. It is well known the efficiency improvement algorithms are based on variable flux. This flux can vary with the variation of the magnetizing inductance, thus if the magnetizing inductance varies with the load, it should be variable. , [D.G. Stanescu, 2013].

Efficiency of the saturated motor supplied with PWM voltages with efficiency optimization for rated, high and low speed is presented on figures below:

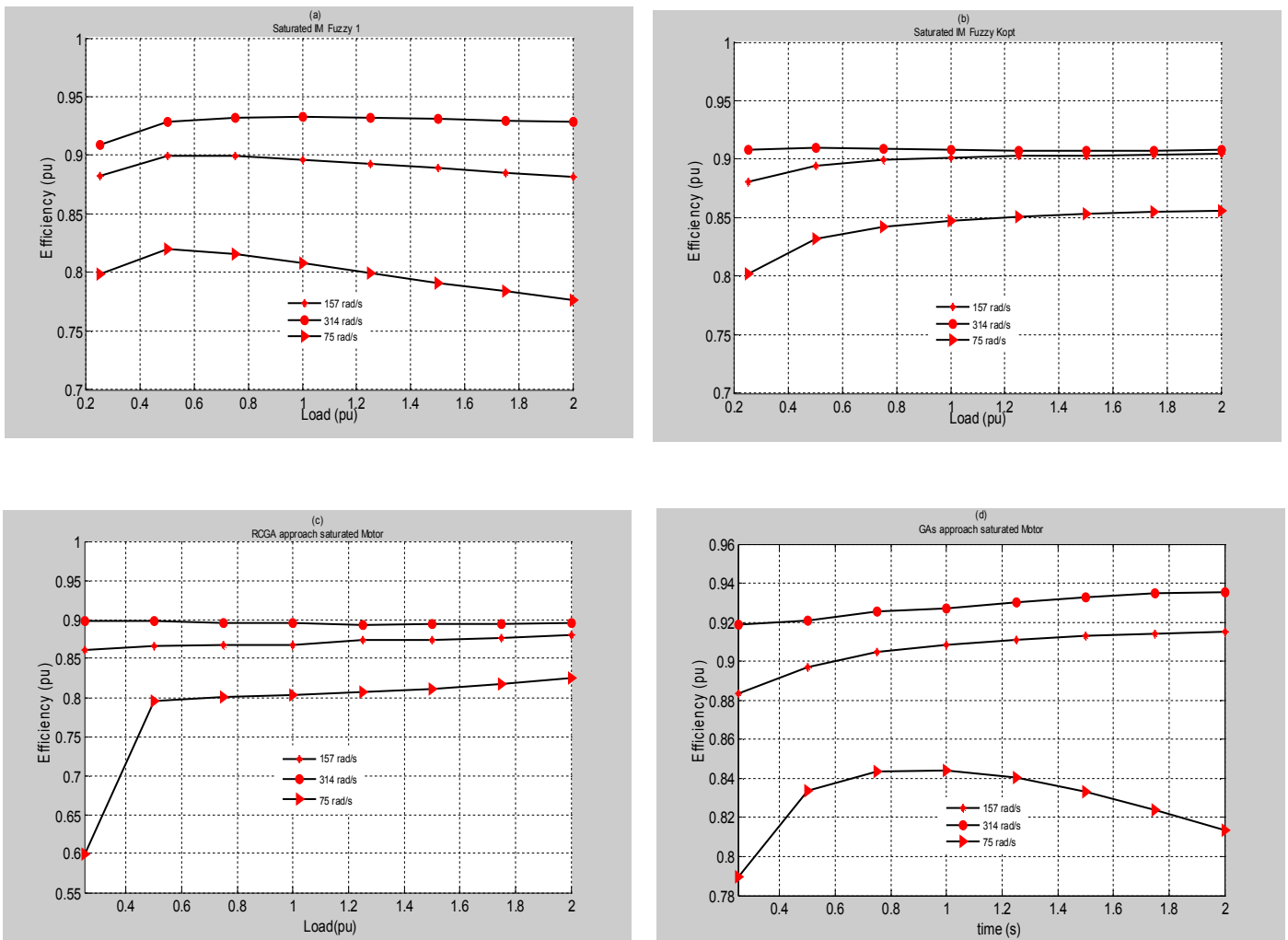


Fig. (4.19).Efficiency (a) First Fuzzy approach , (b) Kopt fuzzy approach,(c) RCGA ,(d) GA's

The enhancement of the motor efficiency with optimized efficiency algorithms is seen clearly from figures (4.19) and it is present for all range of speed and load. At first sight the optimizing approaches based on RCGA and the fuzzy K_{opt} provide very close results it seem a constant efficiency for all loads. Regarding to the first fuzzy approach it gives better results compared to those above cited however at low speed the efficiency for the first fuzzy and the off line GA's approaches decreases when load increases it is probably due to the high stator copper loss which is generated at high load, where the core is saturated.

These results demonstrate that the proposed approaches save more energy than the conventional FOC, it's shown on figure (4.20) where the motor works at nominal speed loaded with 25% of its nominal load torque. Thus we have been able to achieve satisfactory efficiency and torque for IM drive. Likewise figure (4.20) shows that the proposed fuzzy

algorithms provide very close results. In fact the same remarks can be made as the previous case (without magnetizing saturation).

However it should be noticed that the efficiency optimization of saturated motor is better than the unsaturated model as seen on efficiency curves which leads to better energy saving as seen on Figures (4.20.a) and (4.20.b).

Table (4.1) shows the amount of energy saved at $t = 3.15$ s for the proposed algorithms compared to the conventional FOC. For this task the percentage of energy saving is calculated considering the FOC dissipated energy as the reference.

At first sight the saving ratio is practically the same with and without including magnetizing saturation it is about 7% except in the case of GA's where the difference is about 4%.

Table.(4.1) Comparison of Energy saving for saturated and unsaturated Motor

<i>Control Method</i>	Sat IM dissipated Energy(j)	% dissipated Energy	Unsat IM dissipated Energy(j)	% dissipated energy
<i>FOC</i>	452.3386	100	446.0749	100
<i>RCGA</i>	129.6701	28.67	133.1467	29.29
<i>GA's</i>	104.131	23.02	124.1109	27.3
<i>Fuzzy K_{opt}</i>	106..2514	23.49	108.0182	23.76
<i>Fuzzy 1</i>	104.2282	23.04	106.3692	23.40

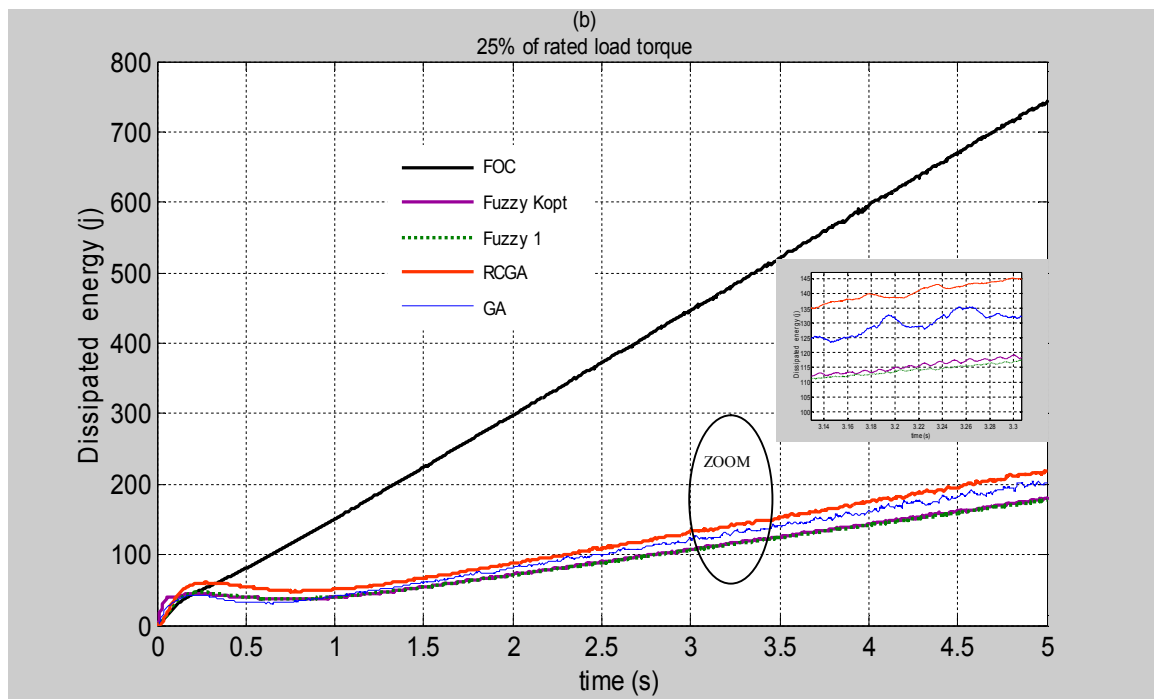
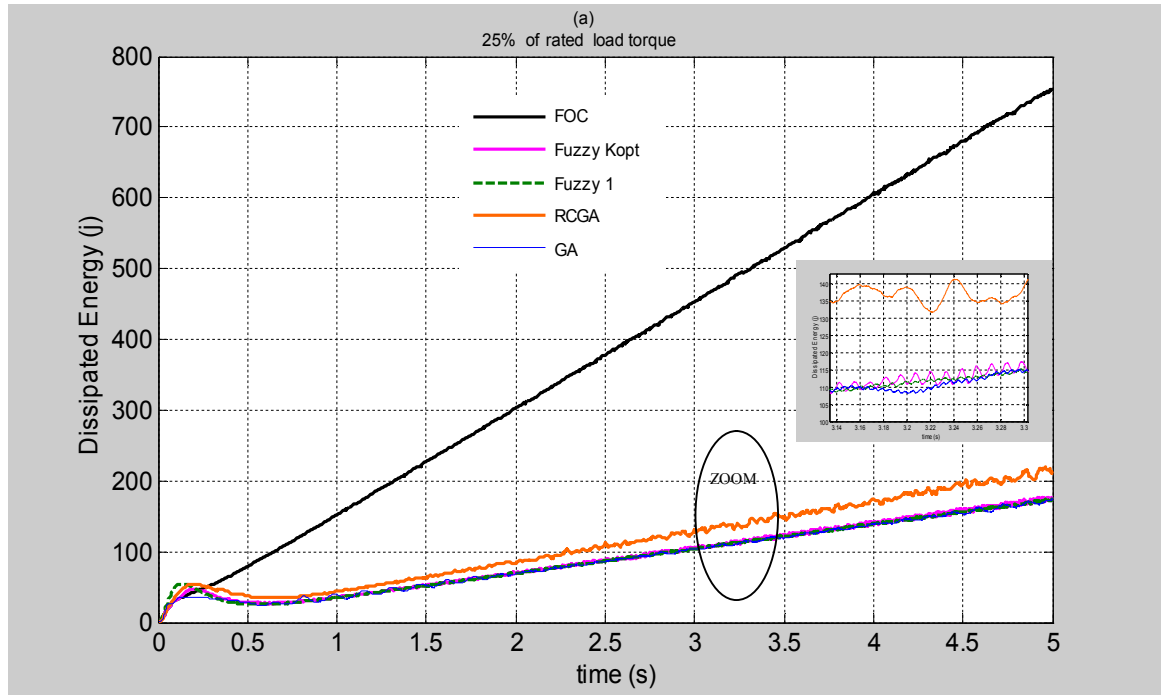


Fig. (4.20). Energy saving for (a) Saturated Motor, (b) Unsaturated Motor

4.4 3.rotor resistance Variation Effect On efficiency optimization

It is well known that R_r variation leads to a detuning effect of the FOC produces a coupling effect between the flux and torque as a consequence the rotor flux deviate from its reference value as shown on figure (4.21)

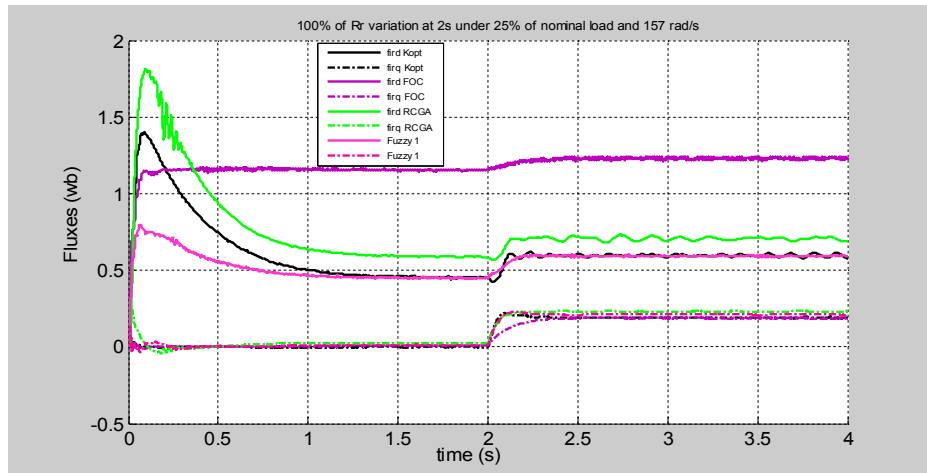


Fig. (4.21).Effect of R_r variation on fluxes

Figure (4.22) shows the efficiency for a 100% R_r variation, one can see that the optimizing efficiency is not affected by this variation while it is decreasing for the classical FOC

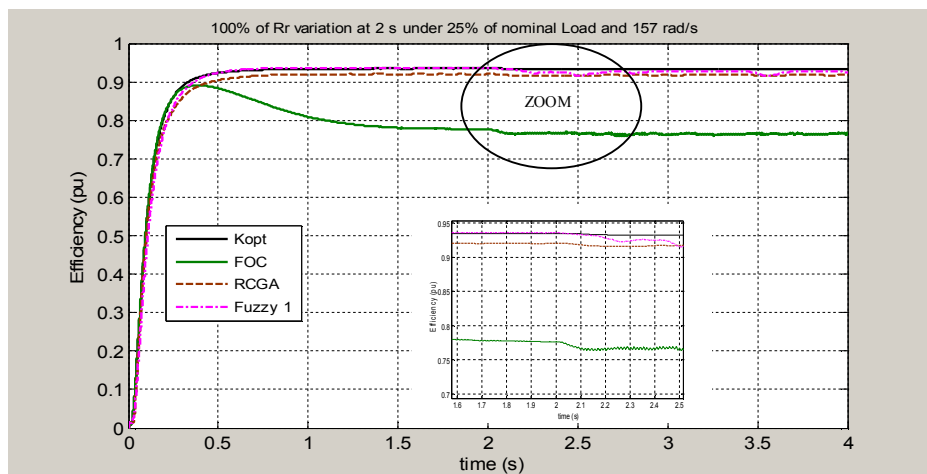


Fig. (4.22).Effect of R_r variation on efficiency

To maintain the FOC performances in addition to the energetic performances, a rotor resistance adaptation mechanism is used based on the fuzzy approach proposed by [Karanayil,2001.]

4.4 Summary

This chapter showed the great energy saving in IFOC induction motor drive obtained when we introduce an efficiency algorithm based on the flux variation.

Efficiency optimization algorithms presented are based on fuzzy logic and genetic algorithms. The proposed control strategies save more energy due to the achievement of an optimal flux the plotted results validate the proposed approaches.

The present work concerns an important field of electrical engineering application which is the energy saving in electrical machines. The growth in the interaction of technical, economical, and environmental constraints in today's industry requires advanced approaches to control and design of electric machines; as well as the increase in global energy demand make this study relevant for both technologic level and the current needs of the society. The subject was addressed from the angle of control system.

This thesis followed the same line target .It's contribution to the ongoing research on effective methods based on intelligent techniques for energy saving of IM drives with FOC schemes.

As first step the review of IM drives efficiency improvement methods has been provided this identifies the problem of parameters dependency for the LMC category and intelligent techniques based on Fuzzy logic and GA have been proposed to overcome this problem.

In second step

A brief description of the fundamentals of intelligent techniques like ANN , PSO; fuzzy logic controller and GA was provide in chapter one. The basic idea of fuzzy sets, membership functions, fuzzy inference engine and defuzzification have been presented also the parameters of GAs have been presented. The optimization of the fuzzy speed controller of the IM drive was presented also

As the motor is controlled by a voltage inverter it is necessary to take into account the converter losses, thus based on the approach given by [Abrahamsen,2000] the loss model was developed to be incorporating in loss minimization strategy.

The proposed approaches for IM efficiency optimization were described in chapter three, after providing details of IM drive losses.

The proposed controllers based loss minimization by programming the flux component by using fuzzy logic and real coded genetic algorithms techniques online and offline.

Results were presented in chapter four which provides details of the implementation Simulation results show encouraging energetic and dynamic performances of the proposed

algorithms in all the load range. Nevertheless it is necessary to note that the converter losses lead to a decrease of approximately 2% of the overall efficiency of the drive of low power motors.

In order to see the robustness of the proposed control with respect to the parameters variation the rotor resistance and saturation effect were investigated. Obtained results show the great adaptation of the proposed algorithms and it may be surprising at first sight the energy saving in saturated model was greater than the energy saving in a linear motor model while the rotor resistance change affects the dynamic performance. To overcome this problem and maintain good performance an adaptation mechanism based on fuzzy logic was introduced in the drive scheme.

It was observed that, the fuzzy approach based K_{opt} adaptation gives excessive losses in transient and since the optimization procedure is only available in stationary regime the nominal flux was restored when the speed error maintains a particular value.

The main contributions of this thesis:

- A development of a simple and robust online efficiency controllers based loss minimization model approach using intelligent techniques what made them parameter independent
- In the field of energy optimal control of induction motors the importance of including magnetic saturation and converter losses in the control algorithms is proven by obtained results.

Concerning the future work in the field of energy optimal control, it will be interesting to this work to move towards adaptive approaches of the loss model of the motor to ensure robust optimal flux control with respect to variations of the IM parameters.

Another way of advancement is the experimental validation of the proposal to increase energy saving.

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Appendix 1

Motor Parameters [Mendes 1994]

- $P_n = 1.1 \text{ kw}$
- $U = 220/380 \text{ V}$
- $I = 4.7/2.7 \text{ A}$
- $f = 50\text{Hz}, 1400 \text{ tr/min}$
- $R_s = 8\Omega, R_r = 1.2 \Omega$
- $L_s = L_r = 0.47 \text{ H}$
- $P = 2$
- $J = 0.06\text{kgm}^2$
- $f = 0.042 \text{ Nms}$
- $C_r = 7\text{Nm}$