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Des nouvelles approches de commande et d'estimation non linéaires robustes dédiées aux entraînements électriques

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Abstract

The purpose of the research presented in this thesis is to propose a methodology for the control and observation of the induction motor (IM) based on the algorithms using the mean value theorem (MVT) and the transformation by sector non-linearity approach. In the first step, the different control techniques of electric drives were identified and analyzed. A robust state and estimation feedback control approach is then developed with variable parameters.

In the field of low power, the removal of the mechanical speed sensor can be of economic interest and improve operational safety. We have presented two categories of methods that allow reconstructing and controlling the rotor speed with desired quantities under field-oriented control of the IM's machine, the MVT observer and the robust MVT controller respectively. All the solutions have been validated by numerical simulation and affirmed by experimental tests to compare the accuracy and dynamics characteristics of the different methods with the MVT control. Finally, new robust control and estimation approaches with a novel representation for uncertain systems with varying parameters based on the MVT and sector nonlinear addressed to control the IM 's machine with FOC control. The results of the various simulation tests and the different experimental trials put into evidence the robustness and the success properties of the proposed algorithms. The thesis ends with a review of our contribution in terms of research.

Keywords:

Induction motor IM, mean value theorem, sector non-linearity approach, MVT control, MVT observer, robust MVT controller, uncertain representation, robust controlH_∞.

ملخص

الغرض من البحث المقدم في هذه الأطروحة هو اقتراح منهجية للتحكم والمراقبة في المحرك التعريفي (IM) بناءً على الخوارزميات باستخدام نظرية القيمة المتوسطة (MVT) والتحويل حسب نهج القطاع الغير الخطي. في الخطوة الأولى، تم تحديد وتحليل تقنيات التحكم المختلفة في المحركات الكهربائية. ثم يتم تطوير نهج قوي للتحكم في التغذية الراجعة والحالة باستخدام البارامترات المتغيرة.

في مجال الطاقة المنخفضة، يمكن أن تكون إزالة مستشعر السرعة الميكانيكي ذات فائدة اقتصادية وتحسن السلامة التشغيلية. لقد قدمنا فئتين من الطرق التي تسمح بإعادة بناء سرعة الدوار والتحكم فيها بالكميات المرغوبة تحت التحكم الميداني لآلة IM، بمراقب ووحدة التحكم MVT القوية على التوالي. تم التحقق من صحة جميع الحلول من خلال المحاكاة العددية والتأكد من خلال الاختبارات التجريبية لمقارنة الدقة وخصائص الديناميكيات للطرق المختلفة مع تحكم MVT. أخيرًا، مناهج تحكم وتقدير قوية جديدة مع تمثيل جديد للأنظمة غير المؤكدة ذات البارامترات المتغيرة بناءً على MVT والقطاع غير الخطي الموجه للتحكم في آلة IM مع التحكم FOC. أظهرت نتائج اختبارات المحاكاة المختلفة والتجارب التجريبية المختلفة متانة وخصائص نجاح الخوارزميات المقترحة. تنتهي الأطروحة بمراجعة مساهمتنا من حيث البحث

الكلمات المفتاحية

المحرك الحثي IM، نظرية القيمة المتوسطة، القطاع غير الخطي، مراقبMVT ، وحدة تحكم قوية اعتمادا على MVT، والتحكم عند حدوث تغيير البارامترات H_∞.

Résumé

Le but de la recherche présentée dans cette thèse est de proposer une méthodologie pour le contrôle et l'observation du moteur à induction (IM) basée sur les algorithmes en utilisant le théorème de la valeur moyenne (MVT) et l'approche des transformations par secteur non-linéarité. Dans un premier temps, les différentes techniques de contrôle des entraînements électriques ont été identifiées et analysées. Des approches robustes de contrôle et d'estimation d'état ont été ensuite développées pour les systèmes incertains avec des paramètres variables.

Dans le domaine des faibles puissances, la suppression du capteur de vitesse mécanique peut présenter un intérêt économique et améliorer la sécurité de fonctionnement. Nous avons présenté deux catégories de méthodes qui permettent de reconstruire et de contrôler la vitesse du rotor avec des quantités souhaitées de la machine l'IM sous FOC-control, l'observateur MVT et le contrôleur MVT robuste respectivement. Toutes les solutions ont été validées par simulation numérique et confirmées par des tests expérimentaux pour comparer la précision et les caractéristiques dynamiques des différentes méthodes avec l'approche MVT. Enfin, de nouvelles approches de contrôle et d'estimation robustes avec une nouvelle représentation pour les systèmes incertains à paramètres variables basés sur la méthode MVT et les secteurs non linéaires adressés pour contrôler la machine IM sous FOC control. Les résultats des différents tests de simulation et des différents essais expérimentaux ont mis en évidence la robustesse et l'efficacité des algorithmes proposés. La thèse se termine par un bilan de notre contribution en termes de recherche.

Mots-clés :

Moteur asynchrone IM, théorème de la valeur moyenne, approche par secteur non linéaire, observateur MVT, contrôleur MVT robuste, représentation incertaine, commande robusteH_∞.

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Dedication

To my dear parents,

To my husband

To my children Ahmad and Kumo,

To my brothers and sisters,

To my grandparents,

And to all who count for me

List of publications

Journals

[1] **Meriem Allag**,Abdelkrim Allag,Okba Zeghib,Bilal Hamidani "Robust H∞ Control Based on the Mean Value Theorem for Induction Motor Drive," *Journal of Control, Automation and Electrical Systems*, vol. 20, pp. 426-433, 2019.

[2] **Allag M,** Allag A, Abrar A, Zein and Ayad MY ’’Controller Design for Nonlinear Systems using Takagi Sugeno Model: Closed Loop-FOC of IM Motor Application’’- J Electr Eng Electron Technol Vol: 5 Issue: 1April 19, 2016.

[3] O. Zeghib, A. Allag, **M. Allag**, and B. Hamidani, "An Extended MVT Observer Designed for Induction Motor Drive," *Mediterranean Journal of Measurement and Control*, vol. 13, pp. 805-811, 2017.

[4] O. Zeghib, A. Allag**, M. Allag**, and B. Hamidani, "A robust extended H∞ observer based on the mean value theorem designed for induction motor drives," *International Journal ofSystem Assurance Engineering and Management*, February 08 2019.

[5] Abrar ALLAG, Abdelhamid BENAKCHA, **Meriem ALLAG**, Ismail ZEIN, Mohamed Yacine AYAD ‘’Classical state feedback controller for nonlinear systems using mean value theorem: closed loop-FOC of PMSM motor application’’ Front. Energy 2015, 9 (4): 413–425.

Conferences

1- O. ZEGHIB, A. ALLAG, B. HAMIDANI and **M. ALLAG**, "Input-output linearizing control of Induction Motor based on a newly extended MVT Observer Design," *2018International Conference on Communications and Electrical Engineering (ICCEE)*, El Oued, Algeria, 2018, pp. 1-6.

Table of contents

Abstract.......... II

Acknoledgment.......... V

Dedication.......... VI

List of publications.......... VII

Table of contents.......... VIII

List of figures.......... XIII

Nomenclatures and Abbreviations.......... XVI

Chapter 1: Introduction

1.1 General presentation: 1

1.2 Background 2

1.3 Research motivation.......... 3

1.4 Research aim and objectives.......... 5

1.4.1 Research aim 5

1.4.2 Research objectives 5

1.5 Structure of the thesis.......... 6

Chapter 2: State of art about controllers and observers of non-linear Systems

2.1 Introduction: 7

2.2 State of Art about control of non-linear systems 8

2.2.1 Scalar control.......... 8

2.2.2 Vector control (FOC) 8

2.2.3 DTC control.. 8
2.2.4 Adaptive control 9
2.2.5 Sliding mode control.. 9
2.2.6 Backstepping control... 10
2.2.7 Fuzzy control... 10
2.3 State of Art on the state's estimation of non-linear systems 10
2.3.1 Kalman filters.. 11
2.3.2 Sliding mode observer 11
2.3.3 Non-linear Leunberger observer.. 12
2.3.4 High gain observers 12
2.5 Conclusion 12

Chapter 3: Mean value theorem and T-S fuzzy approach for nonlinear systems; design and stability analysis

3.1 Introduction.. 14
3.2 Mean value theorem 15
3.2.1 Problem statement 15
3.2.2 Mean value theorem for bounded Jacobian systems... 15
3.2.3 Non-linear observer 19
3.2.3.1 Stability analysis.. 20
3.2.4 Non-linear controller...21
3.2.4.1 Stability analysis.. 21
3.3 Robust control and estimation of uncertain nonlinear T-S fuzzy model.................................22
3.3.1 T-S representation uncertain nonlinear..22
3.3.1.1 T-S representation and modelling of nonlinear time-varying parameter systems…........22
3.3.1.2 DFE uncertainty structure approach... 23

3.3.1.3 Modelling using bounded time varying parameters of N.L. uncertain systems approach......25
3.3.2 Control of nonlinear uncertain systems...... 27
3.3.2.1 PDC Control of bounded time varying parameters of N.L. uncertain systems......27
3.3.2.2 PDC Control of DFE uncertainty structure model of nonlinear uncertain systems......29
3.3.2.3 H_∞Control of DFE uncertainty structure model of nonlinear uncertain systems…......30
3.3.3 State and time-varying parameter observer for uncertain nonlinear systems 32
3.3.4 Mass–spring–damper system application......34
3.4 Conclusion...... 36

Chapter 4: Control and states estimation of the induction motor based on the MVT theory

4.1 Introduction 38
4.2 IM machine modeling 38
4.2.1 Three phase IM presentation...... 38
4.2.2 The equivalent circuit of the IM drives...... 41
4.2.3 Study of the electromechanical equations 41
4.2.3.1 Electrical equations …...... 41
4.2.3.2 Magnetic equations 42
4.2.3.3 Mechanical equation of the IM drive …...... 42
4.2.4 Vector model in two axes rotating frame 43
4.2.4.1 The Park transformation...... 43
4.2.4.2 The Park transformation matrices ………...... 44
4.2.4.3 State space form of the IM 45

4.3 Control and states estimation of the IM under FOC based on the MVT and SNL theory…....46
4.3.1 References generator and Open Loop FOC controls..46
4.3.1.1 References generator...46
4.3.1.2 Open Loop FOC...47
4.3.2Robust H_∞ controller based on the MVT approach...48
4.3.2.1 State feedback control.. 49
4.3.2.2Synthesis for H_∞performance..50
4.3.3PI-Controller based observer applied to IM under FOC using the MVT and SNL theory...53
4.3.3.1The control law..53
4.3.3.2 The observer design..54
4.4 Simulation results and discussion...56
4.4.1 Robust $\boldsymbol{P-H_\infty}$controller based on the MVT approach..56
4.4.2 PI controller based observer applied to IM based MVT..60
4.5 Experimental results...64
4.5.1 Robust $\boldsymbol{P-H_\infty}$controller...65
4.5.2 PI controller based observer..68
4.6 Conclusion 71

Chapter 5: Robust MVT Controller and observer of Uncertain Nonlinear Systems: IM- FOC application

5.1 Introduction..72
5.2 Uncertain model of the IM machine with time varying parameters..73
5.3 MVT controllers Design for uncertain nonlinear systems...75
5.3.1 MVT P-Controller of NL uncertain systems time varying parameters..................................76
5.3.1.1Stability analysis...79

5.3.2 MVT$-PI$-H_∞ $-$Controller of NL uncertain systems time varying parameter…….........81

5.3.2.1 Synthesis for H_∞performance...82

5.3.3 FOC control using robust H_∞ PI controller applied to IM machine drive...........................83

5.3.3.1 IM machine model with varying parameters...84

5.3.3.2 Simulation results for closed loop FOC...91

5.4 H_∞Extended MVT observer design for uncertain nonlinear systems......................................93

5.4.1The proof of theorem5.3..96

5.5 Robust PI controller based extended observer design based on the MVT approach for the IM-FOC with uncertain parameters...100

5.5.1Simulation results and discussions...106

5.6 Conclusion 109

Conclusions and future works

Conclusions... 111

Future works 113

References

References 114

Appendixes

Appendix A: Parameters of the induction motor 120

Appendix B... 121

List of figures

Chapter 2: State of art about controllers and observers of non-linear systems and faults detection

Figure 2.1 Illustrative scheme of the DTC 9
Figure 2.2 Different steps of Kalman filtering 11

Chapter 4: Control and states estimation of the induction motor based on the MVT theory

Figure 4.1 An enlarged view of typical IM 39
Figure 4.2 Stator slots and windings 40
Figure 4.3 Squirrel cage rotor 40
Figure 4.4 Per-phase IM equivalent circuit 41
Figure 4.5 Park transformation axes 43
Figure 4.6 The state feedback control design 48
Figure 4.7 The PI control design 54
Figure 4.8 Global diagram of the P control law of the IM based on MVT 57
Figure 4.9 Robust H_∞controller reponses of the IM machine under FOC 58
Figure 4.10 States reponses versus the load torque and parameters variation (R_s and R_r) 59
Figure 4.11 Global schema of the PI cntrol based observer of the IM based on MVT 61
Figure 4.12 PI robust controller based robust extended MVT observer applied to the IM machine 62
Figure 4.13 States reponses versus the load torque and parameters variations (R_s and R_r) 63
Figure 4.14 Real photo of the experimental bench 65

Figure 4.15 The d-axis stator current 66
a) Robust control 66
b) Conventional control 66
Figure 4.16 The q-axis stator current 66
a) Robust control 66
b) Conventional control 67
Figure 4.17 The d-axis rotor flux 67
a)Robust control 67
b) Conventional control 67
Figure 4.18 The q-axis rotor flux 67
a) Robust control 67
b) Conventional control 67
Figure 4.19 The rotor speed 68
a)Robust control 68
b) Conventional control 68
Figure 4.20 The d-axis stator current 69
Figure 4.21 The q-axis stator current 69
Figure 4.22 The dq-axis rotor flux 70
Figure 4.23 The rotor speed 70

Chapter 5: Robust MVT Controller and observer of uncertain Nonlinear systems:IM-FOC application

Figure 5.1 The MVT PI H_∞ control design 81
Figure 5.2 Global scheme of the Robust H_∞ PI control law of the IM based on MVTproposed.83
Figure 5.3 Robust H_∞ PI control law of the IM machine under FOC states reponses.................92

Figure 5.4 PI Robust conroller based robust extended MVT observer applied to the IM machin 101

Figure 5.5 States responses versus the load troque and parameters variation(R_s and R_r)...........108

Figure A.1 The nameplate of the used IM 121

Nomenclatures and Abbreviations

$x(t)$	State vector
$\hat{x}(t)$	Estimated state vector
$x_r(t)$	Reference state vector
$e(t)$	State estimation error
$u(t)$	Input vector
$y(t)$	Output vector
$n(t)$	disturbance vector
w_r, w_s	Rotor and stator speed
w_{rr}	Rotor speed reference
w_{sr}	Electrical stator speed reference
θ_r	Rotor position
Ψ_{rd}, Ψ_{rq}	The (d,q) Rotor flux
Ψ_r	Rotor flux reference
i_{sd}, i_{sq}	The (d,q) stator currents
U_{ds}, U_{qs}	The (d,q) stator voltages
U_{dsr}, U_{qsr}	The (d,q) open loop controls
L_r, L_s	Rotor and stator inductances
R_r, R_s	Rotor and stator resistances
J	Moment of inertia
b	Friction coefficient
P_n	Nominal power of the induction motor
n_p	Pole pair number
T_L	Load torque
M	Mutual inductance

MVT	Mean value theorem
IM	Induction motor
T-S	Takagi-Sugeno
P	Proportional
PI	Proportional Integral
LPV	Linear parameter varying
LTI	Linear time invariant
LMI’s	Linear matrix inequalities
FOC	Field-oriented control
HP	Horsepower
PDC	Parallel distributed compensator
SNL	Sector non liniare

Chapter 1:
Introduction

1.1 General presentation:

Induction machine (IM) receives its name from the fact that electrical current is induced in the rotor by magnetic fields generated by the stator windings. It is therefore required that the rotor of an IM contains an electrically conducting material. In fact, if the rotor is a solid cylinder of metal the machine could operate as an IM, though not a very good one. This conducting material may consist of two or three phase windings similar to those on the stator, this is known as a wound rotor IM, but many induction machine rotors have a squirrel cage design.

The IM's machine had the most uses among the electrical machines in industrial applications due to their simple, high efficiency, high power density and higher torque to weight ratio. Owing to the intrinsic nonlinear coupling between the dynamics of the electrical part and of the mechanical part, strongly coupled time-varying systems, the rotor variables are not measurable, inaccessibility for the rotor flux, system-parameter variations, and IM's are multivariable nonlinear, the IM drives feedback control and state's estimation are so difficult[1] .

It is known that the occurrence of paramter variations can degrade the control performances and in some cases lead to the instability of the system. Consequently, many strategies for parameters variations and fault detection, so robust control is introduced to tolerate the effect and maintain system stability [1-3].Generally speaking, adaptive and fault tolerant control is a control that possesses the ability to accommodate system failures automatically, maintain overall system stability with acceptable performance even in such situation.

1.2 Background

Due to the disadvantages of nonlinear systems, many authors propose to represent the nonlinear and coupling systems as specific forms of systems, such as Lipschitz systems. Different approaches have been studied and applied according to the IM, among them, the high gain observer in [4] and the using of the flux linkage observer as in [5], many other strategies were proposed in literature among them: sliding mode observers, an extended Kalman filter, a Model Reference Adaptive System (MRAS) observers, nonlinear Luenberger observers and others. In detail, an extended sliding mode observer to estimate the rotor flux for IM control was proposed in [6] and the authors in [7] propose a second-order sliding mode observer for the sensor-less control of IM drives, whereas in [8] Regaya et al. present an adaptive sliding mode speed observer for IM drive control. An extended Kalman filter method for the speed and the flux observation of the IM was illustrated in [9, 10]. The MRAS observers are used for the IM control as in [11] where the authors proposed an MRAS observer for the IM control that estimates the speed and the rotor flux, wherein[12] Kandoussi et al. propose an improved MRAS observer for sensorless control of the IM drives. Nonlinear Luenberger observers were proposed for the IM speed servo drive in [13]. A nonlinear observer was used to estimate the IM flux which proved to be satisfactory as in [14]. A technique relied on the changing of the original system into a linear system was proposed by Alonge et al. in [15].

Many modern control techniques have been designed to overcome the tracking problem. Adaptive control methods are proposed in [16, 17], fuzzy control has been treated in [18, 19] and a sliding mode and backstepping controls have been adopted by [20] and [21] respectively. In [16] a backstepping adaptive control for IM was designed with uncertainties, while the authors in [17] propose an adaptive controller based on sliding mode neuro-fuzzy control of an IM without mechanical sensors. A fuzzy self-tuning speed control of indirect field oriented control of IMs is studied in [18], the paper [19] shows a novel fuzzy sliding mode structure for the speed control of IMs. DTC of IM with feedback linearization has been presented in [22].

In all mentioned estimation and control methods above it was so difficult to reach them owing a strong conditions, because of the dependency between the observers ,controllers and the states of the IM machine. In most cases, they are suffering and have not a systematic and general methodology for proving the stability conditions when the controller, observer and IM's machine with faults and parameters variations are occurred**.**

1.3 Research motivation

Due to an increasing demand for higher performances, safety and reliability, model-based fault diagnosis (detection and isolation) is of practical importance and has received considerable interest these past years. The state estimation problem can be viewed as the heart of control systems and model-based diagnosis (Chen and Patton [1999]), (Basseville [1998]). The design of observers, reconstructing state variables out of a limited set of measurements, is a possible approach for dealing with the measurement problem. However, due to time-varying behavior of dynamical processes, the introduction of time-varying parameters in the system models leads to a higher level of complexity with more challenging problems in estimation. In this case, conventional observers essentially developed for time invariant systems cannot directly be used, and so-called adaptive observers developed for joint state and unknown parameter estimation has to be implemented.

To remedy the disadvantages of the previous observation methods and the control concepts which have been quoted above, a controller or observer based on the MVT approach[23, 24] with parameters variations or faults leads to an unified method to prvent and give more possibilty to avoid any undesirable situations (instability or performance degradations).

The MVT approach was recently used in [25-27] for the observation of the states of IM's machine drives with fixed parameters , where the authors transfer the nonlinear model of the IM into the Lipschitz form and use the MVT and sector non-linearity approaches to find the observer gains by solving the LMI's which are obtained from the Lyapunov theory. A systematic approach to joint state and time-varying parameter estimation for nonlinear systems is proposed in this work. Applying the sector nonlinearity transformation to both the system nonlinearities and the time-varying parameters, the original system is equivalently rewritten as an LPV system with unmeasurable premise variables. A joint state and parameter observer whose parameters are varying is designed by solving an LMI optimization problem is then proposed. The target application is a realistic model of the IM's machine drives plant, being an uncertain nonlinear system affected by a time-varying parameter. The contribution of this thesis is to use the MVT theory combined with sector non-linearity approach in order to control and estimate the extended states and parameters of the IM machines with a minimum disturbance effect to the control and joint estimation errors. The used approach is based on the transfer of the nonlinear system of the IM into the Lipschitz form, and then the nonlinear error dynamics (states and parameters) of the proposed controller and observer are designed for the IM's machine drives, which is expressed as a convex combination of known matrices with time-varying coefficients as LPV systems. Using the Lyapunov theory [28], the stability conditions are obtained and expressed in terms of LMI's that are solved through the YALMIP software in order to obtain the gains. The main contribution of the MVT approach in this work is to find, also, a robust controller gains, which is calculated offline that stabilizes the control error of the IM even in presence of disturbances and parameters variations.

In this work, the design of various robust controllers and observers for FOC of IM based on MVT applied to a class of Lipchitz nonlinear system are presented. This demonstrates the feasibility and effectiveness of the proposed controllers and observers with a simple implementation .In our work, we have exploited the performances of the parameters variations with robust state feedback tracking control based extended observer for IM drive using the MVT and SNL approaches. The aim is to guarantee the stability and the operating in safe despite the occurrence of parameter variations by augmenting the system containing the tracking error and the estimation error, and then a robust state feedback-tracking controller-based observer is designed with a development of two theorems for the first time in automatic control of these kind of the uncertain systems.

Up to my knowledge, this is the first contribution where the extended parameter and state estimation problem is addressed is such a way for the nonlinear uncertain systems. Moreover, most of the works devoted to joint parameter and state estimation for nonlinear systems only consider constant parameters, where as time-varying parameters are here treated. The main result is to establish the convergence conditions of the state and parameter estimation errors will be derived by solving an LMI optimization problem obtained from the Lyapunov theory. The minimized criterion is the L2-gain of the transfer from the disturbance inputs to the state and parameter estimation errors. In this work, the design of various robust controllers and observers for FOC of IM based on MVT applied to a class of Lipchitz nonlinear system are presented. This demonstrates the feasibility and effectiveness of the proposed controllers and observers with a simple implementation.

1.4 Research aim and objectives

1.4.1 Research aim

The aim studies are on the control and estimate of the IM‘s machine under field oriented control based on the MVT and SNL approaches to accurately modelling the system. It further seeks to develop new control strategies and an extended state and parameters observers for the IM where the model is supposed to be nonlinear with parameter varying. Next, we concentrate upon the stability, which should be proven in a systematic methodology contrarily to other methods. The work includes the development of robust state feedback-tracking controller based an extended observer of the IM through the MVT and SNL approaches.

1.4.2 Research objectives

The first main research goal and contribution of this work is to simplify and model nonlinear time-varying systems using the MVT representation. For that, each time-varying parameter is rewritten under a particular form. Secondly, the control and the observation for IM‘s drives control with efficiency and performance similar to previous methods even in the presence of parameters and disturbances variations. In order to fulfill the research goal a number of objectives are identified and prioritized as follows:

Objective 1: develop a new model representation of a nonlinear time-varying systems using the MVT theory and SNL approaches.

Objective 2:develop a new extended robust observer using MVT and SNL that does not depend on the states of the IM and can estimate both parameters and, of course, the IM states.

Objective 3:develop a robust MVT controller that makes the IM subject to control conditions even in presences of perturbations and parameters variations.

Objective 4:check the effectiveness of the approaches through various simulation and experimental tests..

1.5 Structure of the thesis

This thesis is organized as follows:

The previous works for the observation and the control of the nonlinear systems and some are given in Chapter 2. Firstly, the review mainly focused on FOC and DTC, and state observers such as Kalman filter and others, the previous works are discussed briefly and compared with each other. Secondly, the most popular technics in the IM and their effects is clearly proposed.

Chapter 3 presents the MVT approach for the class of non-linear systems and the T-S model of non-linear and uncertain systems. The stability of each kind is discussed and through the Lyapunov theory either for controllers or either for observers.

Chapter 4 presents a generalized dynamic mathematical model of the IM machine, which can be used to construct various equivalent circuit models in the d-q rotating reference frame. Then, the design of controllers and observers for the IM based on the MVT theory is presented. These observers and controllers based on the MVT approach are checked through illustrative simulation tests and with different experiments in order to prove the effectiveness of the MVT approach.

Chapter 5 is devoted to the robust state feedback-tracking controller based robust extended observer approach for the IM using the MVT approach considering time varying parameters and disturbance inputs. The extended observer is chosen for the design of a robust control that makes the IM submit all control conditions even in the presence of the parameter variations in order to estimate both the states and parameters assuring the stability of all the system.

Chapter 6 presents conclusions based on findings and outlines perspectives for future work.

Chapter 2:

State of art about controllers and observers of non-linear systems

2.1 Introduction:

In this chapter, we present some works and methods of control theory, which are used now in the industry with their benefits associated with some drawbacks, and we illustrate also the observers in the literature review, each observer is mentioned with their advantages and disadvantages. In order to avoid the drawbacks of the previous methods for control and observation of non-linear systems ,the mean value theorem (MVT) and PDC approach based T-S models are very interesting to be employed and can be considered an alternative approaches. Both of the MVT and the T-S mathematical representation of nonlinear systems will be introduced in the next chapter with more details to model the nonlinear system, which allow representing any nonlinear system, whatever its complexity, by a simple structure based on linear models interpolated by nonlinear functions positive or null and bounded for the T-S and MVT model approaches.

The current chapter is organized as follows: in the first section, the previous control technics for the IM are distinctly presented. Whereas, the observers in the literature review for the state's estimation of the IM are proposed subsequently. In the last section, we introduce new concepts of control theory for uncertain nonlinear systems that can be used for the IM machine drives. This chapter will be closed by a conclusion.

2.2 State of Art about control of non-linear systems:

In the literature review, there are many control types was of control for nonlinear systems were applied to the electrical machines. In control, theory there is no perfect method; any control approach has advantages and drawbacks at the same time. In followings, we will mention manykinds of control for nonlinear systems with their benefits and drawbacks.

2.2.1 Scalar control:

The scalar control method is based on varying two parameters simultaneously. First, the speed can be varied by increasing or decreasing the supply frequency resulting the change of impedances. This change of impedances then also increases or decreases the current. If it is small, the motor torque automatically decreases. In addition, if the frequency decreases or increases, the motor coils can be burned or saturated that can occur in the iron of the coils. To avoid these problems, it is necessary to vary simultaneously the frequency and the voltage at the same time[29].Scalar control is cheap and easy to implement, though it is not as sufficient in controlling drives with dynamic behavior. Overall, the scalar control is low-performance, but stable.

2.2.2 Vector control (FOC):

Field-oriented vector control makes it possible to decouple the field components into two independent, single-controlled currents instead. The flux-produce current while the torque produce current. With vector-based control, you can achieve tighter speed control, higher starting torque, and higher low-speed torque[30]. With a field-oriented vector, you can control the currents independently, allowing it to operate with fast responses, making it much more appropriate for dynamic drives. The main disadvantages of the vector control are the huge computational capability required and the compulsory good identification of the motor parameters.

2.2.3 DTC control:

DTC has a very fast response and simple structure, which makes it, be more popular used in the industrial world. This method of control implies a comparative control of the torque and the stator fluxes which must fall into two separate certain bands (limits) to be applicable[22]. In

DTC it's possible to control directly the stator flux and the torque by selecting the appropriate inverter state.

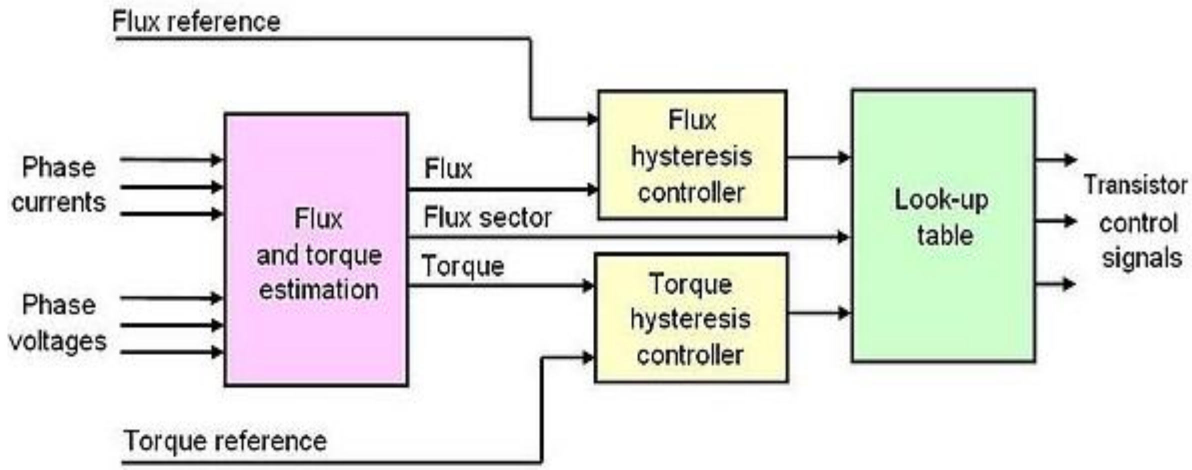


Figure 2.1Illustrative scheme of the DTC

2.2.4 Adaptive control:

The origin of adaptive control goes back to 1950: automation engineers quickly realized that a controller with fixed parameters was not always able to ensure the desired performance, for example in the case where the parameters of the system varied with time. Adaptive control strategies include direct methods, such as MRAC, whose objective is to design a reference model whose performance coincides with that of the closed-loop system. The command is to eliminate any divergence between the response of the model and that of the system regardless of the input signal and the disturbance conditions (internal or external).Indirect methods are based on the real-time identification of the process and the placement of poles. Each method uses different techniques but for the same purpose the cancellation of the error between the reference and the model output[31, 32].

2.2.5 Sliding mode control:

SMC is a particularly interesting technique. it dates back to the 1970s with Utkin's work[33]. The principle consists in bringing, whatever the initial conditions, the point representative of the evolution of the system on a hypersurface of the phase space by the integration of switching elements in the control law. The SMC scheme is a well-known robust control scheme for dynamic uncertain systems. However, SMC suffers from the dangerous chattering effect, which prevents them from being extensively used in practice. In addition, the performance of sliding mode control depends heavily on the sliding surface. If the sliding surface is not designed properly, it may lead to adverse effects[34].

2.2.6 Backstepping control:

The technique of backstepping appeared in the 1990s by P.Kokotovic. The history of the backstepping is summarized in [35]and the approach is extensively studied. Nonlinear control with input-state linearization or input-output leads to the cancellation of nonlinearities that might be useful. Backstepping is less restrictive and does not force the system to become linear. The basic idea of backstepping is to synthesize the control law in a recursive way. Some components of the state vector are considered "virtual commands" and intermediate control laws are developed. Backstepping is strictly applied totriangular non-linear systems[35]. The process terminates when the final external control is reached.

2.2.7 Fuzzy control:

The fuzzy logic, introduced by Lotfi Zadeh[36], Fuzzy models have the property of approximating any nonlinear function. The main advantage of fuzzy logic control is that it is possible to "do without" an explicit model of the process[37]. This approach is based on two concepts: that of the decomposition of a discourse universe of one or more variables measured in the form of linguistic symbols: "small", "medium", "large" ... and rules coming from of the expertise of the human operator, which express, again, in the form of a language, how the system controls must evolve according to the variables. Fuzzy systems can be classified into three groups: linguistic Fuzzy systems or Mamdani systems, relational fuzzy systems, and functional consequence systems, or known as T-S Kang fuzzy systems.

2.3 State of Art on the state's estimation of non-linear systems:

There are various types of observers in literature for the state's estimation, for the nonlinear systems, this topic becomes a challenge in the actually researches, except the observers for nonlinear systems those are considered so difficult. In this part, we will describe some kinds of observers for nonlinear systems:

2.3.1 Kalman filter:

The purpose of Kalman filter is to predict the trajectory of a moving system in real time, updating the estimate at the previous epoch by exploiting the new observations and the dynamics of the system (assumed to be predictable). This estimate is sub-optimal with respect to the joint use of all the data in post-processing, which can be obtained by Least Squares (batch solution).

Despite the stability and convergence of evidence established in the case of linear systems and can't be extended generally to the case of nonlinear systems, this method remains the most popular and widely studied in the field of nonlinear observation systems[38, 39]. In the next figure, the different steps to the state's estimation by Kalman filter was illustrated.

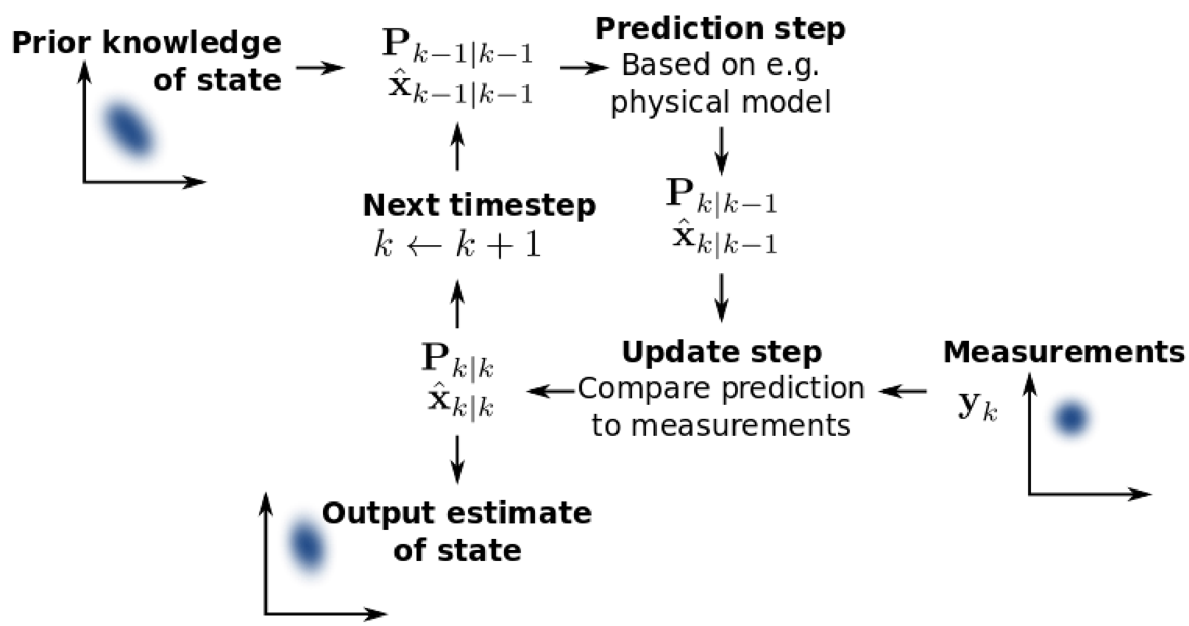


Figure 2.2Different steps of Kalman filtering

2.3.2 Sliding mode observer:

Based on the same theory of the SMC, The sliding mode observer uses non-linear high-gain feedback to drive estimated states to a hypersurface where there is no difference between the estimated output and the measured output. The non-linear gain used in the observer is typically implemented with a scaled switching function. Hence, due to this high-gain feedback, the vector field of the observer has a crease in it so that observer trajectories slide along a curve where the estimated output matches the measured output exactly. Therefore, if the system is observable from its output, the observer states will track the actual system states. Additionally, by using the sign of the error to drive the sliding mode observer, the observer trajectories become insensitive to many forms of noise. Hence, some sliding mode observers have attractive properties similar to the Kalman filter but with a simpler implementation.[40, 41].

2.3.3 Non-linear Luenberger observer:

The Luenberger observer has been proposed by[42], the idea of this technique is to add a second gain inside the non-linear part depend on the estimated states of the system to the constant gain of the Luenberger observer. This type of observer can cause instabilities that manifest themselves away from the point of operation, that is why it is rarely used in practice[43].

2.3.4 High gain observers:

High gain observers are observers based on Lyapunov stability conditions, they appear for the first time in 1973 by[44]. The principle of this kind of observers is to get a high gain of the observer that make up for the non-linearity terms of the system. The high gain observers have some advantages such as they are relatively simple to design, as you do not need to solve complex differential equations nor use complicated formulae. For a large class of nonlinear systems, they can provide global or semi-global stability results for a large class of systems. They can be relatively fast. In spite of high gain observers have the previous benefits, they have some drawbacks as they are sensitive to measurement noise, they suffer from the 'peaking' phenomenon, where, due to the high-gain, there is an initial sharp spike in the response of the state estimates. This phenomenon can cause instability for some types of systems[45].

2.5 Conclusion:

In this chapter, we have presented some literature review of the control, the state’s estimation and applied to the three-phase IM machines driver. Firstly, we have mentioned the known control methods those are used in the industry with their benefits and drawbacks. Then, different kinds of observers were also proposed. We illustrate these works with their disadvantages in order to show the effectiveness of the MVT approach that will be used ,which is based on the mean value theorem and sector nonlinearities approaches of the non-linear system and how it can remedy the disadvantages of the previously technics. The topic of the next chapter will be the T-Sand the MVT representation of non-linear systems approach including the stability analysis for the two concepts.

Chapter 3:
T-S fuzzy and MVT approaches for nonlinear and uncertain systems

3.1 Introduction:

In order to avoid the drawbacks of the previous methods for control and observation of non-linear systems (mentioned in the last chapter), the mean value theorem (MVT) and PDC approach based T-S models are very interesting to be employed. Both of the MVT and the T-S mathematical representation of nonlinear systems are introduced at the level of the model of the nonlinear system. They allow representing any nonlinear system, whatever its complexity, by a simple structure based on linear models interpolated by nonlinear functions positive or null and bounded for the T-S and MVT model approaches. In this chapter, we focus the state of the art on the design of robust fuzzy controllers and observers for uncertain nonlinear systems using Takagi-Sugeno (T-S) model based approach. A T-S fuzzy model is used here to approximate the uncertain nonlinear systems where the nominal model and uncertain terms of the consequent parts of the fuzzy model are identified by a sector nonlinear and MVT approach's and then they can be expressed in a form suitable for robust fuzzy controller design[46-48] and [49]. With the derived T-S fuzzy model, various types of robust fuzzy controllers and observers are designed that guarantee not only stability but also satisfy the specified performance criteria of the closed-loop control system. These models make it possible to accurately represent nonlinear systems. They have a simple structure with interesting properties making them easily exploitable from a mathematical point of view and allowing the extension of some results from the linear domain to nonlinear systems. In the following, the MVT approach for the case of non-linear uncertain systems will be introduced and discussed in fifth chapter.

3.2 Mean value theorem:

3.2.1 Problem statement :

This section presents an efficient methodology for designing observers for the class of nonlinear systems with invariant parameters described by:

$$\begin{cases} \dot{x} = Ax + \varphi(x) + g(u, y) \\ y = Cx \end{cases} \tag{3.1}$$

where x is the state vector, u is the input vector and y is the output measurement vector. $A \; and \; C$ are appropriate matrices. The functions $\varphi(x)$ and $g(u, y)$ are nonlinear. The function $\varphi(x)$ is assumed to be differentiable.

The observer will be assumed to be of the form

$$\dot{\hat{x}} = A\hat{x} + \varphi(\hat{x}) + g(u, y) + L(y - C\hat{x}) \tag{3.2}$$

The estimation error introductions are then seen to be given by

$$\dot{e} = (A - LC)e + (\varphi(x) - \varphi(\hat{x})) \tag{3.3}$$

Where $e = x - \hat{x}$ and L is the observer gain.

3.2.2 Mean value theorem for bounded Jacobian systems:

In this sub-section, we present mathematical tools, which are used subsequently to develop the observer gain in the next section. First, we present the scalar mean value theorem and the mean value theorem for vector functions. Then, we define the canonical basis for writing a vector function with a composition form. Lastly, we present a new modified form of the mean value theorem for vector functions.

Lemma 3.1: Scalar MVT:

Let consider $f(x)$ be a function continuous on $[a, b]$ and differentiable on (a, b). There exist numbers $c \in (a, b)$ such as[27]:

$$f(a) - f(b) = \left.\frac{df}{dx}\right|_{x=c} \times (a-b) \tag{3.4}$$

The equation (3.4) can also be rewritten as

$$f(a) - f(b) = \left(\delta_1 \left.\frac{df}{dx}\right|_{x=c_1} + \delta_2 \left.\frac{df}{dx}\right|_{x=c_2}\right) \times (a-b)$$
$$\delta_1, \delta_2 > 0, \qquad \delta_1 + \delta_2 = 1 \tag{3.5}$$

Where $c_1, c_2 \in (a, b)$ and δ_1, δ_2 are parameters depend on the value of a and b.

The proof of Lemma 3.1 is presented in [50].

Lemma 3.2: MVT for a vector function[23]

Let consider $f(x)$ be a function continuous on $[a, b]$ and differentiable on the convex hull of a set (a, b) with a Lipchitz continuous gradient ∇f . There exist numbers $c \in (a, b)$ such as

$$f(a) - f(b) = \nabla f(c) \times (a-b) \tag{3.6}$$

However, we cannot directly use the mean value theorem of equation (3.6), since is a varying parameter that continuously changes with the values of$a$ and b. Thus $\nabla f(c)$is an unknown and changing matrix. We need to modify the mean value theorem before it can be utilized.

Lemma 3.3: canonical basis [24]

Let's define the vector function as

$$f(x) = \left[f_1(x), f_2(x), \dots, f_q(x)\right]^T \tag{3.7}$$

Where $f_i(x)$ is the i^{th} component of $f(x)$

The function $f(x)$ can be written as

$$f(x) = \sum_{i=1}^{q} e_q(i) f_i(x) \tag{3.8}$$

Where

$$e_q(i) = (0, \dots, 0,1,0, \dots, 0), \qquad i = 1,2, \dots, q \tag{3.9}$$

Now, we are ready to state and prove a modified form of the mean value theorem for a vector function.

Theorem3.1: modified MVT for a vector function [23]

Let consider $f(x)$ be a function continuous on $[a, b]$ and differentiable on the convex hull of a set (a, b) with a Lipchitz continuous gradient ∇f . There exist $\delta_{ij}{}^{max}$ and $\delta_{ij}{}^{min}$ for $i, j = 1,2, \dots n$ such that:

$$f(a) - f(b) = \left[\left(\sum_{i,j=1}^{n,n} Z_{ij}{}^{max}\delta_{ij}{}^{max}\right) + \left(\sum_{i,j=1}^{n,n} Z_{ij}{}^{min}\delta_{ij}{}^{min}\right)\right](a-b) \tag{3.10}$$

Where

$$h_{ij}{}^{max} \geq max\left(\frac{\partial f_i}{\partial x}\right)\ and\ h_{ij}{}^{min} \leq min\left(\frac{\partial f_i}{\partial x}\right)\ \forall x \in (a, b)$$

And

$$Z_{ij}{}^{max} = e_n(i)e_n{}^T(j)h_{ij}{}^{max}\ and\ Z_{ij}{}^{min} = e_n(i)e_n{}^T(j)h_{ij}{}^{min}$$

Based on Lemma 3.2, we have

$$f(a) - f(b) = \nabla f(c) \times (a-b) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} [(a-b)] \tag{3.11}$$

Lemma 3.1 shows that each derivative function can be replaced with a convex combination of 2 values of the derivative of the function. Hence, the derivative function $\frac{\partial f_i(c)}{\partial x_j}$ can be replaced by

$$\frac{\partial f_i}{\partial x_j}(c) = \delta_{ij}{}^{max}\frac{\partial f_i}{\partial x_j}(\gamma) + \delta_{ij}{}^{min}\frac{\partial f_i}{\partial x_j}(\varepsilon)$$
$$\delta_{ij}{}^{max}, \delta_{ij}{}^{min} > 0, \qquad \delta_{ij}{}^{max} + \delta_{ij}{}^{min} = 1 \tag{3.12}$$

Where

$\gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$ *and* $\varepsilon = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n)$ *with* $\gamma, \varepsilon \in (a, b)$

The values of $\frac{\partial f_i}{\partial x_j}(\gamma)$ and $\frac{\partial f_i}{\partial x_j}(\varepsilon)$ need to be chosen as follows in order to satisfy lemma 1

$$\frac{\partial f_i}{\partial x_j}(\gamma) = h_{ij}{}^{max} \geq max\left(\frac{\partial f_i}{\partial x_j}\right), \qquad and \qquad \frac{\partial f_i}{\partial x_j}(\varepsilon) = h_{ij}{}^{min} \leq min\left(\frac{\partial f_i}{\partial x_j}\right) \tag{3.13}$$

Then the equation (3.12) can be rewritten as

$$\frac{\partial f_i}{\partial x_j}(c) = \delta_{ij}{}^{max}h_{ij}{}^{max} + \delta_{ij}{}^{min}h_{ij}{}^{min}$$
$$\delta_{ij}{}^{max}, \delta_{ij}{}^{min} > 0, \qquad \delta_{ij}{}^{max} + \delta_{ij}{}^{min} = 1 \tag{3.14}$$

With $\delta_{ij}{}^{max}$ *and* $\delta_{ij}{}^{min}$ are parameters that vary with the value of a and b. Subsequently, the equation (3.11) become as

$$f(a) - f(b) = \begin{bmatrix} \delta_{11}{}^{max}h_{11}{}^{max} & \delta_{12}{}^{max}h_{12}{}^{max} & \dots & \delta_{1n}{}^{max}h_{1n}{}^{max} \\ \delta_{21}{}^{max}h_{21}{}^{max} & \delta_{22}{}^{max}h_{22}{}^{max} & \cdots & \delta_{2n}{}^{max}h_{2n}{}^{max} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1}{}^{max}h_{n1}{}^{max} & \delta_{n2}{}^{max}h_{n2}{}^{max} & \dots & \delta_{nn}{}^{max}h_{nn}{}^{max} \end{bmatrix}[(a-b)]$$
$$+ \begin{bmatrix} \delta_{11}{}^{min}h_{11}{}^{min} & \delta_{12}{}^{min}h_{12}{}^{min} & \dots & \delta_{1n}{}^{min}h_{1n}{}^{min} \\ \delta_{21}{}^{min}h_{21}{}^{min} & \delta_{22}{}^{min}h_{22}{}^{min} & \cdots & \delta_{2n}{}^{min}h_{2n}{}^{min} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1}{}^{min}h_{n1}{}^{min} & \delta_{n2}{}^{min}h_{n2}{}^{min} & \dots & \delta_{nn}{}^{min}h_{nn}{}^{min} \end{bmatrix}[(a-b)] \tag{3.15}$$

Use the canonical basis from Lemma 3.3, then $f(a) - f(b)$ can be written as

$$f(a)-f(b)=\left[\left(\sum_{i,j=1}^{n,n} Z_{ij}{}^{max}\delta_{ij}{}^{max}\right)+\left(\sum_{i,j=1}^{n,n} Z_{ij}{}^{min}\delta_{ij}{}^{min}\right)\right](a-b) \tag{3.16}$$

Where $Z_{ij}{}^{max}=e_n(i)e_n{}^T(j)h_{ij}{}^{max}$ and $Z_{ij}{}^{min}=e_n(i)e_n{}^T(j)h_{ij}{}^{min}$

$h_{ij}{}^{max}\geq max\left(\frac{\partial f_i}{\partial x_j}\right)$ and $h_{ij}{}^{min}\leq min\left(\frac{\partial f_i}{\partial x_j}\right)$

The equation (3.16) can be modified as

$$f(a)-f(b)=\left(\sum_{i=1}^{2n\times n} h_i\,\tilde{A}_i\right)(a-b) \tag{3.17}$$

With

$$\tilde{A}_i=\sum_{i,j,r=1}^{n,n,2} Z_{ij}{}^{r}$$

3.2.3 Nonlinear observer:

Based on the equation (3.17) the dynamics of the estimation error (3.3) can be expressed as

$$\dot{e}=(A-LC)e+\left(\sum_{i=1}^{2n\times n} h_i\,\tilde{A}_i\right)(x-\hat{x}) \tag{3.18}$$

Then the dynamics of the estimation error can be expressed as follows

$$\dot{e}=(A-LC+\sum_{i=1}^{2n\times n} h_i\,\tilde{A}_i)e \tag{3.19}$$

It is possible to rewrite the dynamics of the estimation error as the next final form

$$\dot{e}=\sum_{i=1}^{2n\times n} h_i\,(A-LC+n\times n\times\tilde{A}_i)e \tag{3.20}$$

3.2.3.1 Stability analysis:

In this subsection, and in order to get the observer gain, the stability is studied by the Lyapunov quadratic function that's given as follows[26]

$$V\big(e(t)\big) = e^T(t)Pe(t) \tag{3.21}$$

The stability is checked when the derivative of the Lyapunov function (3.21) is lower than zero

$$\dot{V}\big(e(t)\big) \leq 0 \tag{3.22}$$

The state estimation error asymptotically converges to zero if there exists a matrix$P = P^T > 0$ such as the following LMI's be verified:

$$A^T P + PA + n \times n \times \tilde{A}_i^{\ T} P + n \times n \times P\tilde{A}_i - MC - M^T C^T + \tilde{\alpha}P < 0 \tag{3.23}$$

Where

$\tilde{\alpha}$ is a coefficient depend reversely on the response time of the estimation error

And $i = (1,2, \dots ,2n \times n)$

Then the observer gain can be easily obtained by solving the LMI's (3.23), so the observer gain is:

$$L = P^{-1}M \tag{3.24}$$

3.2.4 Nonlinear controller:

The tracking error is given by if we neglect the perturbation including the main forcing signals (input commands):

$$\dot{e_c} = (A - BK)e_c + (\varphi(x) - \varphi(x_c)) \tag{3.25}$$

Where $e_c = x - x_c$ with x_c is the reference state and K is the controller gain.

By introducing the MVT and sector nonlinear approaches mentioned above to $(\varphi(x) - \varphi(x_c))$, so the final form of the tracking error becomes as

$$\dot{e_c} = \sum_{i=1}^{2n\times n} h_i(\xi)\,(A - BK + n \times n \times \bar{\bar{A}}_i)e_c \tag{3.26}$$

3.2.4.1 Stability analysis:

In this subsection, and in order to get the controller gain, the stability is studied by the Lyapunov quadratic function that's given as follows[51, 52]

$$V\big(e_c(t)\big) = {e_c}^T(t)Pe_c(t) \tag{3.27}$$

The stability is checked when the derivative of the Lyapunov function (3.27) is less than zero

$$\dot{V}\big(e_c(t)\big) \leq 0 \tag{3.28}$$

The state estimation error asymptotically converges to zero if there exists a matrix$P = P^T > 0$ such as the following LMI's be verified:

$$AP + PA^T + n \times n \times \bar{\bar{A}}_i P + n \times n \times P\bar{\bar{A}}_i^{\,T} - BY - B^T Y^T + \alpha P < 0 \tag{3.29}$$

Where α is coefficient depend reversely on the response time of the tracking error

And $i = (1,2, \ldots ,2n)$

Then the controller gain can be easily gotten by solving the LMI's (3.29), the controller gain is calculated as

$$K = YP^{-1} \tag{3.30}$$

3.3 Robust control and estimation of uncertain nonlinear T-S fuzzy model:

3.3.1 T-S representation of uncertain nonlinear:

In some control design literatures [46, 49], the parameters of the nominal fuzzy model are assumed to have certain amount of perturbation and these are not estimated from the uncertainty of the original system. Therefore, for these applications, the interval fuzzy identification of uncertain nonlinear systems has become an important topic of scientific research. We discuss the structured fuzzy model of uncertain nonlinear systems suitable for robust fuzzy control. The fuzzy model is expressed by linear and uncertain terms, which represent the nominal system and parametric uncertainties respectively. The nominal model and the bounds of the uncertain terms of the fuzzy model are identified and the approaches will be based on the method proposed by Skrjanc et al. [53] and [48, 49, 54]. The model identified in this step cannot be directly employed in robust fuzzy control design and it must be expressed in another special form (structured form) or TS with varying parameters. The uncertain terms are expressed in suitable form as norm bounded uncertain matrices accompanied by constant real matrices. These systems have been synthesized by an extended H_∞observer and controller which based on the DEF representation and in TS structure with varying parameters.

3.3.1.1 T-S representation and modelling of nonlinear time-varying parameter systems:

Since most of the control law and fault detection residual design [23, 24] are based on estimated state variables, the observer design for nonlinear systems can be viewed as the heart of system control and model-based diagnosis. Unfortunately, the introduction of time-varying parameters in the system models, needed to accurately represent the system behavior, which leads to more challenging problems in estimation. In this case, conventional observers and controllers, essentially developed for time invariant systems cannot be directly used, and so-called adaptive observers developed for joint state and unknown parameter estimation are needed [48]. The main difficulty in control and estimating the state of such systems comes from the lack of knowledge on the parameter evolution. The nonlinear time-varying parameter systems where the parameters are inaccessible (non measurable) and may be considered as model disturbances, uncertainties or faults acting on the system evolution.

Numerous approaches were proposed in order to deal with nonlinear system control and estimation or diagnosis [50, 53]. An efficient way if we can rewrite the original nonlinear system in a simpler form, like the Takagi-Sugeno (T-S) model. Originally introduced by [55], the T-S representation allows to exactly describing nonlinear systems, under the condition that the nonlinearities are bounded. This is reasonable since state variables as well as parameters of physical systems are bounded [46, 56].

3.3.1.2 DFE uncertainty structure approach:

It is well known that a Takagi–Sugeno fuzzy model can be a universal approximate of a smooth nonlinear dynamics [46, 54, 57]. Therefore, a smooth nonlinear control system of the following form, with the state$x(t)$ as a vector,$u(t)$ is the input vector and $y(t)$ is the output vector; the state model can be represented:

$$\begin{cases} \dot{x}(t) = f\big(x(t), \theta(t)\big) + g(x, \theta(t))u(t) + D_w w(t) \\ y(t) = Cx(t) \end{cases} \tag{3.31}$$

A fuzzy dynamic model has been proposed by Takagi and Sugeno[53] to represent local linear input/output relations of nonlinear systems. This fuzzy linear model is described by fuzzy If–Then rules and will be employed to deal with the control design problem of the nonlinear system (3.31). The if-then rule of this fuzzy model for the nonlinear system (3.31) in local case is of the following form[46]:

$$\begin{aligned} \dot{x}(t) &= \frac{\sum_{i=1}^{r} w_i\big(\xi(t)\big)\{A_i x(t) + B_i u(t)\}}{\sum_{i=1}^{r} w_i\big(\xi(t)\big)} + D_w w(t) \\ &= \sum_{i=1}^{r} h_i\big(\xi(t)\big)\{A_i x(t) + B_i u(t)\} + D_w w(t) \end{aligned} \tag{3.32}$$

And

$$\begin{aligned} y(t) &= \frac{\sum_{i=1}^{r} w_i\big(\xi(t)\big)\, C_i x(t)}{\sum_{i=1}^{r} w_i\big(\xi(t)\big)} \\ &= \sum_{i=1}^{r} h_i\big(\xi(t)\big)\, C_i x(t) \end{aligned} \tag{3.33}$$

Secondly, to account for the modeling error, we introduce the following notation

$$e(x,u) = \left[f(x,\theta) - \sum_{i=1}^{r} h_i\big(\xi(t)\big)A_i x(t)\right] + \left[g(x,\theta) - \sum_{i=1}^{r} h_i\big(\xi(t)\big)B_i\right]u(t) \tag{3.34}$$

In addition, we assume that the modeling error term $e(x,u)$ satisfies the following norm-bounded assumption.

Assumption (sector-type assumption): There exits some $\alpha_1 \geq 0, \alpha_2 \geq 0$such that $\|e(x,u)\| \leq \alpha_1\|x\| + \alpha_2\|u\|$ for all $x(t) \in R^n\ and\ u(t) \in R^m$. Moreovre, denote the corresponding modeling error set by $\Omega(x,u) = \{e(x,u): \|e(x,u)\| \leq \alpha_1\|x\| + \alpha_2\|u\|\}$.

The aforementioned result is expressed in terms of DEF structure to characterize the modeling error. To this end, we observe that there exist two norm-bounded uncertainty matrices $F_1$and F_2satisfying $F_1^t F_1 \leq I$ and$F_2^t F_2 \leq I$, respectively, such that

$$e(x,u) = \alpha_1 F_1 x + \alpha_2 F_2 u$$

$$e(x,u) = \left(\frac{\alpha_1}{\eta_1}\ I\right)F_1(\eta_1 I)x + \left(\frac{\alpha_2}{\eta_2}\ I\right)F_2(\eta_2 I)u \tag{3.35}$$

$$e(x,u) = \underbrace{\begin{bmatrix}\frac{\alpha_1}{\eta_1}I & \frac{\alpha_2}{\eta_2}I\end{bmatrix}}_{D}\underbrace{\begin{bmatrix}F_1 & 0\\ 0 & F_2\end{bmatrix}}_{F}\underbrace{\begin{bmatrix}\eta_1 I\\ 0\end{bmatrix}}_{E_1}x + \underbrace{\begin{bmatrix}\frac{\alpha_1}{\eta_1}I & \frac{\alpha_2}{\eta_2}I\end{bmatrix}}_{D}\underbrace{\begin{bmatrix}F_1 & 0\\ 0 & F_2\end{bmatrix}}_{F}\underbrace{\begin{bmatrix}0\\ \eta_2 I\end{bmatrix}}_{E_2}\mathrm{u}$$

$=\mathrm{DF}E_1 x + \mathrm{DF}E_2 u$Where $\eta_1 > 0, \eta_2 > 0$

3.3.1.3Modelling using bounded time varying parameters of N.L. uncertain systems approach:

In order to model nonlinear time-varying systems using the T-S or polytopic representation, for that, each time-varying parameter will be rewritten under a particular form. Let us consider the nonlinear time-varying T-S system represented by equation (3.31) with n time-varying parameters $\theta(t)$[48, 54]:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} \mu_i(\xi(t))\Big(A_i(\theta(t))x(t) + B_i(\theta(t))u(t)\Big) + D_w w(t) \\ y(t) = Cx(t) \end{cases} \tag{3.36}$$

With $\theta(t) = [\theta_1(t) \quad \dots \quad \theta_{n_\theta}(t)]$ and

$$\begin{aligned} A_i(\theta(t)) &= \bar{A}_i + \sum_{j=1}^{n_\theta} \theta_j(t)\,\bar{A}_{ij} \\ B_i(\theta(t)) &= \bar{B}_i + \sum_{j=1}^{n_\theta} \theta_j(t)\bar{B}_{ij} \end{aligned} \tag{3.37}$$

According to the SNT [46],each parameter $\theta_j(t)$is expressed as a function of its upper and lower bounds, respectively denoted $\theta_j^1$and θ_j^2such that:

$$\theta_j(t) = \tilde{\mu}_j^1\left(\theta_j(t)\right)\theta_j^1 + \tilde{\mu}_j^2\left(\theta_j(t)\right)\theta_j^2 \tag{3.38}$$

Where $\tilde{\mu}_j^1\left(\theta_j(t)\right)$ and $\tilde{\mu}_j^2\left(\theta_j(t)\right)$are defined by

$$\begin{aligned} \tilde{\mu}_j^1\left(\theta_j(t)\right) &= \frac{\theta_j(t) - \theta_j^2}{\theta_j^1 - \theta_j^2} \\ \tilde{\mu}_j^2\left(\theta_j(t)\right) &= \frac{\theta_j^1 - \theta_j(t)}{\theta_j^1 - \theta_j^2} \end{aligned} \tag{3.39}$$

And satisfy the convex sum property:

$$\begin{gathered} \tilde{\mu}_j^1\left(\theta_j(t)\right) + \tilde{\mu}_j^2\left(\theta_j(t)\right) = 1 \\ 0 \le \tilde{\mu}_j^1\left(\theta_j(t)\right) \le 1 \end{gathered}$$

Replacing (3.39) in (3.37), it becomes:

$$A_i(\theta(t)) = \bar{A}_i + \sum_{j=1}^{n_\theta}\sum_{k=1}^{2} \tilde{\mu}_j^k\left(\theta_j(t)\right)\theta_j^k\bar{A}_{ij} \tag{3.40}$$

$$B_i\big(\theta(t)\big) = \bar{B}_i + \sum_{j=1}^{n_\theta}\sum_{k=1}^{2} \tilde{\mu}_j^k\left(\theta_j(t)\right)\theta_j^k\,\bar{B}_{ij}$$

The time-varying matrices $A_i\big(\theta(t)\big)$and $B_i\big(\theta(t)\big)$can now be written as polytopic matrices, firstly, due to (3.40), it follows that

$$\begin{aligned}\sum_{j=1}^{n_\theta}\theta_j(t)\bar{A}_{ij} &= \sum_{j=1}^{n_\theta}\left[\tilde{\mu}_j^1\left(\theta_j(t)\right)\theta_j^1 + \tilde{\mu}_j^2\left(\theta_j(t)\right)\theta_j^2\right]\bar{A}_{ij} \\ &= \sum_{j=1}^{n_\theta}\left[\left[\tilde{\mu}_j^1\left(\theta_j(t)\right)\theta_j^1 + \tilde{\mu}_j^2\left(\theta_j(t)\right)\theta_j^2\right]\bar{A}_{ij}\left[\prod_{k=1 k\neq j}^{n_\theta}\sum_{m=1}^{2}\tilde{\mu}_k^m\big(\theta_k(t)\big)\right]\right]\end{aligned} \tag{3.41}$$

Thus, equation (3.41) can be written as

$$\begin{aligned}A_i\big(\theta(t)\big) &= \sum_{j=1}^{2^{n_\theta}}\tilde{\mu}_j\left(\theta(t)\right)AA_{ij} \\ B_i\big(\theta(t)\big) &= \sum_{j=1}^{2^{n_\theta}}\tilde{\mu}_j\left(\theta(t)\right)BB_{ij}\end{aligned} \tag{3.42}$$

$$\tilde{\mu}_j^1\big(\theta(t)\big) = \prod_{k=1}^{n_\theta}\tilde{\mu}_k^{\sigma_j^k}\big(\theta_k(t)\big) \tag{3.43}$$

$AA_{ij} = \bar{A}_i + \sum_{k=1}^{n_\theta}\tilde{\theta}_k^{\sigma_j^k}\bar{A}_{ik}$ and $BB_{ij} = \bar{B}_i + \sum_{k=1}^{n_\theta}\tilde{\theta}_k^{\sigma_j^k}\bar{B}_{ik}$

Finally, using equations (3.43), the nonlinear time-varying TS system (3.36) becomes:

$$\begin{cases}\dot{x}(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^{n_\theta}}\mu_i\left(\xi(t)\right)\tilde{\mu}_j\big(\theta(t)\big)\left(AA_{ij}x(t) + BB_{ij}u(t)\right) + D_w w(t) \\ y(t) = Cx(t)\end{cases} \tag{3.44}$$

In fuzzy literature, the technique for representing nonlinear systems by TS fuzzy models is based on exact fuzzy modeling technique [21, 22]where the output of the constructed fuzzy model is mathematically identical to that of original nonlinear system. Most plants in the industry have severe nonlinearity and uncertainties, posing additional difficulties to the exact modeling techniques.

3.3.2 Control of nonlinear uncertain systems:

3.3.2.1 PDC Control of bounded time varying parameters of N.L. uncertain systems:

Based on the model found in equation (3.44):

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^{n_\theta}} \mu_i\left(\xi(t)\right)\tilde{\mu}_j\left(\theta(t)\right)\left(AA_{ij}x(t) + BB_{ij}u(t)\right) \\ y(t) = Cx(t) \end{cases} \quad (3.45)$$

If we neglect, firstly, the effect of the disturbed signal $D_w w(t)$ and after changing (3.45) to the following expression with another representation:

$$\dot{x}(t) = \sum_{i=1}^{m} h_i\left(\zeta(t)\right)\left(A_i x(t) + B_i u(t)\right) \quad (3.46)$$

With $m = r * 2^{n_\theta}$and the new defined premise variable$\zeta = (\xi, \theta)$.

According to the state feedback PDC control law adopted, the control vector is given by

$$u(t) = -\sum_{j=1}^{m} h_j\left(\zeta(t)\right)K_j x(t)$$

Now, based on the PDC concept, it is possible to rewrite the system (3.31) as follows:

$$\dot{x}(t) = \sum_{i=1}^{m}\sum_{j=1}^{m} h_i(\zeta(t))h_j(\zeta(t))\left(A_i - B_i K_j\right)x(t) \quad (3.47)$$

We define

$G_{ij} = A_i - B_i K_j$

Then

$$\dot{x}(t) = \sum_{i=1}^{m}\sum_{j=1}^{m} h_i(\zeta(t))h_j(\zeta(t))\big(G_{ij}\big)x(t) \\ + 2\sum_{i=1}^{m}\sum_{j=1}^{m} h_i(\zeta(t))h_j(\zeta(t))\left(\frac{G_{ij}+G_{ji}}{2}\right)x(t) + \tag{3.48}$$

Theorem 3.3 [58] :

The uncertain T-S model is asymptotically stable if there is a matrix $P = P^T$ and K_j such as:

$$\text{With}\begin{cases} G_{ii}{}^T P + PG_{ii} < 0 \\ \left(\frac{G_{ij}+G_{ji}}{2}\right)^T P + P\left(\frac{G_{ij}+G_{ji}}{2}\right) < 0 \end{cases}$$

$h_i\big(\zeta(t)\big)h_j\big(\zeta(t)\big) = 0$ for $i = j$.

Such that $G_{ij} = A_i - B_i K_j$

3.3.2.2 PDC Control of DFE uncertainty structure model of nonlinear uncertain systems:

Given the nonlinear uncertain systems with the DEF structure with $w(t)$=0,[57]:

$$\dot{x}(t) = \sum_{i=1}^{n} h_i\big(\xi(t)\big)\Big(\big(A_i + \Delta A_i(t)\big)x(t) + \big(B_i + \Delta B_i(t)u(t)\big)\Big) \tag{3.49}$$

With $\Delta A_i(t) = A\sum_A(t)\,E_A$ and $\Delta B_i(t) = B\sum_B(t)\,E_B$

Shch that :

$$\sum\nolimits_{\mathrm{A}}^{\mathrm{T}}(\mathrm{t})\sum\nolimits_{\mathrm{A}}(\mathrm{t}) \le \mathrm{I};\text{and } \sum\nolimits_{\mathrm{B}}^{\mathrm{T}}(\mathrm{t})\sum\nolimits_{\mathrm{B}}(\mathrm{t}) \le \mathrm{I};\forall \mathrm{t} \tag{3.50}$$

We consider the following PDC control form:

$$u(t) = -\sum_{j=1}^{n} h_j\big(\xi(t)\big)K_j x(t) \tag{3.51}$$

So , $\dot{x}(t) = \sum_{i=1}^{n}\sum_{j=1}^{n} h_i\big(\xi(t)\big)h_j\big(\xi(t)\big)\left(A_i - B_iK_j + \Delta A_i(t) - \Delta B_i(t)K_j\right)x(t)$ (3.52)

For the stability analysis,one can consider the following Lyapunov function :

$$V\big(x(t)\big) = x^T(t)Px(t) \tag{3.53}$$

For the stability we have to assure the following LMI's conditions[57]:

$$\begin{pmatrix} A_iP_1 - B_iR_j + P_1A_i^T - R_j^TB_i^T + \gamma_A AA^T + \gamma_B BB^T & P_1E_A^T & R_j^TE_B^T \\ * & -\gamma_A I & 0 \\ * & * & -\gamma_B I \end{pmatrix} < 0, i, j = 1, \dots, n \tag{3.54}$$

With$P_1 = P^{-1}$and γ_A, γ_Bpositive scalar .

The controller gains are given by:

$$K_j = R_jP_1^{-1}\text{for}\, i, j = 1, \dots, n \tag{3.55}$$

3.3.2.3 H_∞ Control of DFE uncertainty structure model of nonlinear uncertain systems:

Based on fuzzy systems with DFE uncertainty structure[46, 47, 49, 54], we assume that the nonlinear control system is represented by the Takagi–Sugeno fuzzy model which both plant modeling uncertainty and exogenous modeling uncertainty and exogenous signal uncertainty$w(t)$are considered for each individual rule $R_i = 1, \dots, r$.

If $z_1$is $F_1^i$and ...and $z_p$is F_p^i

Then $\dot{x}(t) = (A_i + D_iFE_1)x(t) + (B_i + D_iFE_2)u(t) + D_W w(t)$ (3.56)

Subsystem $D_i, E_1, F_2$are known matrices and $F$is uncertain parameter matrix satisfying $F^tF \leq I$.

$$\dot{x}(t) = \sum_{i=1}^{r} h_i(\xi(t))\,[(A_i + D_i F E_1)x(t) + (B_i + D_i F E_2)u(t)] + D_W w(t) \tag{3.57}$$

A linear state feedback controller for each rule of the fuzzy model, known as parallel distributed compensation(PDC)[46] is designed to stabilize the uncertain fuzzy system(3.57) with a given level of disturbance attenuation for all admissible uncertainty satisfying $F^t F \leq I$.They are formulated as

If z_1 is F_1^i and ...and z_p is F_p^i

Then $u(t) = -\sum_{j=1}^{r} h_i(\xi(t))K_j x(t)$ (3.58)

Substituting (3.58) into (3.57), the closed –loop system becomes

$$\dot{x}(t) = \sum_{i=1}^{r}\sum_{j=1}^{r} h_i\,(\xi(t))h_j(\xi(t))\,\left[(A_i + D_i F E_1) + (B_i + D_i F E_2)K_j\right]x(t) + D_W w(t) \tag{3.59}$$

Associated with the closed-loop system (3.59) is the H^{∞}control criterion when initial condition is considered [51].

$$\int_0^{\infty} y^t(t)y(t)dt < x^t(0)Px(0) + \rho^2 \int_0^{\infty} w^t(t)w(t)dt \tag{3.60}$$

Where $y(t)$is the controlled output

$$y(t) = Cx(t).$$

The objective is to exploit the robust H^{∞} control and quadratic stabilizability of an uncertain fuzzy system in which a DFE structure with norm-bounded uncertainty $F^t F \leq I$.

Introducing a new variables $S = P^{-1}$and $X_j = \varepsilon_j Y_j$,(3.60)can be reformulated as Riccati-like inequalities shown below[46],such that

$$S[A_i - B_i R^{-1} E_2^t E_1]^t + [A_i - B_i R^{-1} E_2^t E_1]S + \frac{1}{\varepsilon_j} S E_1^t [I - E_2 R^{-1} E_2^t] E_1 S + SC^t CS + \rho^{-2} D_w D_w^t + \varepsilon_j {D_i}^t + \left[X_j (\varepsilon_j R)^{-1} X_j^t - B_i R^{-1} X_j^t - X_j R^{-1} B_i^t\right] < 0 \tag{3.61}$$

Using Schur complements to (3.61), the following parameter dependent LMI's is obtained:

$$\begin{pmatrix} \begin{pmatrix} S[A_i - B_i R^{-1} E_2^t E_1]^t + \\ [A_i - B_i R^{-1} E_2^t E_1] S - \\ B_i R^{-1} X_j^t - X_j R^{-1} B_i^t + \\ \rho^{-2} D_w D_w^t + \varepsilon_j {D_i}^t \end{pmatrix} & X_j & S E_1^t [I - E_2 R^{-1} E_2^t] \; SC^t & 0 \\ X_j^t & -\varepsilon_j R & 0 & 0 \\ [I - E_2 R^{-1} E_2^t] E_1 S & 0 & -\varepsilon_j I & 0 \\ CS & 0 & 0 & -I \end{pmatrix} < 0 \tag{3.62}$$

Furthermore, the local controller gain are

$K_j = -(E_2^t E_2)^{-1} \left(X_j^t S^{-1} + E_2^t E_1 \right)$ if (3.62) satisfied

3.3.3 State and time-varying parameter observer for uncertain nonlinear systems:

For the obtained T-S model (3.44), with the weighting functions $h(\xi(t)), (\theta(t))$depending on the system state x(t) and the parameter θ(t), a joint state and parameter observer have been be implemented [48, 54]. With a *L2* attenuation, approach was proposed to minimize the effect of the time-varying parameters on the state and parameter error estimations.

Based on the nonlinear time-varying T-S system given by (3.44):

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} \sum_{j=1}^{2^{n_\theta}} \mu_i \left(\xi(t)\right) \tilde{\mu}_j \left(\theta(t)\right) \left(AA_{ij} x(t) + BB_{ij} u(t) \right) \\ y(t) = Cx(t) \end{cases} \tag{3.63}$$

The state and parameter observer of system (3.63) is presented as the following:

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^{n_\theta}} \mu_i\left(\hat{\xi}(t)\right)\tilde{\mu}_j\left(\hat{\theta}(t)\right)\left(AA_{ij}\hat{x}(t) + BB_{ij}u(t)\right) + L_{ij}\left(y(t) - \hat{y}(t)\right) \\ \dot{\hat{\theta}}(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^{n_\theta}} \mu_i\left(\hat{\xi}(t)\right)\tilde{\mu}_j\left(\hat{\theta}(t)\right)\left(-\alpha_{ij}\hat{\theta}(t) + K_{ij}\left(y(t) - \hat{y}(t)\right)\right) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \quad (3.64)$$

Where $L_{ij} \in R^{n_x \times m}$,$K_{ij} \in R^{n_\theta \times m}$ *and* $-\alpha_{ij} \in R^{n_\theta \times n_\theta}$ (3.65)

The gains were determined such that the estimated state and parameter converge to the actual system state and parameter.

The state estimation error $e_x(t)$and the parameter estimation error $e_\theta(t)$were defined by

$$e_x(t) = x(t) - \hat{x}(t) \quad (3.66)$$

$$e_\theta(t) = \theta(t) - \hat{\theta}(t) \quad (3.67)$$

The dynamics of the state and parameter estimation errors are given by

$$\dot{e}_a(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^{n_\theta}} \mu_i\left(\hat{\xi}(t)\right)\tilde{\mu}_j\left(\hat{\theta}(t)\right)\left(\emptyset_{ij}e_a(t) + \psi_{ij}\omega(t)\right) \quad (3.68)$$

With

$$e_a(t) = \begin{pmatrix} e_x(t) \\ e_\theta(t) \end{pmatrix}, \omega(t) = \begin{pmatrix} x(t) \\ \theta(t) \\ \dot{\theta}(t) \\ u(t) \end{pmatrix} \quad (3.69)$$

and

$$\emptyset_{ij}(t) = \begin{pmatrix} AA_{ij} - L_{ij}C & 0 \\ -K_{ij}C & -\alpha_{ij} \end{pmatrix}$$
$$\psi_{ij}(t) = \begin{pmatrix} \Delta A(t) & 0 & 0 & \Delta B(t) \\ 0 & \alpha_{ij} & I & 0 \end{pmatrix} \quad (3.70)$$

Theorem 3.4 [48]: There exists an extended robust state and parameter observer (3.64) for a nonlinear time-varying parameter system (3.63) with a L_2 gain from $x(t)$ to $e_a(t)$bounded by $\beta(\beta > 0)$if there exists symmetric positive definite matrices: $P_0 \in R^{n_x \times n_x}$, $P_1 \in R^{n_\theta \times n_\theta}$

$\Gamma_2^0 \in R^{n_x \times n_x}$, $\Gamma_2^1 \in R^{n_\theta \times n_\theta}$, $\Gamma_2^2 \in R^{n_\theta \times n_\theta}$, $\Gamma_2^3 \in R^{n_u \times n_u}$ and positive scalars $\beta, \lambda_1, \lambda_2 > 0$ solutions of the following optimization problem

$$min_{P_0,,P_1,R_{ij},F_{ij},\bar{\alpha}_{ij}\lambda_1,\lambda_2\Gamma_2^k}(\beta) \tag{3.71}$$

Under the following constraints:

$\Gamma_2^k < \beta I \; for \; k = 0,1,2,3.$

$$\begin{pmatrix} Q_{ij}^{11} & -C^T F_{ij}^T & 0 & 0 & 0 & 0 & P_0 A & P_0 A \\ * & Q_{ij}^{22} & 0 & \bar{\alpha}_{ij} & P_1 & 0 & 0 & 0 \\ * & * & Q_{ij}^{33} & 0 & 0 & 0 & 0 & 0 \\ * & * & * & -\Gamma_2^1 & 0 & 0 & 0 & 0 \\ * & * & * & * & -\Gamma_2^2 & 0 & 0 & 0 \\ * & * & * & * & * & Q_{ij}^{66} & 0 & 0 \\ * & * & * & * & * & * & -\lambda_1 I & 0 \\ * & * & * & * & * & * & 0 & -\lambda_2 I \end{pmatrix} \prec 0$$

for $i = 1, \dots, r \; and \; j = 1, \dots, 2^{n_\theta}$ with

$$Q_{ij}^{11} = P_0 A_{ij} + A_{ij}^T P_0 - R_{ij} C - C^T R_{ij}^T + I_{n_x}$$
$$Q_{ij}^{22} = -\bar{\alpha}_{ij} - \bar{\alpha}_{ij}^T + I_n$$
$$Q_{ij}^{33} = -\Gamma_2^0 + \lambda$$

3.3.4 Mass–spring–damper system application:

The dynamic equation of a mass–spring–damper mechanical system borrowed from[46] is given by

$$M\,\ddot{y}(t)+g\big(y(t),\dot{y}(t)\big)+f\big(y(t)\big)=\phi\big(\dot{y}(t)\big)u(t)+w(t) \tag{3.72}$$

Where $M=1$ is the mass and assume that

$$y(t)\in[-1.5\ 1.5],\dot{y}(t)\in[-1.5\ 1.5],$$

And $\theta_1(t)\in[-1\ \ 1]$,$c(t)=1.175+0.655\cos(2\pi t)$=1.175+$\theta_2(t)$

Denoting $x(t)=[x_1\quad x_2]^t=[\dot{y}(t)\quad y(t)]^t$, we can obtain the state space representation of system (3.72) with parameters $\theta_1 and\ \theta_2$

$$\dot{x}(t)=F\big(x,\theta(t)\big)x(t)+G(x,t)u(t)+D_w w(t) \tag{3.73}$$

Where

$$F(x,t)=\begin{bmatrix}-1-0.1\big(1+\theta_1(t)\big)x_1^2 & -1.175-0.01\theta_1(t)-\theta_2(t)\\ 1 & 0\end{bmatrix} \tag{3.74}$$

$G(x,t)=\begin{bmatrix}1+0.13x_1^3\\ 0\end{bmatrix}$ and$D_w=\begin{bmatrix}1\\0\end{bmatrix}$.

A two-rule TS fuzzy model is designed to approximate the uncertain nonlinear system

If $z_1$is about F_1^iIf $z_1$is about F_1^i

Then $\dot{x}(t)=(A_i+D_1\Delta_1E_d)x(t)+B_iu(t)+D_w w(t\,)$ (3.75)

Where $i=1{,}2$ and the local system matrices are

$$A_1=A_2=\begin{bmatrix}-1 & -1.175\\ 1 & 0\end{bmatrix},B_1=\begin{bmatrix}1.329\\0\end{bmatrix},E_d=\begin{bmatrix}0.671\\0\end{bmatrix}$$

$$D_1=\begin{bmatrix}-0.1 & -0.655\\ 0 & 0\end{bmatrix},\Delta_1=\begin{bmatrix}\delta_d(t) & 0\\ 0 & \cos(2\pi t)\end{bmatrix},E_d=\begin{bmatrix}0.1\\1\end{bmatrix}$$

Note that the uncertain term $D_1\Delta_1E_d$with $\Delta_1^t\Delta_1\leq I$ comes from the uncertainty $\delta_d(t)$and $c(t)$ in the nonlinear system (3.72).The firing strength $\mu_i s$ of fuzzy sets F_1^i are

$$\mu_1=0.5+\frac{x_1}{3},\qquad \mu_2=1-\mu_1$$

The overall uncertain fuzzy approximated system becomes

$$\dot{x}(t) = \sum_{i=1}^{2} \mu_i \left[A_i x(t) + B_i u(t)\right] + D_1 \Delta_1 E_d x(t) + D_w w(t) \tag{3.76}$$

The modeling error $e(x,t)$becomes

$$e(x,t) = \begin{bmatrix} -0.1\left(1+\delta_d(t)\right)x_1^2 & 0 \\ 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0.13x_1^3 - 0.329\mu_1 - 0.329\mu_2 \\ 0 \end{bmatrix} u(t) \tag{3.77}$$

By further calculation on $\|e(x,t)\|$with $x_1 \in [-1.5 \quad 1.5]$and $\delta_d(t) \in [-1 \quad 1]$, we have

$$\begin{aligned} \|e\| &\le max_{x_{1,\delta_d(t)}}\{0.1\|1+\delta_d(t)\|\|x_1^2\|\}\|x\| + max_{x_1}\{\|0.13x_1^3 - 0.329\mu_1 + 0.329\mu_2\|\}\|u\| \\ &= \alpha_1\|x\| + \alpha_2\|u\| \end{aligned}$$

Where $\alpha_1 = 0.45, \alpha_2 = 0.1098.$ The modeling error $e(x,t)$ can be turn into

$$e(t) = \begin{bmatrix} \alpha_1 f_1(t) & 0 \\ 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} \alpha_2 f_2(t) \\ 0 \end{bmatrix} u(t)$$

$$= D_2 \Delta_2 E_{e1} x(t) + D_2 \Delta_2 E_{e2} u(t)$$

Where $\Delta_2^t \Delta_2 \le I \; and$

$$D_2 = \begin{bmatrix} \alpha_1/0.5 & \alpha_2/0.2 \\ 0 & 0 \end{bmatrix}, \Delta_2 = \begin{bmatrix} f_1(t) & 0 \\ 0 & f_2(t) \end{bmatrix}, E_{e1} = \begin{bmatrix} 0.5 & 0 \\ 0 & 0 \end{bmatrix}, E_{e2} = \begin{bmatrix} 0 \\ 0.2 \end{bmatrix} \tag{3.78}$$

Adding the modeling error$e(x,t)$ into the approximated system, we have an uncertain TS fuzzy model representing the nonlinear system (3.72) as:

$$\dot{x}(t) = \sum_{i=1}^{2} [\mu_i (A_i + DFE_1) x(t) + (B_i + DFE_2) u(t)] + D_w w(t) \tag{3.79}$$

Where the uncertain terms DFE_i with $F^t F \le I$ is deduced from the modeling error and the system uncertainties $\delta_d(t)$and$c(t)$

$$D = [D_1 \quad D_2], \quad F = \begin{bmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{bmatrix}, \quad E_1 = \begin{bmatrix} E_d \\ E_{e1} \end{bmatrix}, E_2 = \begin{bmatrix} 0 \\ E_{e2} \end{bmatrix}.$$

Now, we consider a linear controller

$$u(t) = -Kx(t)$$

And a controller output $y(t) = x(t)$.To determine the quadratic stabilizability of the above system with disturbance attenuation level $\rho = 1$, a feasible solution to a set 2 LMI's does exist via LMIs solver, stipulating a linear control law. Here are the findings

$$S = \begin{bmatrix} 2.2341 & -0.4667 \\ -0.4667 & 0.4784 \end{bmatrix}$$

And $X = \begin{bmatrix} 0.2866 \\ 0.0132 \end{bmatrix}, \varepsilon = 0.6027, \; K = [-4.2084 \quad -4.7948.]$

As we see, here, the difficulties to establish the DEF model easily and to design the controller with this a simple example with two states.

3.4 Conclusion:

In this chapter, we have presented the MVT concept and the approaches used based on the T-S representation with DEF structure in order to design the controllers and the observers for the class of the non-linear uncertain systems. We conclude that these methods are not so easy to be applicable for uncertain nonlinear systems contains more parameters and complex non-linearity. Finally, complex system examples, which show how the results proposed in some papers can eliminate and/or reduce serious disadvantages existing in the robust control literature for significant classes of linear and nonlinear uncertain systems

By using the MVT concept, the design of controllers or the observers is simpler due to the unicity gain, which urge us to extend these ideas in a systematic methodology in order to prove the stability of non-linear uncertain systems. The state feedback approach allows us to get the controller and the observer gains with a methodical way by using the stability through the Lyapunov functions.

The topic of the next chapter will be the design ,simulation and the experimental tests of controllers and observers based on the MVT approach applied to the IM machine with invariant parameters. Whereas the MVT approach that will be designed for of the IM machine drives in the fifth chapter and extended to the cases where parameters are varying with exogenous perturbation.

Chapter 4:

Control and states estimation of the induction motor based on the MVT theory

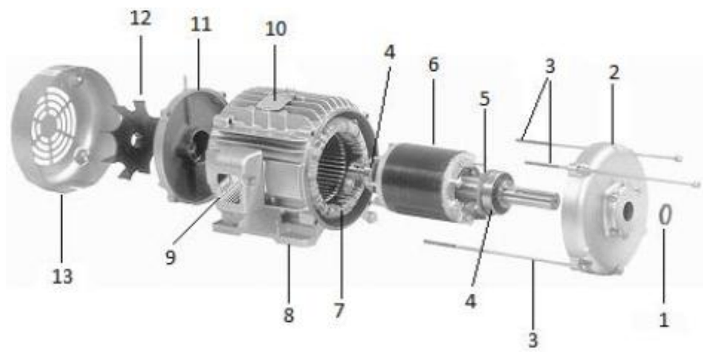
4.1 Introduction:

This chapter is focuse don the notion of a robust state feedback controller and a controller based observer. The mean value theorem and sector non-linearity approaches were implemented for a class of the Lipchitz model of Induction asynchronous machine. IM's machines are widely utilized in industrial motion systems, for their reliability, simple construction and jagged design, low operating costs, direct connection to the power supply, long lifespan and premium energy efficiency[59, 60].Based on these mathematical approaches, the proposed design allows expressing the non-linear error dynamics for the state control and observer as a convex combination of known matrices having time varying coefficients. This is similar to a linear parameter varying (LPV) systems after the representation of non-linear nature of the IM machine in the Lipchitz form. Through the Lyapunov theory, one can obtain and express the stability conditions in a term of linear matrix inequalities (LMI's). The observer and the robust controller gains are separately determined based on the separation principles and have been found by the exploitation of YALMIP software computer. Furthermore, these gains have completely independent from the IM machine states. As a proof of the efficacy of the proposed approach, one applies an illustrative simulation to the sensorless Field Oriented Control (FOC) of the IM drive by utilizing the MATLAB/SIMULINK environment. Simulation and practical results with discussions will be ended by some orientations.

4.2 IM machine modeling:

4.2.1 Three phase IM presentation:

The IM's are constructed from the stator which is connected to the power source and the rotor that spins inside the stator within a precisely engineered air gap. Currents are induced into the rotor via the air gap from the stator side. The stator and the rotor are made of highly magnetizable core sheet providing low eddy current and hysteresis losses[61]. Figure 4.1 shows an exploded view of a typical IM.



Item	Description	item	description	item	description
1	Shaft sealing ring	5	Spring washer	10	Rating plate
2	End shield	6	Rotor, complete	11	End Child
3	Assembly screws	7	Stator, complete	12	Cooling fan
4	Rolling-contact bearing	8	Housing foot	13	Cooling fan cover
		9	Terminal box, complete		

Figure 4.1 An enlarged view of typical IM[60]

- **The stator:**

The stator core is usually made of a doughnut-shaped stack of thin steel laminations with insulated slots. Slots are opening to the inside diameter holding the stator coils (windings) and held together by suitable means. Each core lamination is separated from the other. The teeth are separating the slots and carry the magnetic flux from the stator windings to the rotor through the air gap[60], figure 4.2(a) shows the stator core slots.

Stator windings are made from insulated copper wires embedded in the slots. A number of the identical array of uniform coils are twisted around each stator tooth. Coils are connected together to form the three-phase windings, circulated around the stator, and symmetrically located with respect to one another[60].

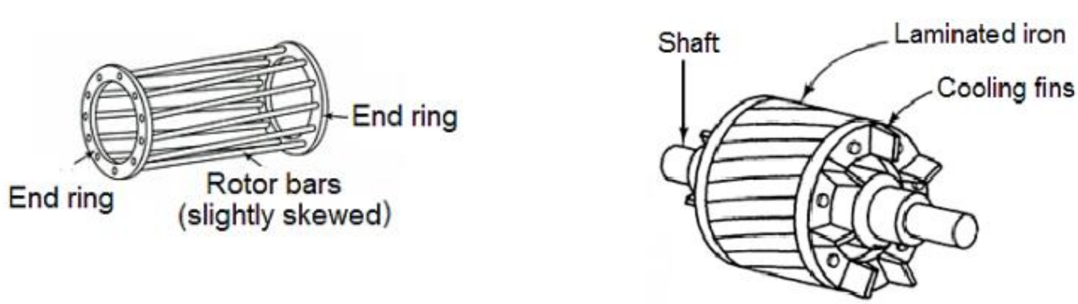
Currents in the stator windings are supposed of equal amplitude but differ in phase by one-third of a cycle ($^{2\pi}/_{3}$) forming a balanced three-phase set. As current flows through the coil on the first tooth, it creates a magnetic field of polarity that opposes the polarity of the opposite tooth, as shown in figure 4.2(b) [62].

a) Stator core slots b) Windings distributions in stator slots

Figure 4.2 Stator slots and windings[63]

- **The rotor:**

The rotor is constructed of the shaft and cage conductors, as shown in Figure 4.3. The rotor shaft is made up of a cylindrical cast iron core. The squirrel cage rotor windings consist of a number of heavy, straight and embedded copper or cast aluminum bars, regularly circulated about the periphery, and connected at both ends by end rings. The slots accommodate the rotor conductors and are skewed to minimize torque pulsations. Blades are attached to the end rings to function as a cooling fan[62].



a) Cage construction b) assembled

Figure 4.3 Squirrel cage rotor[64]

4.2.2 The equivalent circuit of the IM drive:

Due to the similarity, in the steady-state case, the three-phase IM is generally represented in the same way as a three-phase transformer. The stator windings represent the primary windings and the rotor windings represent the secondary windings. The stator and rotor iron transfer the flux between them acting as a core inthe transformer [63]. Figure 4.4 presents the one phase equivalent circuit of the three-phase IM.

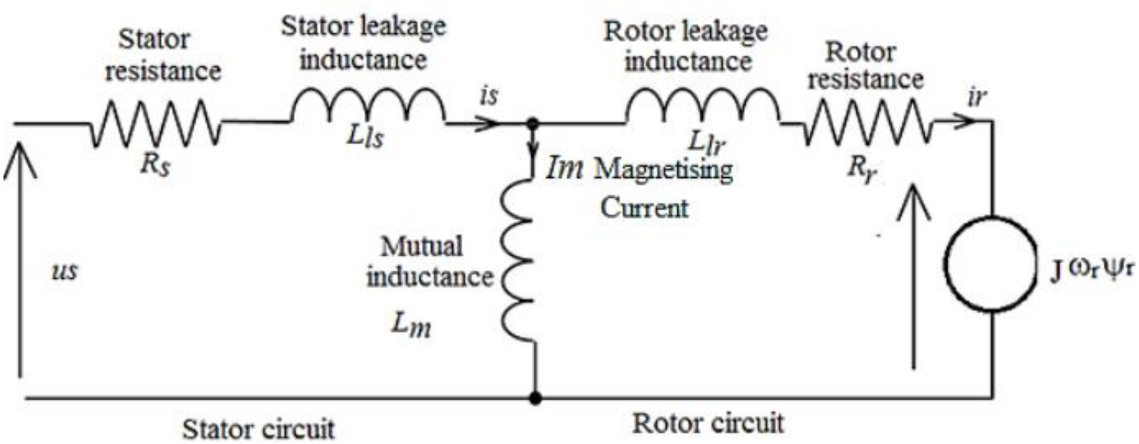


Figure 4.4 Per-phase IM equivalent circuit [60]

4.2.3 Study of the electromechanical equations:

4.2.3.1 Electrical equations:

The electrical equations of the IM can be divided into two terms linked with stator and rotor circuits, the equations (4.1) present the stator and the rotor electrical equations:

$$\begin{cases} \left.[V_s] = [R_s] \times [I_s] + \dfrac{d[\emptyset_s]}{dt}\right\}_{stator} \\ \left.[V_r] = 0 = [R_r] \times [I_r] + \dfrac{d[\emptyset_r]}{dt}\right\}_{rotor} \end{cases} \tag{4.1}$$

Where

$$[V_{s,r}] = \begin{bmatrix} V_{s,rA} \\ V_{s,rB} \\ V_{s,rC} \end{bmatrix}, [I_{s,r}] = \begin{bmatrix} I_{s,rA} \\ I_{s,rB} \\ I_{s,rC} \end{bmatrix}, [\emptyset_{s,r}] = \begin{bmatrix} \emptyset_{s,rA} \\ \emptyset_{s,rB} \\ \emptyset_{s,rC} \end{bmatrix}, [R_{s,r}] = \begin{bmatrix} R_{s,r} & 0 & 0 \\ 0 & R_{s,r} & 0 \\ 0 & 0 & R_{s,r} \end{bmatrix}$$

4.2.3.2 Magnetic equations:

The magnetic equations of the IM drive are related to the stator and the rotor parts, and can be presented as the following matrix form[65]:

$$\begin{cases} [\emptyset_s] = [L_{ss}] \times [I_s] + M_{sr}[R(\theta_r)] \times [I_r]\}_{stator} \\ [\emptyset_r] = [L_{rr}] \times [I_r] + M_{sr}[R(\theta_r)] \times [I_s]\}_{rotor} \end{cases} \tag{4.2}$$

With:

$$[L_{ss}] = \begin{bmatrix} L_s & M_s & M_s \\ M_s & L_s & M_s \\ M_s & M_s & L_s \end{bmatrix}, [L_{rr}] = \begin{bmatrix} L_r & M_r & M_r \\ M_r & L_r & M_r \\ M_r & M_r & L_r \end{bmatrix},$$

And

$$[R(\theta_r)] = \begin{bmatrix} \cos(\theta_r) & \cos\left(\theta_r + {}^{2\pi}/_{3}\right) & \cos\left(\theta_r + {}^{4\pi}/_{3}\right) \\ \cos\left(\theta_r + {}^{4\pi}/_{3}\right) & \cos(\theta_r) & \cos\left(\theta_r + {}^{2\pi}/_{3}\right) \\ \cos\left(\theta_r + {}^{2\pi}/_{3}\right) & \cos\left(\theta_r + {}^{4\pi}/_{3}\right) & \cos(\theta_r) \end{bmatrix}$$

Where:

L_s, L_r: are the stator and rotor proper inductance of one phase respectively.

M_s, M_r: are the stator and the rotor mutual inductance between two phases respectively.

M_{sr}: represent the maximum mutual inductance between a one stator phase and the rotor phase.

4.2.3.3 Mechanical equation of the IM drive:

The next equation illustrates the mechanical operation of the IM which is depended on the rotor speed an torque as indicated as follows:

$$J\frac{d\omega_r}{dt} = T_{em} - b\omega_r - T_L \tag{4.3}$$

Where:

ω_r: is the rotor speed, where its unity is $\left[{}^{rad}/_{sec}\right]$.

b: is the friction coefficient.

T_{em}, T_L: is the electromagnetic torque (depend on the stator and rotor currents) and load torque respectively.

The model of the IM obtained has the disadvantage of being relatively complex insofar as the matrices contain variable elements as a function of the rotation angle θ_r.

To remedy the previously disadvantage, the IM model in two axes rotating frame make sure to do so based on the application of a mathematical tool known as the Park Transformation.

4.2.4 Vector model in two axes rotating frame:

4.2.4.1 The Park transformation:

The park transformation allows to transfer a three-phase system (a,b,c) to another three-phase system (d,q,o), where its third component is null if we consider the (a,b,c) system is balanced, the figure 4.5 shows the passage using the park transformation from (a,b,c) to (d,q,o) axes:

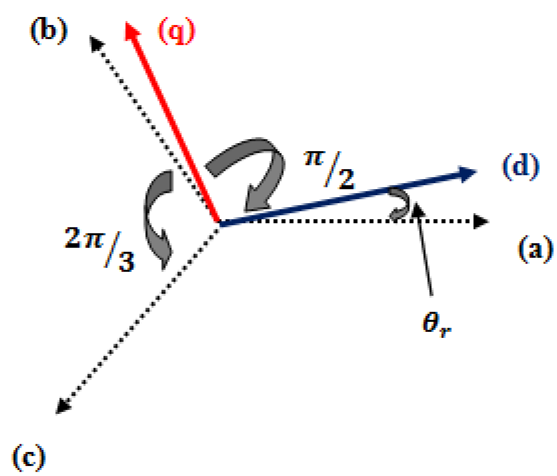


Figure 4.5 Park transformation axes

4.2.4.2 The Park transformation matrices:

The passage and the inverse passage from a three axes system (a,b,c) to two axes system in the rotating frame (d,q,o) need requiring to use the next matrices $P(\theta_r)$ and $P^{-1}(\theta_r)$respectively.

$$[P(\theta_r)] = \frac{\sqrt{2}}{\sqrt{3}}\begin{bmatrix} \cos(\theta_r) & \cos\left(\theta_r - {}^{2\pi}/_{3}\right) & \cos\left(\theta_r - {}^{4\pi}/_{3}\right) \\ -\sin(\theta_r) & -\sin\left(\theta_r - {}^{2\pi}/_{3}\right) & -\sin\left(\theta_r - {}^{4\pi}/_{3}\right) \\ {}^{1}/_{\sqrt{2}} & {}^{1}/_{\sqrt{2}} & {}^{1}/_{\sqrt{2}} \end{bmatrix} \tag{4.4}$$

$$[P^{-1}(\theta_r)] = \frac{\sqrt{2}}{\sqrt{3}}\begin{bmatrix} \cos(\theta_r) & -\sin(\theta_r) & {}^{1}/_{\sqrt{2}} \\ \cos\left(\theta_r - {}^{2\pi}/_{3}\right) & -\sin\left(\theta_r - {}^{2\pi}/_{3}\right) & {}^{1}/_{\sqrt{2}} \\ \cos\left(\theta_r - {}^{4\pi}/_{3}\right) & -\sin\left(\theta_r - {}^{4\pi}/_{3}\right) & {}^{1}/_{\sqrt{2}} \end{bmatrix} \tag{4.5}$$

The application of the park transformation to (4.1), (4.2) and (4.3) allows to get the followings equations [65]:

$$\begin{cases} \left.\begin{aligned} U_{sd} &= R_s i_{sd} + \frac{d\emptyset_{sd}}{dt} \\ U_{sq} &= R_s i_{sq} + \frac{d\emptyset_{sq}}{dt} \end{aligned}\right\}_{\boldsymbol{stator}} \\ \left.\begin{aligned} 0 &= R_r i_{rd} + \frac{d\emptyset_{rd}}{dt} + \omega_r \emptyset_{rq} \\ 0 &= R_r i_{rq} + \frac{d\emptyset_{rq}}{dt} + \omega_r \emptyset_{rd} \end{aligned}\right\}_{\boldsymbol{rotor}} \end{cases} \tag{4.6}$$

And

$$\begin{cases} \left.\begin{aligned} \emptyset_{sd} &= L_s i_{sd} + M i_{rd} \\ \emptyset_{sq} &= L_s i_{sq} + M i_{rq} \end{aligned}\right\}_{\boldsymbol{stator}} \\ \left.\begin{aligned} \emptyset_{rd} &= L_r i_{rd} + M i_{sd} \\ \emptyset_{rq} &= L_r i_{rq} + M i_{sq} \end{aligned}\right\}_{\boldsymbol{rotor}} \end{cases} \tag{4.7}$$

And the mechanic equation of the IM becomes as:

$$J\frac{d\omega_r}{dt} = T_{em} - b\omega_r - T_L \tag{4.8}$$

Whereas:

$$T_{em} = n_p\frac{M}{L_r}\left(\emptyset_{rd}i_{sq} - \emptyset_{rq}i_{sd}\right)$$

4.2.4.3 State space model of the IM machine:

From equations (4.6) and (4.7) it's possible to rewrite the IM model in the state space form where the stator currents (i_{sd} and i_{sq}), the rotor fluxes ($\emptyset_{rd}$ and $\emptyset_{rq}$) and the rotor speed (ω_r)are considered as the state variables . with $x(t)$ is the state vector, $u(t)$ is the input vector and $y(t)$ is the output vector, the state model of the IM can be represented as:

$$\begin{cases}\dot{x}(t) = f(x(t)) + Bu(t) + v(t) \\ \quad\quad y(t) = Cx(t)\end{cases} \tag{4.9}$$

Where:

$$f(x(t)) = \begin{bmatrix} -\gamma i_{sd} + \omega_s i_{sq} + \frac{k_s}{\tau_r}\emptyset_{rd} + k_s n_p \omega_r \emptyset_{rq} \\ -\omega_s i_{sd} - \gamma i_{sq} - k_s n_p \omega_r \emptyset_{rd} + \frac{k_s}{\tau_r}\emptyset_{rq} \\ \frac{M}{\tau_r} i_{sd} - \frac{1}{\tau_r}\emptyset_{rd} + \left(\omega_s - n_p\omega_r\right)\emptyset_{rq} \\ \frac{M}{\tau_r} i_{sq} - \left(\omega_s - n_p\omega_r\right)\emptyset_{rd} - \frac{1}{\tau_r}\emptyset_{rq} \\ \frac{n_p M}{J L_r}\left(\emptyset_{rd}i_{sq} - \emptyset_{rq}i_{sd}\right) - \frac{b}{J}\omega_r \end{bmatrix} \tag{4.10}$$

With

$$\gamma = \left(\frac{1}{\sigma\tau_s} + \frac{1-\sigma}{\sigma\tau_r}\right), \quad k_s = \frac{M}{\sigma L_s L_r}, \qquad \tau_r = \frac{L_r}{R_r}, \quad \tau_s = \frac{L_s}{R_s}, \quad \sigma = 1 - \frac{M^2}{L_s L_r},$$

And

$x(t) = [i_{sd} \quad i_{sq} \quad \emptyset_{rd}\emptyset_{rq} \quad \omega_r]^T$

$$B = \begin{bmatrix} \frac{1}{\sigma Ls} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{\sigma Ls} & 0 & 0 & 0 \end{bmatrix}^T$$

$$u(t) = \begin{bmatrix} U_{sd} \\ U_{sq} \end{bmatrix}$$

$$v(t) = \begin{bmatrix} 0 & 0 & 0 & 0 & -\frac{1}{J}T_L \end{bmatrix}^T$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

4.3 Control and states estimation of the IM under FOC based on the MVT and SNL theory:

4.3.1 References generator and Open Loop FOC controls:

The desired states of the IM are obtained taking in consideration the FOC conditions, where the importance of the FOC theory is to make the coupled and the nonlinear system of IM behave as a direct current (DC) machine with a constant flux; this is through the proportionality between the torque and the q-axis stator current (i_{sq}).

4.3.1.1 References generator:

In this part, the reference states are obtained by the exploitation of the FOC strategy by considering the rotor flux is aligned to the d-axis as the next equation indicates:

$$\begin{cases} \emptyset_{rd} = \emptyset_r \\ \emptyset_{rq} = 0 \end{cases} \tag{4.11}$$

The substitution of the states of the system (4.9) by the desired states: $[i_{sdr} \quad i_{sqr} \quad \emptyset_r 0 \quad \omega_{rr}]^T$in it make sure to have references under the FOC conditions[1], we obtain:

$$\begin{bmatrix} \dot{i}_{sdr} \\ \dot{i}_{sqr} \\ \dot{\emptyset}_r \\ 0 \\ \dot{\omega}_{rr} \end{bmatrix} = \begin{bmatrix} -\gamma i_{sdr} + \omega_{sr} i_{sqr} + \frac{k_s}{\tau_r}\emptyset_r + \frac{1}{\sigma Ls} U_{sdr} \\ -\omega_{sr} i_{sdr} - \gamma i_{sqr} - k_s n_p\, \omega_{rr} \emptyset_r + \frac{1}{\sigma Ls} U_{sqr} \\ \frac{M}{\tau_r} i_{sdr} - \frac{1}{\tau_r}\emptyset_r \\ \frac{M}{\tau_r} i_{sqr} - \left(\omega_{sr} - n_p\, \omega_{rr}\right)\emptyset_r \\ \frac{n_p M}{J\, L_r}\left(\emptyset_r i_{sqr}\right) - \frac{b}{J}\omega_{rr} - \frac{1}{J} T_L \end{bmatrix} \tag{4.12}$$

Where:

$$\omega_{sr} = \frac{M}{\tau_r\, \emptyset_r} i_{sqr} + n_p\, \omega_{rr}$$

The reference of the q-axis rotor flux is chosen 0, while the desired of d-axis rotor flux is taken the same as the rated rotor flux, whereas the reference of the rotor speed is chosen as we like. Through the third and the last equations of the system (4.12), the reference states of the d and q-axis stator currents (i_{sdr}, i_{sqr}) are :

$$\begin{cases} i_{sdr} = \frac{\tau_r}{M}\left(\dot{\emptyset}_r + \frac{1}{\tau_r}\emptyset_r\right) \\ i_{sqr} = \frac{L_r}{\emptyset_r n_p\, M}\left(J\dot{\omega}_{rr} + b\omega_{rr} + T_L\right) \end{cases} \tag{4.13}$$

4.3.1.2 Open Loop FOC controls:

From the first two equations of (4.12) and using (4.13), the formula of the open loop FOC controls of the IM drive is obtained as follows[66]:

$$\begin{cases} U_{sdr} = \sigma Ls\left(\dot{i}_{sdr} + \gamma i_{sdr} - \omega_{sr} i_{sqr} - \frac{k_s}{\tau_r}\emptyset_r\right) \\ U_{sqr} = \sigma Ls\left(\dot{i}_{sqr} + \gamma i_{sqr} + \omega_{sr} i_{sdr} + k_s n_p\, \omega_{rr}\emptyset_r\right) \end{cases} \tag{4.14}$$

Although the simplicity of the open loop FOC that clear from the (4.14), it is possible to base on it in industrial applications. To prove the effectiveness of this approach, simulationresultsare mentioned in the next subsection.

4.3.2 Robust $P - H_\infty$ controller based on the MVT approach:

The important idea of this kind of control based on the MVT is to get the controller parameters that make the states of the IM track their references with a minimum effect of the disturbance on the control error.

The model of the IM that is used in this part is similar to the system mentioned previously in (4.9), with $v(t)$is substituted by $Dw(t)$,

Where $D = \begin{bmatrix} 0 & 0 & 0 & 0 & -\frac{1}{J} \end{bmatrix}^T$ and $w(t) = T_L$

Passing by the T-S representation, we can represent the IM nonlinear system (4.9) as the Lipchitz form as [25]:

$$\begin{cases} \dot{x}(t) = A_0 x(t) + Bu(t) + \emptyset(x) + Dw(t) \\ y = C_0 x(t) \end{cases} \tag{4.15}$$

Where

$$\emptyset(x) = \sum_{i=1}^{r} h_i\big(\xi(t)\big)\big(\bar{A}_i x(t)\big)$$

And

$A_0 = \frac{1}{r}\sum_{i=1}^{r} A_i$ such that $\bar{A}_i = A_i - A_0$

Where A_i, B_i and $h_i$are obtained from the T-S model [2, 66].

The state vector of the control error is written as:

$$e(t) = x(t) - x_c(t) \tag{4.16}$$

Where x_c is the reference state and it has supposed as a stepwise signal, so the dynamics of the state error as the following form:

$$\dot{e}(t) = \dot{x}(t) - \dot{x}_c(t) = \dot{x}(t) = A_0x(t) + Bu(t) + \emptyset(x) + Dw(t) \tag{4.17}$$

4.3.2.1 State feedback control:

The control law of the classical proportional controller has the following form:

$$u(t) = -K_0e(t) \tag{4.18}$$

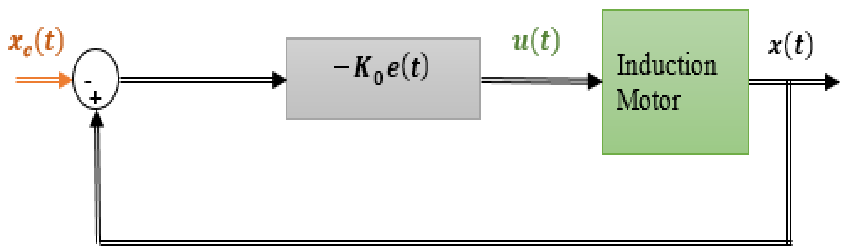


Figure 4.6 The state feedback control design

Combining (4.17) with (4.18), the dynamics of the control error becomes as:

$$\dot{e}(t) = (A_0 - BK_0)e(t) + A_0x_c(t) + \emptyset(x) + Dw(t) \tag{4.19}$$

By using the MVT approach [25, 51, 67] (Section 3.2), we have:

$$\emptyset(x) = \emptyset_c(x_c) + \frac{\partial\emptyset}{\partial x}(\varepsilon)(x - x_c) \tag{4.20}$$

Where $\varepsilon(t) \in [x(t), x_c(t)]$

By substituting (4.20) in (4.19), the dynamics of the control error can be expressed as:

$$\dot{e}(t) = (A_0 - BK_0 + \frac{\partial\emptyset}{\partial x}(\varepsilon))e(t) + A_0x_c(t) + \emptyset_c(x_c) + Dw(t) \tag{4.21}$$

Considering that, the reference signal $x_c$is a stepwise signal, the component$\emptyset_c(x_c) = 0$

Utilizing the sector nonlinearity approach[23, 51, 68], the dynamics of the state feedback control error is given:

$$\dot{e}(t) = \sum_{i=1}^{r} h_i(\xi)\,(A_0 - BK_0 + \mathcal{A}_i)e(t) + Dw(t) + A_0x_c(t) \tag{4.22}$$

We define that:

$S_i = \breve{A}_i - BK_0$

Where $\breve{A}_i = A_0 + \mathcal{A}_i$ $\quad D_w = [A_0 \quad D]$ $\quad \bar{w}(t) = \begin{bmatrix} x_c(t) \\ w(t) \end{bmatrix}$

Such as $\mathcal{A}_i$ represent $\emptyset(x) - \emptyset_c(x_c)$after the introducing the MVT and the sector nonlinearity approaches.

The dynamics of the state feedback error (4.22) is written as:

$$\dot{e}(t) = \sum_{i=1}^{r} h_i(\xi)\left(S_i e(t) + D_w \bar{w}(t)\right) \tag{4.23}$$

4.3.2.2 Synthesis for H_∞performance:

The existence of the disturbances $\bar{w}(t)$ will affect to the control performances. So as to minimize the effect of the disturbance $\bar{w}(t)$, the H_∞ performances has been taken into account [69].

$$\int_0^\infty e^T(t)\,e(t)\,dt \le \gamma^2 \int_0^\infty \bar{w}^T(t)\,\bar{w}(t)\,dt \tag{4.24}$$

Consider the quadratic Lyapunov function as:

$$V\big(e(t)\big) = e^T(t)Pe(t) \tag{4.25}$$

Where $P = P^T > 0$

So as to develop the asymptotic stability of (4.25) and to attain the H_∞ performance of the state control error, we have:

$$\dot{V}\big(e(t)\big) + e^T(t)e(t) - \gamma^2 \bar{w}^T(t)\bar{w}(t) < 0 \tag{4.26}$$

The previous equation becomes an LMI's form as next:

$$\dot{e}^T(t)Pe(t) + e^T(t)P\dot{e}(t) + e^T(t)e(t) - \gamma^2\bar{w}^T(t)\bar{w}(t) < 0 \tag{4.27}$$

This is equivalent to:

$$\sum_{i=1}^{r} h_i(\xi)\, e^T(t)\left[S_i{}^T P + PS_i + I\right]e(t) + \bar{w}^T(t)\left[D_w{}^T P\right]e(t) + e^T(t)[PD_w]\bar{w}(t) - \gamma^2\bar{w}^T(t)\bar{w}(t) < 0 \tag{4.28}$$

Then, it is possible to present the last equation as:

$$\begin{bmatrix} e^T(t) & \bar{w}^T(t) \end{bmatrix} \begin{bmatrix} \sum_{i=1}^{r} h_i(\xi)\left[S_i{}^T P + P\bar{S}_i + I\right] & PD_w \\ D_w{}^T P & -\gamma^2 I \end{bmatrix} \begin{bmatrix} e(t) \\ \bar{w}(t) \end{bmatrix} < 0 \tag{4.29}$$

The stability is considered by the following part:

$$\begin{bmatrix} \sum_{i=1}^{r} h_i(\xi)\left[S_i{}^T P + PS_i\right] + I & PD_w \\ D_w{}^T P & -\gamma^2 I \end{bmatrix} < 0 \tag{4.30}$$

After, we can present (4.30) as:

$$\begin{bmatrix} \sum_{i=1}^{r} h_i(\xi)\left[S_i{}^T P + PS_i\right] & PD_w \\ D_w{}^T P & -\gamma^2 I \end{bmatrix} \begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix} < 0 \tag{4.31}$$

This main:

$$\begin{bmatrix} \sum_{i=1}^{r} h_i(\xi)\left[S_i{}^T P + PS_i\right] & PD_w \\ D_w{}^T P & -\gamma^2 I \end{bmatrix} \begin{bmatrix} I \\ 0 \end{bmatrix} \begin{bmatrix} I & 0 \end{bmatrix} < 0 \tag{4.32}$$

Depending on the Schur's complement, (4.32) becomes as follow:

$$\begin{bmatrix} \sum_{i=1}^{r} h_i(\xi)\left[{S_i}^T P + P S_i\right] & P D_w & I \\ {D_w}^T P & -\gamma^2 I & 0 \\ I & 0 & -I \end{bmatrix} < 0 \tag{4.33}$$

The stability dependson:

$$\begin{bmatrix} {S_i}^T P + P S_i & P D_w & I \\ {D_w}^T P & -\gamma^2 I & 0 \\ I & 0 & -I \end{bmatrix} < 0 \tag{4.34}$$

By applying the congruence transformation, multiplying to the right and to the left by the $diag\ [P^{-1}, \quad I, \quad I]$we get:

$$\begin{bmatrix} P^{-1} & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix}\begin{bmatrix} {S_i}^T P + P S_i & P D_w & I \\ {D_w}^T P & -\gamma^2 I & 0 \\ I & 0 & -I \end{bmatrix}\begin{bmatrix} P^{-1} & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} < 0 \tag{4.35}$$

The previous equation can be developed to:

$$\begin{bmatrix} P^{-1}\left[{S_i}^T P + P S_i\right]P^{-1} & P^{-1} P D_w & P^{-1} \\ {D_w}^T P P^{-1} & -\gamma^2 I & 0 \\ P^{-1} & 0 & -I \end{bmatrix} < 0 \tag{4.36}$$

If we consider that $X^{-1} = P$ and $Y = K_0 P^{-1} = K_0 X$, we obtain the final LMI's to solving that are written in the following form:

$$\begin{bmatrix} \breve{A}_i X + X {\breve{A}_i}^T - BY - Y^T B^T + \alpha X & D_w & X \\ {D_w}^T & -\gamma^2 I & 0 \\ X & 0 & -I \end{bmatrix} < 0 \tag{4.37}$$

The exploiting of the YALMIP software computer allows finding the proportional controller gain that is gotten as:

$$K_0 = Y X^{-1} \tag{4.38}$$

Where its value is:

$$K_0 = \begin{bmatrix} -751.115 & -0.0213 & 328.710 & -0.1189 & 3.1556 \\ 1.7226 & -325.371 & 0.9184 & 101.7710 & -422.997 \end{bmatrix}$$

4.3.3 PI-Controller based observer applied to IM under FOC using the MVT and SNL theory:

In this part we will present an PI controller based observer using the MVT theory applied to the IM drive where the goals are to get the controller and the observer gains with:

- A systematic methodology
- The stability of all the system is proven
- The parameters don't depend on the IM states

4.3.3.1The control law:

To eliminate the effects of disturbance and the parametric uncertainty in the steady state, it is better to add an integral action, so the control is rewritten as:

$$u(t) = -[K_1 \quad K_2]\begin{bmatrix} e(t) \\ e_I(t) \end{bmatrix} = K_I\bar{e}(t) \tag{4.39}$$

Such as the error state bound the integral action is:

$$e_I(t) = \int (x(t) - x_c(t))\mathrm{dt} \tag{4.40}$$

and $e(t)$ is as mentioned previously in (4.27).

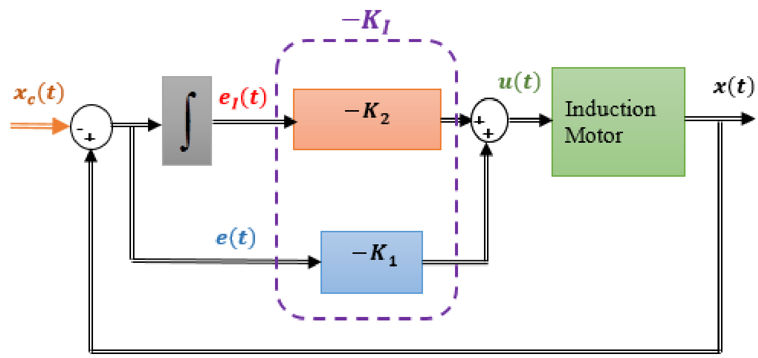


Figure 4.7 The PI control design

The combining of the MVT theory with the sector nonlinearity approach allows to get the following dynamics of the augmented state control error:

$$\dot{\bar{e}}(t) = \sum_{i=1}^{r} h_i(\xi)\left(\bar{S}_i \bar{e}(t)\right) + \bar{D}\bar{w}(t) \tag{4.41}$$

Where

$\bar{S}_i = \bar{A}_i - \bar{B}K_I$

And

$$\bar{A}_i = \begin{bmatrix} A_0 + {}^r/_2 \times \mathcal{A}_i & 0 \\ I & 0 \end{bmatrix} \qquad \bar{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}$$

$$\bar{D} = \begin{bmatrix} A_0 & D \\ 0 & 0 \end{bmatrix} \qquad \bar{w}(t) = \begin{bmatrix} x_c(t) \\ w(t) \end{bmatrix}$$

4.3.3.2 The observer design:

We define the state estimation error as:

$$e_0(t) = x(t) - \hat{x}(t) \tag{4.42}$$

The dynamics of the estimation error can be written as(see chapter three):

$$\dot{e_0}(t) = \sum_{j=1}^{r} h_j(\delta)\left(AA_0 - L_0 C_0 + {}^{r}/_{2} \times \mathcal{A}\mathcal{A}_j\right) e_0(t) \tag{4.43}$$

Where $\delta \ \epsilon \ [x, \hat{x}]$

And $C_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

The global system (controller based observer) can be written as it is indicated in the following equation:

$$\begin{bmatrix} \dot{\bar{e}}(t) \\ \dot{e}_0(t) \end{bmatrix} = \sum_{i=1}^{r}\sum_{j=1}^{r} h_i(\xi) h_j(\delta) \begin{bmatrix} \bar{A}_i - \bar{B}\bar{K} & 0 \\ 0 & AA_0 - L_0 C_0 + {}^{r}/_{2} \times \mathcal{A}\mathcal{A}_j \end{bmatrix} \begin{bmatrix} \bar{e}(t) \\ e_0(t) \end{bmatrix} + A_0 \begin{bmatrix} x_c(t) \\ 0 \end{bmatrix} + D \begin{bmatrix} w(t) \\ 0 \end{bmatrix} \tag{4.44}$$

One can obtain the design of the PI controller parameters and the observer gain of the equation (4.44) by using the separation principle [70]. Consequently, one can separately

analyzethe stability of the equations by utilizing a quadratic Lyapunov function for control and observer respectively, [71].

Consider the quadratic Lyapunov function for the controller and observer respectively as:

$$V(\bar{e}(t)) = \bar{e}^T(t) P \bar{e}(t) \tag{4.45}$$

$$VV(e_0(t)) = {e_0}^T(t) S e_0(t) \tag{4.46}$$

Then the stability expressed through the following LMI’s that allow getting the observer and the controller gains separately[28].

$$P\bar{A}_i{}^T + \bar{A}_i P - M^T \bar{B}^T - \bar{B} M + \alpha P < 0 \tag{4.47}$$

And

$$AA_0^T S + SAA_0 + {}^r/_2 \times \mathcal{AA}_j^T S + S \times {}^r/_2 \times \mathcal{AA}_j - C_0{}^T N^T - NC_0 + \beta S < 0 \tag{4.48}$$

Where the PI controller parameters and the observer gains are gotten as:

$$\bar{K} = MP^{-1} \tag{4.49}$$

And

$$L_0 = S^{-1} N \tag{4.50}$$

Whereas their values are:

$\bar{K} = [K_1 \quad K_2]$ with:

$$K_1 = \begin{bmatrix} -551.4350 & -0.0093 & 656.80 & -0.0179 & 0.1558 \\ 0.0476 & -545.3837 & 1.0784 & 651.7380 & -215.0177 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} 0.1972 & -0.0013 & -0.281 & 0 & 0 \\ -0.0003 & 0.2110 & -0.0001 & -0.028 & -0.0080 \end{bmatrix}$$

And

$$L_0 = 10^4 \begin{bmatrix} 1.2925 & -0.0543 & 0.0034 \\ 0.0544 & 1.2789 & -0.1554 \\ -0.0003 & 0.0001 & 0.0002 \\ 0.0001 & -0.0002 & 0.0001 \\ -0.0002 & 0.0771 & 0.3464 \end{bmatrix}$$

4.4 Simulation results and discussion:

4.4.1 Robust $P - H_\infty$controller based on the MVT approach:

The design of proposed control law is implemented through an illustrative simulation test under the MATLAB/Simulink environment. The robust control based on MVT is applied to an IM which its parameters are mentioned in Appendix A. The proposed MVT control law has been tested in simulation results as presented in figure 4. 8:

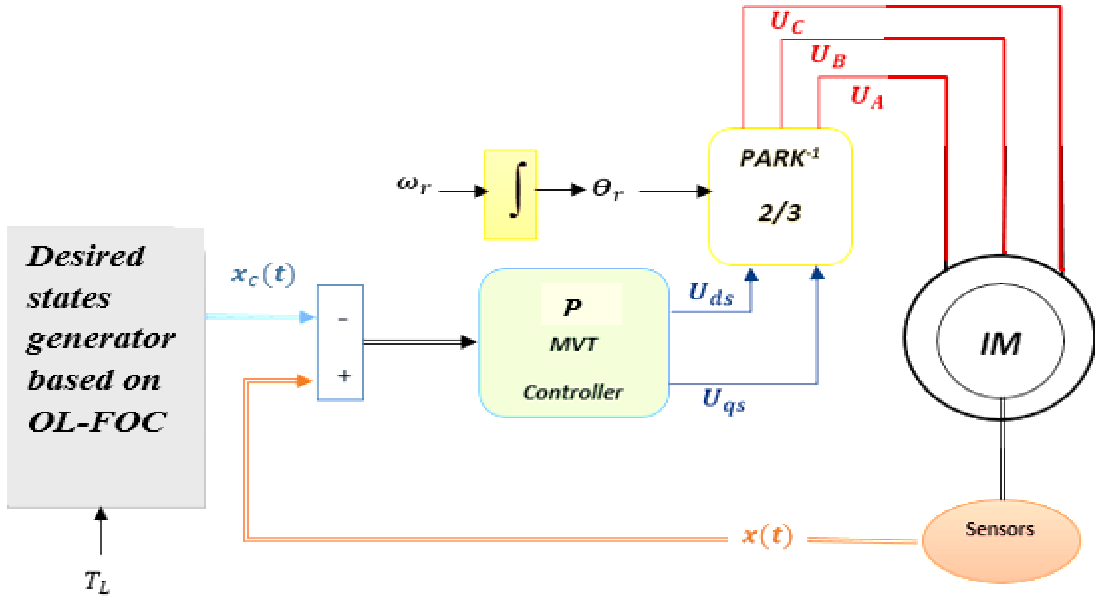


Figure 4.8 Global scheme of the $P - H_\infty$ control law of the IM based on MVT

A rotor speed reference of 180 rad/s is chosen for the high-speed test that started from t = 0s and ends at t = 3sec. While for the medium-speed test, a speed value of 120 rad/sec is applied between the instant t=3sec and t = 6s. In order to obtain the FOC conditions, the q-axis rotor flux reference stays at 0 Wb in all simulation time and the rotor flux reference of the value of 0.851Wb has been oriented along the d-axis. For proving the robustness of the proposed approach, three disturbances are taken into consideration those are the load torque and the variation of the stator and rotor resistances. Initially, the motor is unloaded, after that, a load torque of 4 N.m is applied to the IM from t = 2.5sec and degraded to 2N.m s at t=4secuntil the end of the simulation time. For the parameters variation test, at t= 2sec the R_r is considered to be 60% from the nominal value at t= 1.5sec, while $R_s$decreased to -50% of the nominal value at t= 2.5sec. All stats responses with disturbances tests are presented in figures 4.9and 4.10

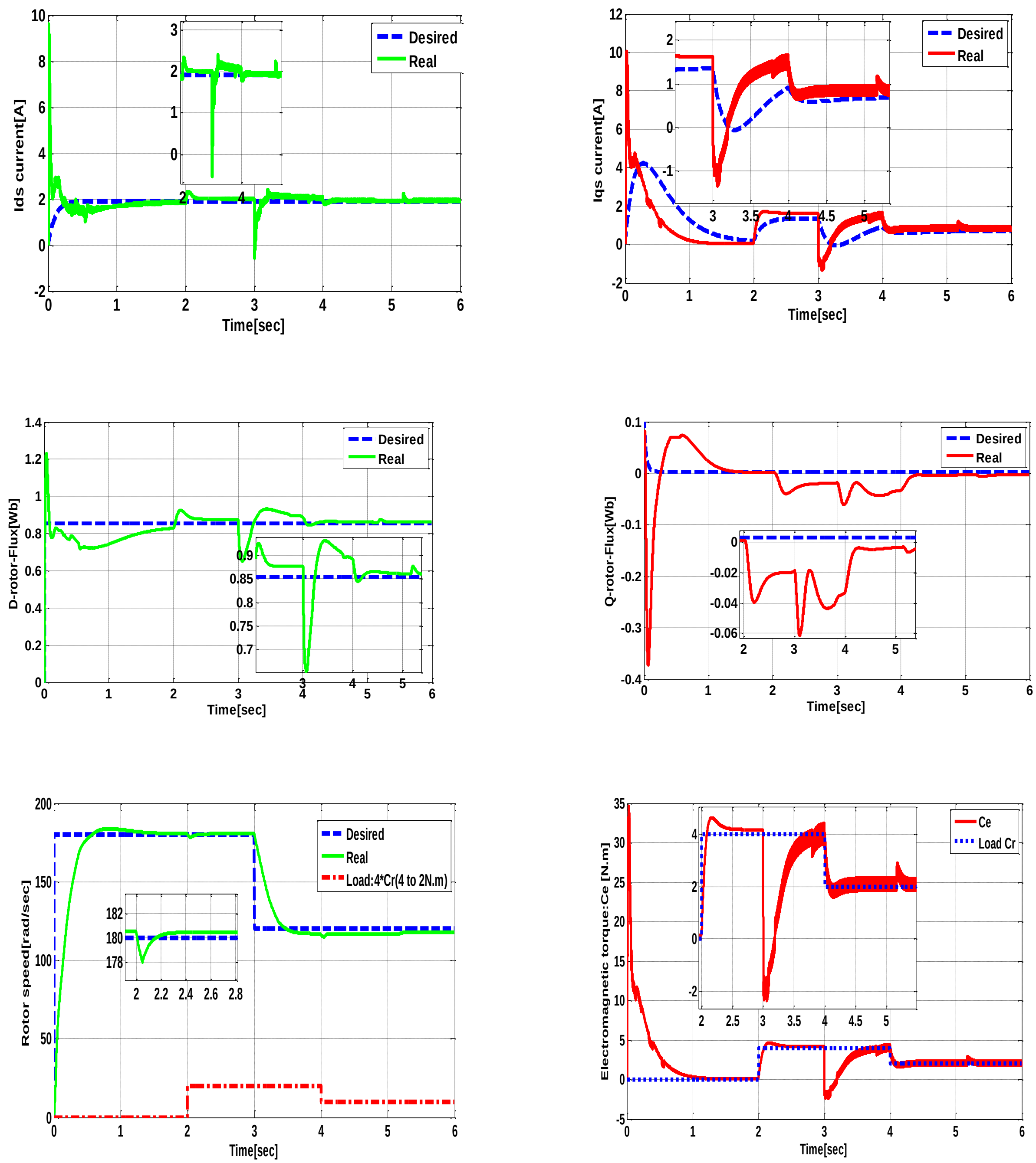


Figure 4. 9 Robust $P-H_{\infty}$ controller states reponses of the IM machine under FOC

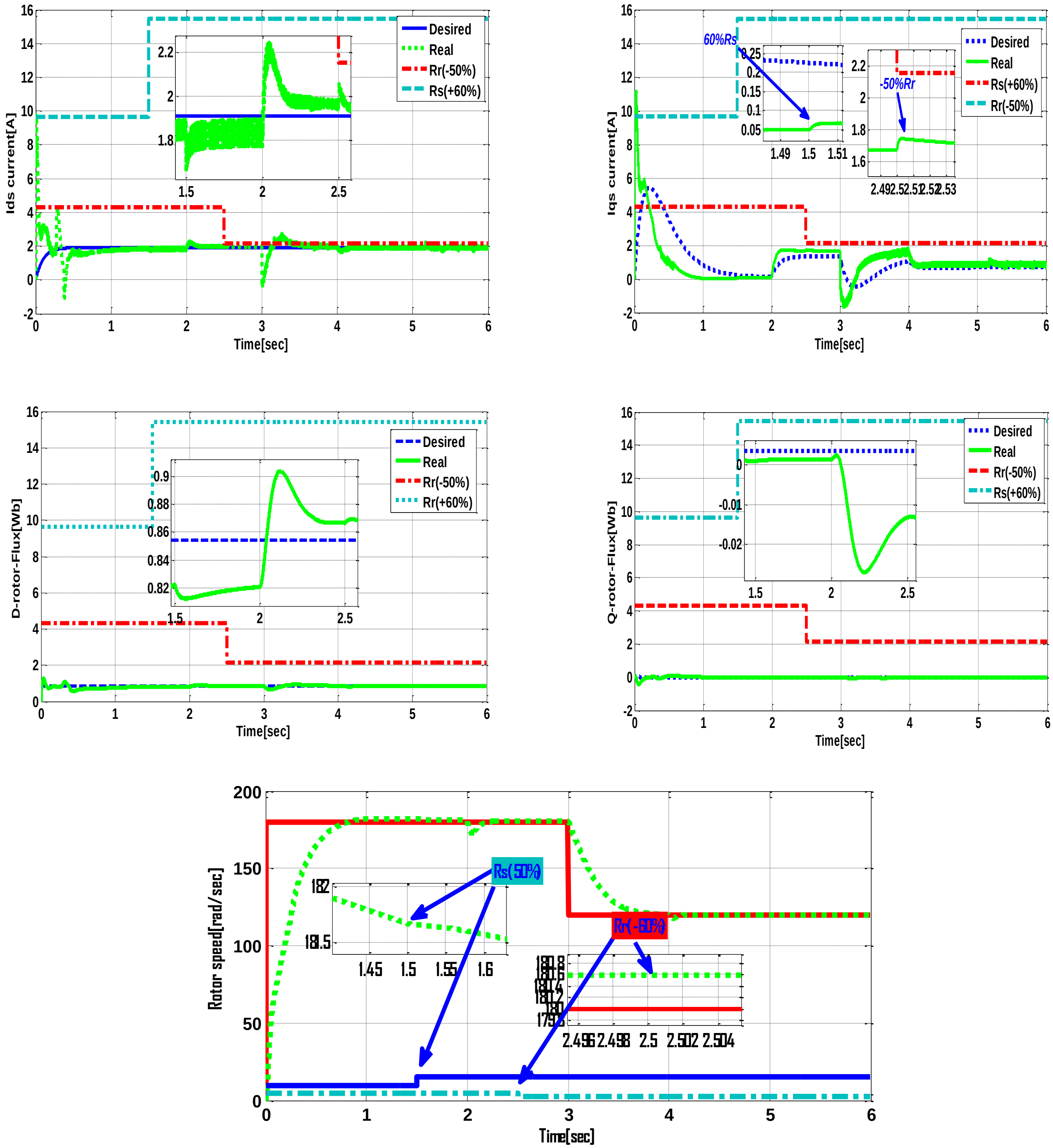


Figure 4.10States responses versus the load torque and parameters variations (Rs and Rr).

The simulation results of the MVT robust control based H_∞ concept mentioned above show the effectiveness of this technic. For all the IM states, it's clear that the real states still close to their desired values with a minimum errors. The rotor speed still close to its desired value with a minimum effect of the load torque and the parameters variations to the tracking error as indicated in the previous figure. However of the high parameters variation of the rotor and stator resistances, the tracking error is approximately not considerable for all the IM states, this due to the independency between the controller gain and the IM states and the also to the missing of the decoupling block which is considered depend to the IM parameters in other methods of control. From the figure , we can note that the impact of the based $\mathrm{P}-\mathrm{H}_\infty$-*MVT* controller when load torque is applied to the IM's machine an important reduction of the rotor speed error which shows the robustness of the proposed controller. We can notice also the d-axis stator flux remain near its value ($0.851Wb$), while the q-flux remains closer to zero Wb (=0Wb) in all conditions wich demonstrates the decoupling and assure the field oriented control conditions. This shows also the efficiency of the proposed controller.

These simulation results prove and affirm the high effectiveness of the suggested robust $\mathrm{P}-\mathrm{H}\infty\mathrm{MVT}$ controller. The rotor speed and the stator currents track the reference signals, which affirm the robustness of the proposed algorithm for load torque and parameters variations.

4.4.2PI controller based observer applied to IM based MVT:

The proposed control based observer design based on MVT is implemented through an illustrative simulation check under the MATLAB/Simulink environment. The PI control based observer based on MVT is applied to an IM under FOC control which its parameters are mentioned in Appendix A. The global scheme of the controller is presented in figure 4.11:

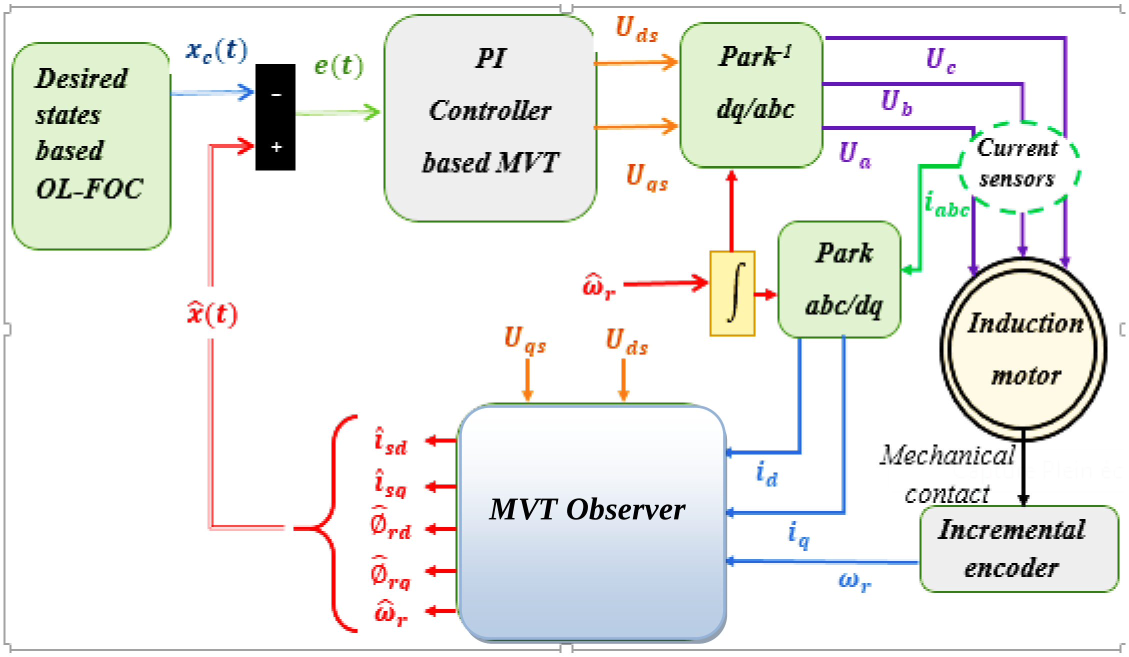


Figure 4. 11 Global scheme of the PI control based observer of the IM based on MVT

The reference of the rotor speed has evenly divided into three thirds of the simulation time(6 sec); the first is chosen 180 rad/sec, after it has decreased to 120 rad/sec. In order to show the robustness of the concept, a nominal load torque of 4 N.m is applied to the IM at t=2 sec as indicated in figure 4.12and the effectiveness of the MVT observer with initial states were taken as: $[1.5 \quad 4 \quad 0.4 \quad -0.5 \quad -50]$. The desired states are presented in the blue lines where the dashed green lines indicate the real states of the IM machine and the estimated states by the red lines.From simulation results, we notice that the states present a chattering phenomenon, because of the switching nature of the inverter.

For the parameters variation test, we introduce variations in the resistance R_r to 60% from the nominal value at t= 1.5sec, while R_s decreased to -50% of the nominal value at t= 2.5sec. All stats response and disturbances tests are presented in figures 4.13.

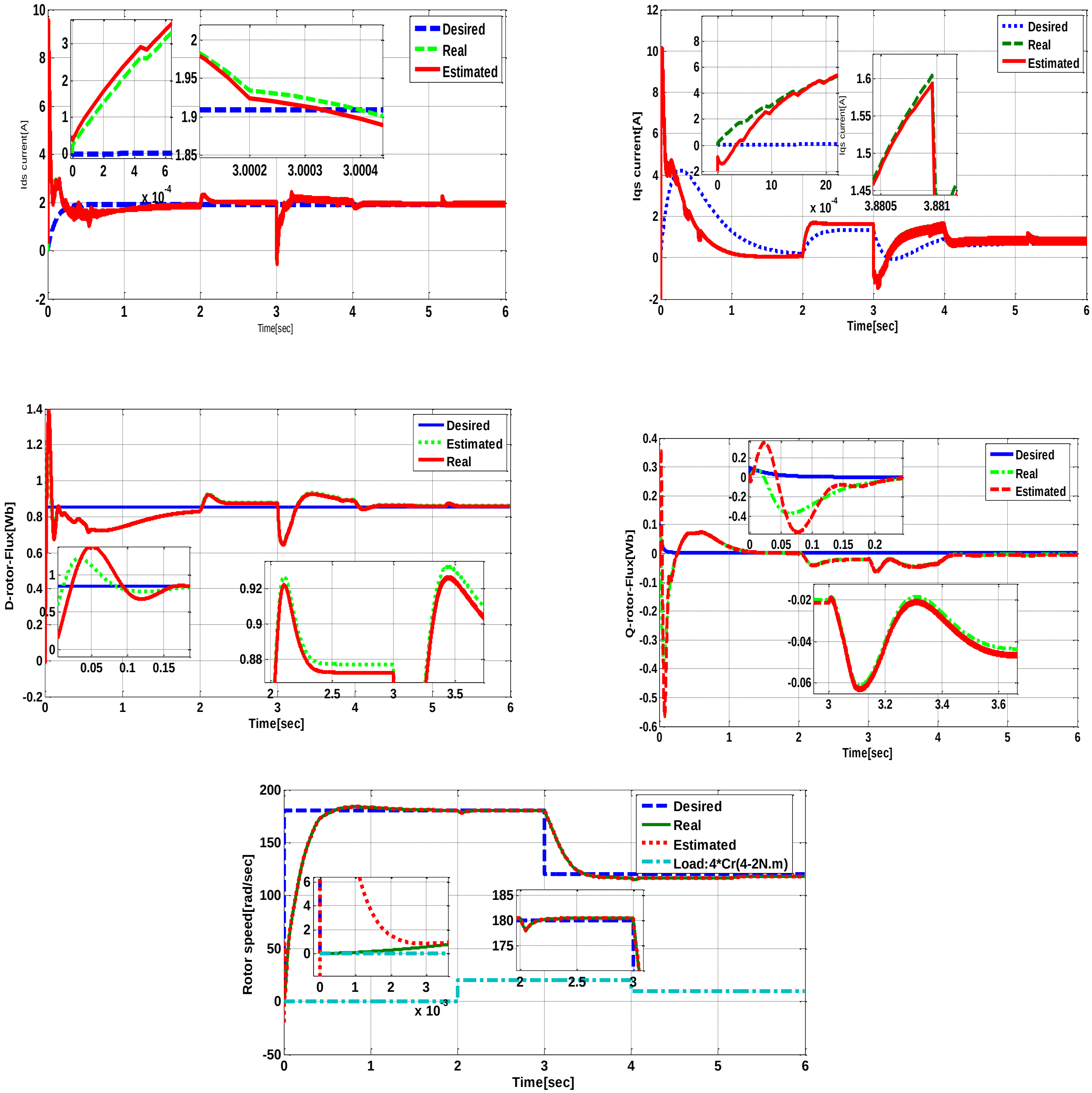


Figure4.12PI-robust controller based robust extended MVT observer applied to the IM machine

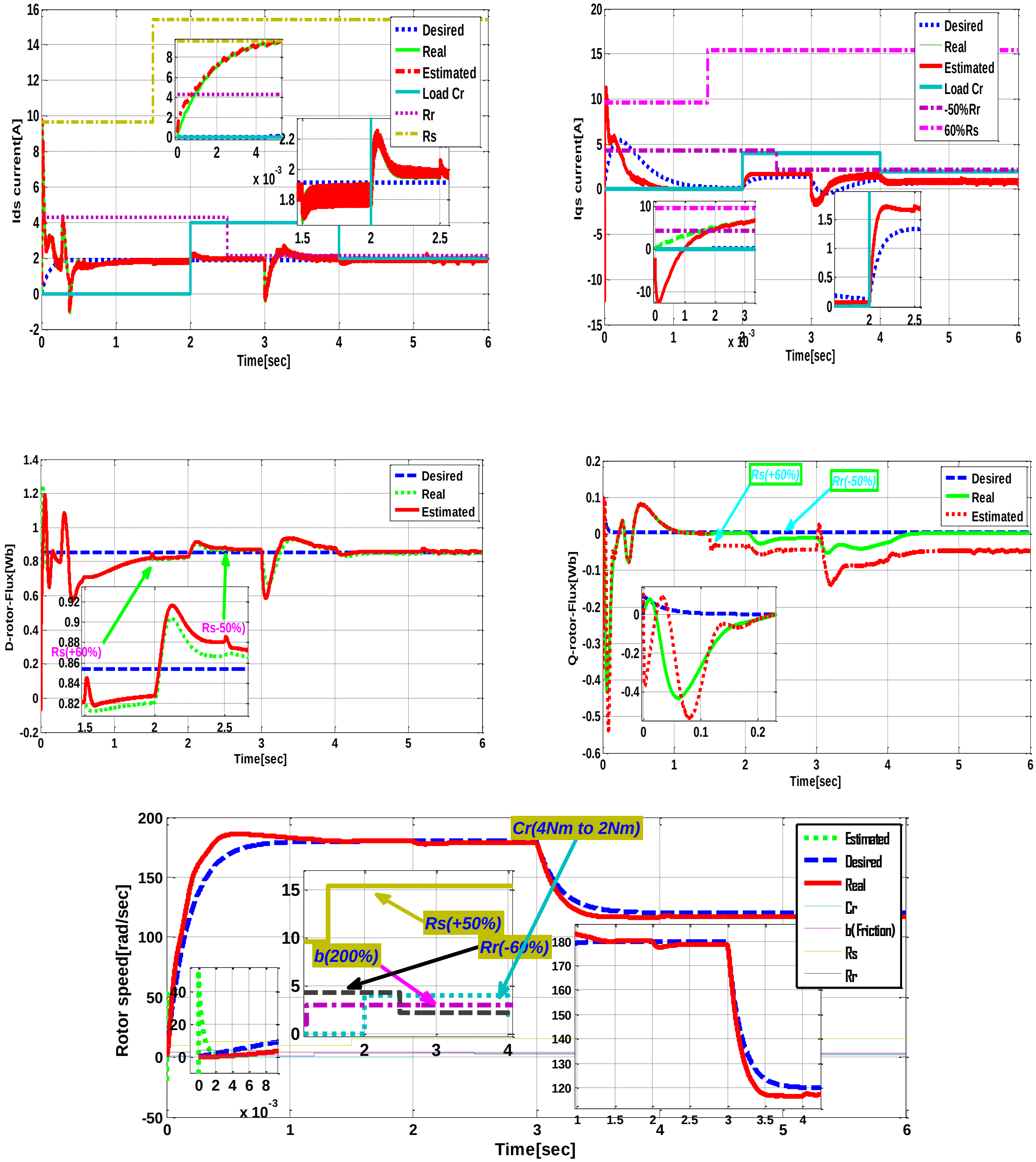


Figure 4.13states responses versus the load torque and parameters variations (Rs , Rr and b).

The real q-axis stator current tracks its desired at the same time where the estimated state does the same, it's clear from figures that the q-axis stator current is a reproduction of the electromagnetic torque that proves that the FOC is assured. The estimated d-axis stator current follows its real where they track the desired value. It was also observed that the real and the estimated states of q-axis rotor flux stayed near zero ($\emptyset_{rq} = 0$), whereas its d-axis is around the rated rotor flux reference (0.1 Wb) which shows that the FOC is assured at the moment where the estimation errors is approximately zero as shown in figures, it is very clear that the estimated and the real states of the rotor speed are in closer proximity to its desired value. In despite of the application of the nominal load torque at t = 2 sec, the rotor speed still subject to the control and the estimation conditions with a minimum effect on these conditions. The estimated states are closer to their real values despite the fact that the starting conditions of the estimated states are not zero.

Through the simulation results given above, there is a guarantee of the success for the proposed PI-MVT controller based observer and competitive with other technics in the industrial applications due to its effectiveness, simplicity and low cost.

4.5 Experimental results:

To study the effectiveness of the proposed controllers and observers based on the MVT theory, some tests of control and states estimation of the IM were constructed in the laboratory of ***UTM-PROTON Future Drive Laboratory, University Technology Malaysia, Johor Bahru, Malaysia***. The set-up consists of a ¼ HP IM which its parameters are listed in Appendix B, a 3-phase voltage source inverter based IGBT 's, hall effect current sensors (La-55), incremental encoder, a DC motor considered as a load and a dSPACE 1104 controller board. A real photo of the experimental bench is presented in figure 4.14.

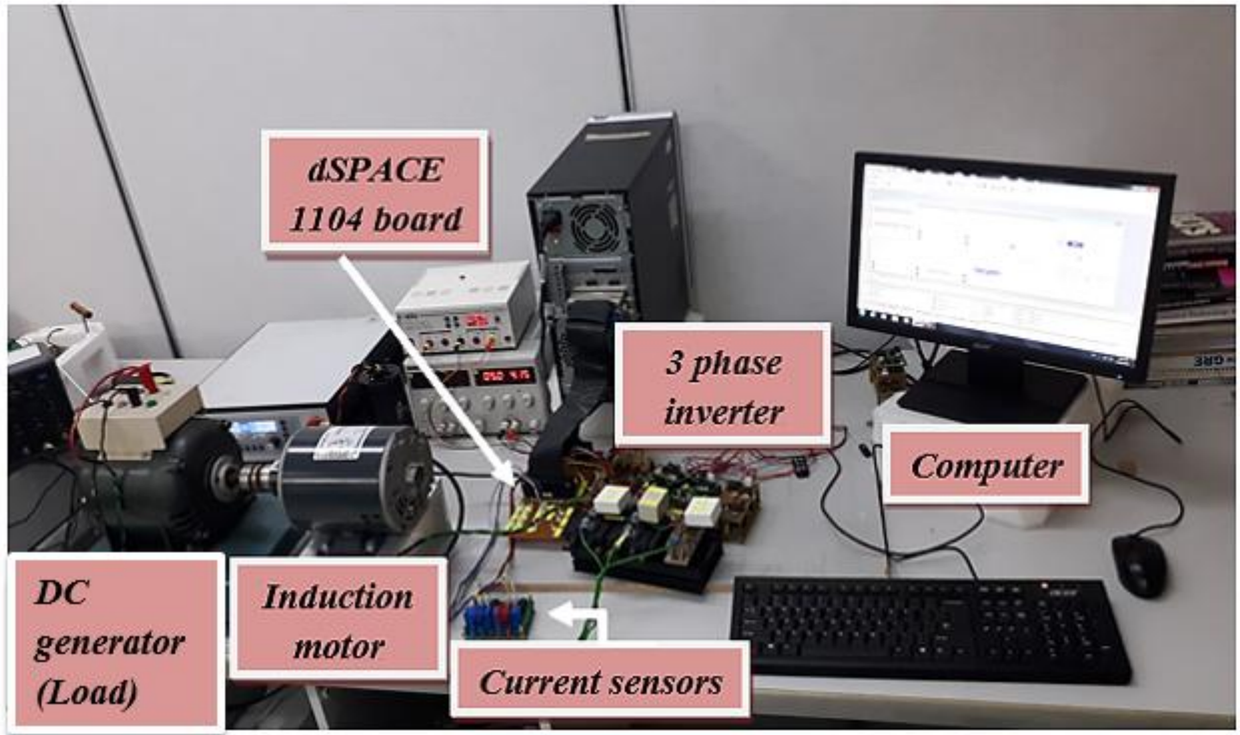
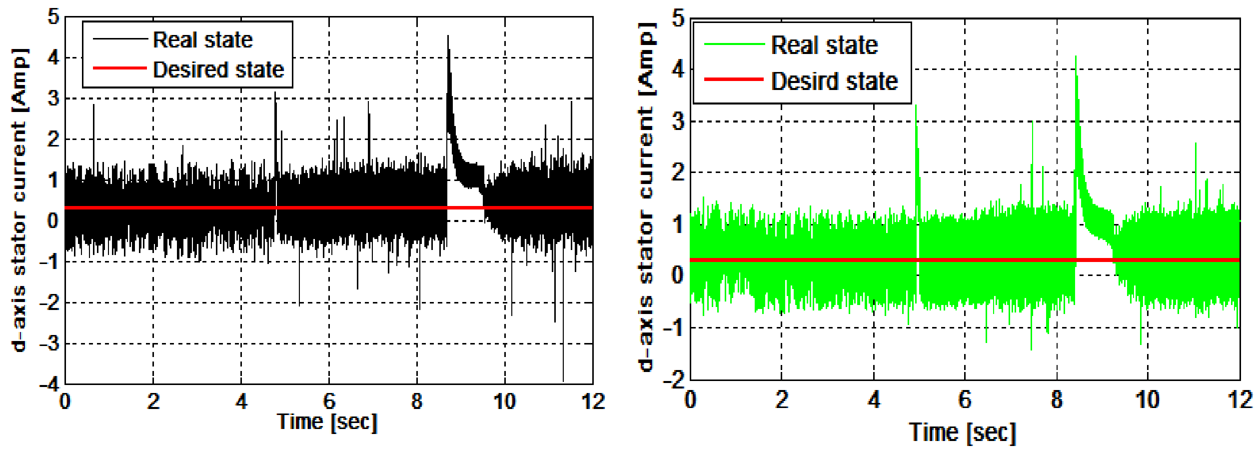


Figure 4.14Real photo of the experimental bench

4.5.1 Robust $P - H_\infty$controller:

The design of the proposed robust H_∞ for IM control strategy is previously shown in figure 4.8. The desired states $[i_{sdr} \quad i_{sqr} \quad \emptyset_r 0 \quad \omega_{rr}]^T$ are generated based on FOC conditions ($\emptyset_{rq}$=0) the load torque. Two kind of control based MVT approach are compared in this part, the robust control and conventional control those presented in (a) and (b) respectively in the next figures in order to show the robustness of the robust control. The reference of the rotor speed is firstly chosen for null speed test. For the low speed test, a reference speed of 50rad/sec is chosen. Whereas a reference of 150rad/sec is taken for the high speed test. Finally for the reverse speed test, -150rad/sec is taken to prove the effectiveness of the control. The IM motor is unloaded firstly, then a nominal load torque of 0.7 N.m is applied at 5.3 sec through a DC generator connected to the IM machine.

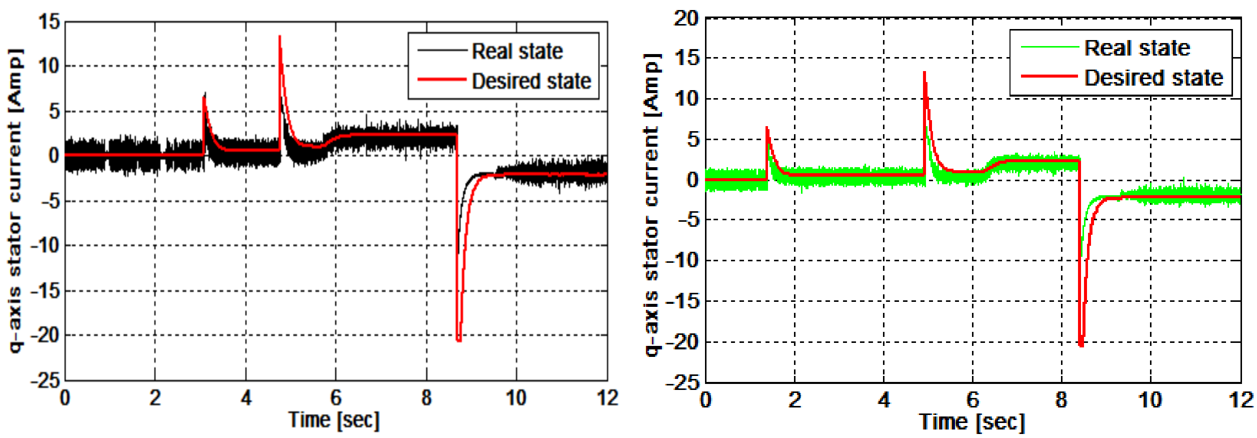


a) **b)**

Figure 4.15The d-axis stator current

$P - H_{\infty}$Robust control (a)

Conventional control (b)

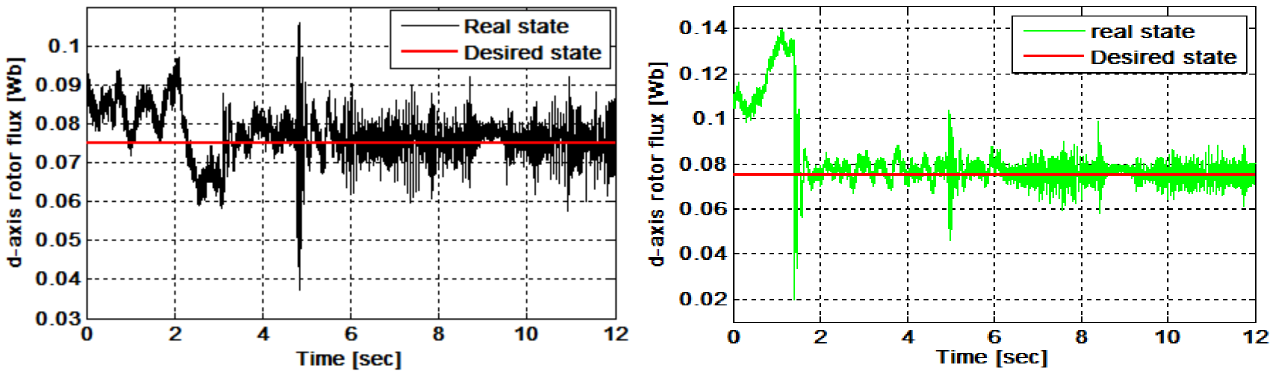


a) **b)**

Figure 4.16The q-axis stator current

$P - H_{\infty}$Robust control (a)

Conventional control (b)

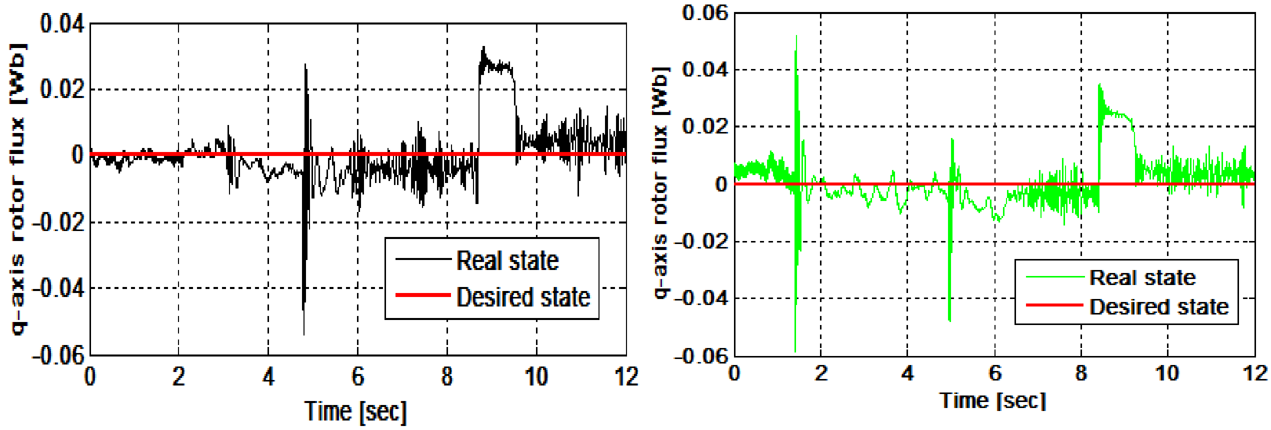


a) **b)**

Figure 4.17The d-axis rotor flux

$P - H_{\infty}$Robust control (a)

Conventional control (b)

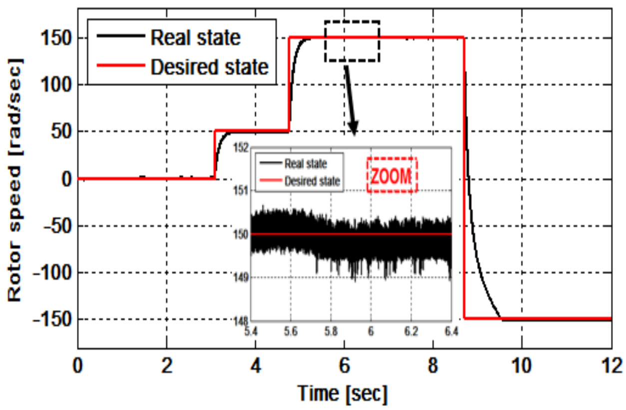


a) **b)**

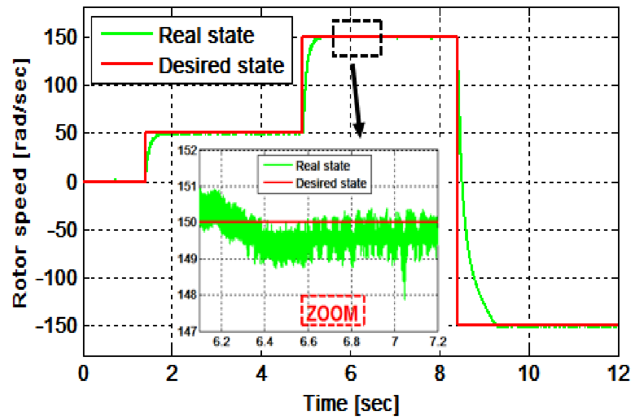
Figure 4.18The q-axis rotor flux

$P - H_{\infty}$Robust control (a)

Conventional control (b)



a)



b)

Figure 4.19The rotor speed

$P - H_{\infty}$Robust control (a)

Conventional control (b)

Based on figures 4.15 and 4.16, the d and q axis stator currents are track their desired values with a minimum error approximately zero in all experimental time even in the application of the nominal load torque. The robust H_{∞} control also show a minimum tracking error for the null speed test except for the rotor fluxes as presented in figures 4.17 and 4.18.The effect of the load torque is not observable for the robust control where the speed decrease by 1rad/sec at the application of the load torque for the normal control as indicated in figure 4.19.

It is clear from the previous experimental results the success of the robust control. However the MVT approach is simple to implement, These results show the effectiveness of the MVT approach, which can be considered a candidate to replace the previous technics, which are more complex when they are implemented in industrial applications.

4.5.2 PI controller based observer:

The proposed PI control based observer strategy based on MVT approach as shown in figure 4.11. As can be seen that the structure of the controller is similar to having PI controllers, one for each state. The desired states $[i_{sdr} \quad i_{sqr} \quad \emptyset_r 0 \quad \omega_{rr}]^T$ are generated from the load torque and FOC conditions ($\emptyset_{rq} = 0$). Where as in linear systems, a Lupberger observer is applied to the IM. By measuring the two line currents and the rotor speed, the MVT observer estimates all the IM states $[i_{sd} \quad i_{sq} \quad \emptyset_{rd}\emptyset_{rq} \quad \omega_r]^T$. The reference of the rotor speed is firstly chosen for null speed test. For the high speed test, a reference speed of 150rad/sec is taken. Whereas a reference of 20rad/sec is taken for the low speed test. The IM motor is unloaded firstly, then a nominal load torque of 0.7 N.m is applied to the IM at t=5.3sec through a DC generator. Because of the missing of the flux sensor, we present just the desired and estimated of the d and q-axis rotor fluxes as figures 4.20.

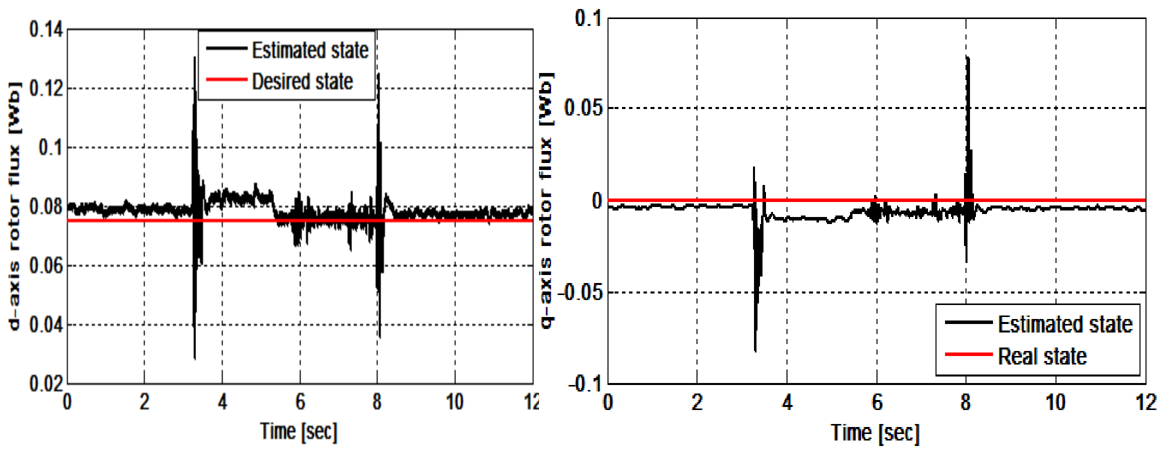


Figure 4.20The -axis rotor flux

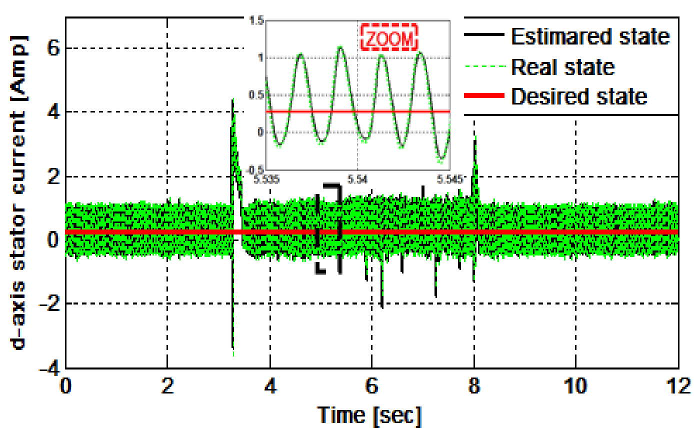


Figure 4.21The d-axis stator current

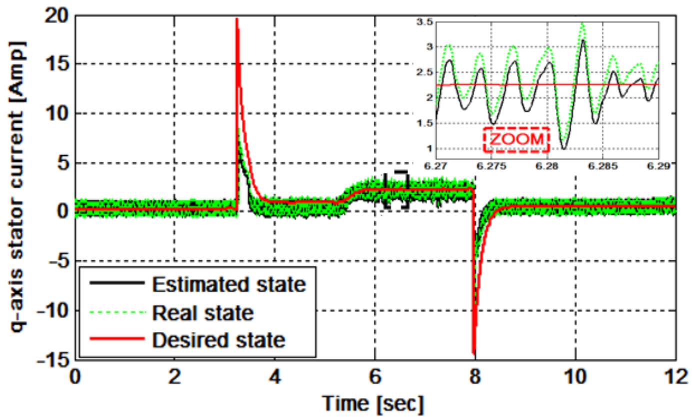


Figure 4.22The q-axis stator current

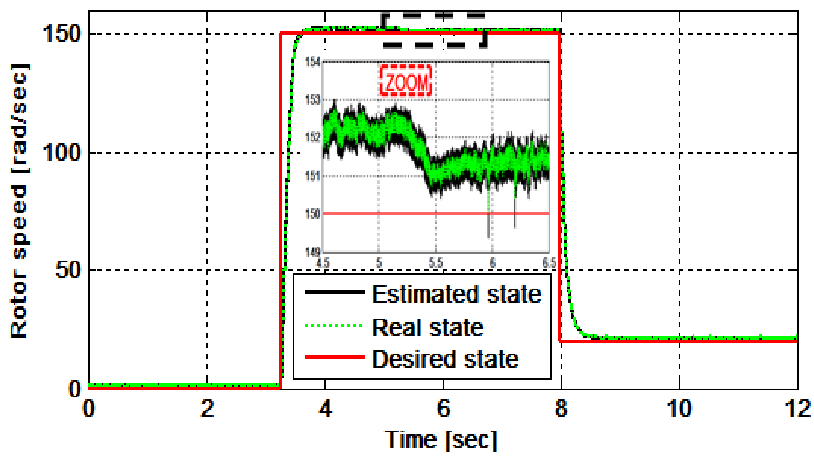


Figure 4.23The rotor speed

The estimation error of d and q axis stator currents is approximately zero, where the real and estimated states of them are around the desired states as proposed in figures 4.21 and 4.22 respectively. A maximum tracking error of 0.008 Wb for the d-axis rotor flux, where it does not exceed 0.01Wb for the q-axis rotor flux as shown in the previous figures. The figure 4.23 indicates the success of the PI control based observer based on the MVT through a minimum effect of the load torque to the control and estimation errors with a minimum effect on different speeds tests.

The MVT approach for control based observer not only has a systematic and proven methodology, the parameters of the controller and observer have been calculated separately and don't depend on the IM states, but also has good performances and efficiency as the previous experimental results show.

4.6 Conclusion:

In this chapter, we have firstly modeled the IM drive system in the two axes rotating frame with OL-FOC and references states generation were presented. Then, the design of the robust control based H_∞ performance based on the MVT approach to the IM drive through the MATLAB/Simulink environment were carried out. In order to show the efficiency of this robust control, a comparison with a control based observer has been presented. Based on the obtained simulated results mentioned above, it is clear that the effectiveness of the robust H_∞ MVT controller gave a minimum effect on the tracking error even during an unpredictable load torque and parameters variations. Although, the controller based on MVT theory conducted to a good performance results due its simplicity, low cost implementation, consuming computation time even with a simple microcontroller showing no dependency between the controller parameters and the IM states in the implementation of the controller design. The main goals of this research work convinced us that theoretical and practical results leading to a general and systematic methodology for proving the stability and determining the off line gains of the controller and observer as it was clarified compared to other technics when it is applied to nonlinear systems. These major advantages of the MVT approach could be a candidate in replacing all the previous control methods in the industrial applications. Next chapter, we suggest determining algorithm taking into a count of parametric uncertainties that will be developed and proved that can be applied to the tolerant fault control and diagnosis systems. The implementation of the MVT controllers and observer design applied to the IM drive in real experimental tests show an agreement with theoretical results.

Chapter 5:

Robust MVT Controller and observer of Uncertain Nonlinear Systems:

IM-FOC applications

5.1 Introduction:

This chapter deals with the analysis and design of robust controllers and observers for uncertain nonlinear systems using MVT and sector nonlinearities model based approach instead of using an uncertain TS fuzzy model. The major problem of this technic is how to approximate the uncertain nonlinear systems with a nominal model with uncertain terms called DEF structure[54, 55, 57],which are expressed in a form suitable for robust fuzzy controller and observer design as introduced in chapter three. In this study, we try to develop a new method to represent an uncertain nonlinear system and subsequently introducing a new concepts and reconfiguration of a various types of robust controllers design that guarantee not only stability but also satisfy the specified performance criteria of the closed-loop control system. The first type of the controller is the MVT-PI robust guarantying cost controller for trajectory tracking for the uncertain nonlinear systems with varying parameters. The fixed Lyapunov function based approach is used to develop the robust controller and the design conditions, which are derived as a problem of solving a set of linear matrix inequalities (LMIs) in evaluating the gains matrices for the controller and observers[46, 49, 53, 57, 69].

In the next step, a systematic approach to joint state and time-varying parameter estimation for uncertain nonlinear systems will proposed in this work. This work will be focused on robust, robust $H\infty$ stabilization for observers of uncertain nonlinear systems by using a class of Lyapunov function for uncertain nonlinear systems with slowly varying uncertainties

[23,26].The design conditions are derived as matrix inequality involving parametric uncertainties and then they are reduced to finite dimensional matrix inequalities. These matrix inequalities are then solved by an iterative LMI based algorithm.

Finally, the results of the state-space MVT system with Lyapunov function based approach are applied to control and estimate the states of the IM machine drives under FOC as an uncertain nonlinear system with time varying parameters. As we know that the control or the estimation of the states of the IM drives never happened without using sensors to get the IM states in order to control them[66]. In the industry, these sensors are partially or completely exhibiting of corruption in any moment, which leads to many issues, may reach the loss of all the system if it does not stop in the appropriate moment. A fault detection approaches could be represented as uncertain nonlinear with varying parameters which will be projected in future as a subject of research using the concept of the mean value theorem or MVT to solve these problems. At the end, simulation results and discussions of the IM-FOC control will be presented closing this chapter.

5.2 Uncertain model of the IM machine with time varying parameters:

Numerous approaches were proposed in order to deal with nonlinear system control and estimation or diagnosis [21,23, 57], with varying parameters. An efficient way if we can rewrite the original nonlinear system in a simpler form, like the Takagi-Sugeno (TS) model. Originally introduced by [23, 51], the T-S representation allows to exactly describing the nonlinear systems, under the condition that the nonlinearities are bounded. This is reasonable since state variables as well as parameters of physical systems are bounded [48, 50].Unfortunately, the introduction of time-varying parameters in the system models, needed to accurately represent the system behavior, leads to more challenging problems in control and estimation. In this case, conventional controller and observers, essentially developed for time invariant systems cannot be directly used, and so-called adaptive controllers and observers developed for extended state and unknown parameter estimation are needed [71].The main difficulty in estimating the state of such systems comes from the lack of knowledge on the parameter evolution. In the present work, we focus on the nonlinear time-varying parameter systems where the parameters are inaccessible (non measurable) and may be considered as model disturbances, uncertainties or faults acting on the system evolution.

In this section, we present the uncertain nonlinear model of the IM with time varying parameters, in our case, we have chosen the parameters (R_r, R_s and the friction coefficient:b) as a time-varying parameters.

Then the nonlinear model can be represented in the following form:

$$\begin{cases} \dot{x}(t) = f\big(x(t), \theta(t)\big) + Bu(t) + D_v v(t) \\ y(t) = C_0 x(t) \end{cases} \tag{5.1}$$

Where:

$$f(x(t), \theta) = \begin{bmatrix} -\gamma i_{sd} + \omega_s i_{sq} + \dfrac{k_s}{\tau_r}\emptyset_{rd} + k_s n_p\,\omega_r \emptyset_{rq} \\ -\omega_s i_{sd} - \gamma i_{sq} - k_s n_p\,\omega_r \emptyset_{rd} + \dfrac{k_s}{\tau_r}\emptyset_{rq} \\ \dfrac{M}{\tau_r} i_{sd} - \dfrac{1}{\tau_r}\emptyset_{rd} + \big(\omega_s - n_p\,\omega_r\big)\emptyset_{rq} \\ \dfrac{M}{\tau_r} i_{sq} - \big(\omega_s - n_p\,\omega_r\big)\emptyset_{rd} - \dfrac{1}{\tau_r}\emptyset_{rq} \\ \dfrac{n_p M}{J L_r}\big(\emptyset_{rd} i_{sq} - \emptyset_{rq} i_{sd}\big) - \dfrac{b}{J}\omega_r \end{bmatrix} \tag{5.2}$$

With

$$\gamma = \left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma\tau_r}\right) = \gamma_n + \frac{\theta_1}{\sigma} + \frac{\theta_2(t)}{\sigma L_r}(1-\sigma), \gamma_n = \left(\frac{R_{sn}}{\sigma L_s} + \frac{1-\sigma}{\sigma\tau_r}\right) \text{and} \frac{1}{\tau_r} = \frac{1}{\tau_{rn}} + \frac{\theta_{2(t)}}{L_r} \tag{5.3}$$

Such that $\begin{cases} R_s = R_{sn} + \theta_1 \\ R_r = R_{rn} + \theta_2 \\ b = b_n + \theta_3 \end{cases}$ and $\begin{cases} \theta_1 = \Delta R_s \\ \theta_2 = \Delta R_r \\ \theta_3 = \Delta b \end{cases}$

Which representing the time varying parameters.

are defined as:

$$x(t) = [i_{sd} \quad i_{sq} \quad \emptyset_{rd} \emptyset_{rq} \quad \omega_r]^T \;;\; B = \begin{bmatrix} \frac{1}{\sigma Ls} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{\sigma Ls} & 0 & 0 & 0 \end{bmatrix}^T ;\; u(t) \begin{bmatrix} U_{sd} \\ U_{sq} \end{bmatrix} \tag{5.4}$$

$D_v = \begin{bmatrix} 0 & 0 & 0 & 0 & -\frac{1}{J} \end{bmatrix}^T$; $v(t) = T_L$ and $C_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

It can, also, be given with the following representation

$$\begin{cases} \dot{x}(t) = A_x\big(x(t), \theta(t)\big)x(t) + Bu(t) + D_v v(t) \\ y(t) = C_0 x(t) \end{cases} \tag{5.5}$$

With

$$A_x(x(t), \theta) = \begin{bmatrix} -\gamma & \omega_s & \frac{k_s}{\tau_r} & k_s\, n_p \omega_r & 0 \\ -\omega_s & -\gamma & -k_s\, n_p \omega_r & \frac{k_s}{\tau_r} & 0 \\ \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & \frac{M}{\tau_r\, \emptyset_r} i_{sq} & 0 \\ 0 & \frac{M}{\tau_r} & -\frac{M}{\tau_r\, \emptyset_r} i_{sq} & -\frac{1}{\tau_r} & 0 \\ 0 & 0 & \frac{n_p M}{J L_r} i_{sq} & -\frac{n_p M}{J L_r} i_{sd} & -\frac{b}{J} \end{bmatrix} \tag{5.6}$$

5.3 MVT controllers design for uncertain nonlinear systems:

This section presents an efficient methodology with a new method for designing controllers and observers and for some class of uncertain nonlinear systems with varying parameters described by[72]:

$$\begin{gathered} \dot{x}(t) = f(x(t), \theta(t)) + g(x(t), \theta(t))u(t) + D_v v(t) \\ y(t) = C_0 x(t) \end{gathered} \tag{5.7}$$

Where $x(t) \in R^n$ is the state vector, $u(t) \in R^{n_u}$ is the input vector, and $y(t) \in R^{n_y}$ is the output measurement vector, are appropriate matrices. The functions $f(x(t), \theta): R^n \to R^n$ and $g(x(t), \theta(t)): R^m \times R^{n_u} \to R^n$ are nonlinear. In addition $f(x(t), \theta)$ is assumed differentiable.

It is simple to rewrite (5.7) in the Lipchitz form based on (5.1) if:

$$g(x(t),\theta(t))u(t) = B_0 u(t) \text{ and}$$
$$\Phi(x(t),\theta(t)) = f(x(t),\theta(t)) - A_0 x(t) \tag{5.8}$$

(5.7) reduced to :

$$\begin{cases} \dot{x}(t) = A_0 x(t) + B_0 u(t) + \Phi(x(t),\theta(t)) + D_v v(t) \\ y(t) = C_0 x(t) \end{cases} \tag{5.9}$$

Where A_0andB_0 are defined as the nominal matrices.

5.3.1 MVT-P-Controller of NL uncertain systems time varying parameters:

Let the following control rule be employed to deal with the design of a P-controller for the system represented by (5.9).

According to the state feedback control law adopted, the control vector $u(t)$is given by:

$$u(t) = -K_0 e_c(t) \tag{5.10}$$

Where K_0 is the controller's gain matrix and $e_c(t)$ is the state error vector given by:

$$e_c(t) = x(t) - x_c(t) \tag{5.11}$$

In (5.11), x_c is the desired states, one can write the control error dynamic equation as:

$$\dot{e}_c(t) = \dot{x}(t) - \dot{x}_c(t) \tag{5.12}$$

To understand the method, we start with stepwise signals(We take a regulation case, because $x_c(t)$ is a stepwise signal, so, $\dot{x}_c(t) = 0$, then from (5.9) with (5.10) can be written as:

$$\dot{e_c}(t) = (A_0 - B_0 K_0)e_c(t) + \Phi(x(t),\theta(t)) + A_0 x_c(t) + D_v v(t) - \dot{x}_c(t) \tag{5.13}$$

So, the objective is to determine the gain matrix K_0 such that the non-linear lipchitz uncertain system (5.13) becomes asymptotically stable.

As the error dynamic equation is given (5.13), it is not easy to stabilize this system, so we need to apply the MVT and sector nonlinearity transformation to the nonlinear part of the Lipchitz system (5.13) (These approaches were presented in the last subsection 4.1.), so, the system becomes:

$$\dot{e}_c(t) = \left(A_0 - B_0K_0 + \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{\partial \emptyset_i}{\partial x_j}(\xi,\theta)\, H_{ij} \right) e_c(t) + D_v v(t) - I\dot{x}_c(t) + \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{\partial \emptyset_i}{\partial x_j}(\xi,\theta)\, H_{ij} x_c(t) + A_0 x_c(t) \quad (5.14)$$

Then it could be transformed to following expression:

$$\dot{e}_c(t) = \left(\sum_{i=1}^{2m} \delta_i(\xi)(\mathcal{A}_i(\theta(t)) - B_0K_0 \right) e_c(t) + D_v v(t) - I\dot{x}_c(t) + \sum_{i=1}^{2m} \delta_i(\xi)(\mathcal{A}_i(\theta(t)) \quad (5.15)$$

Even at this stage, the stabilization of the system is not so easy, one should introduce other transformations to (5.15) which represent an important contribution in our work, because the $\mathcal{A}_i(\theta(t))$ are not time invariant so:

With $\theta(t) = [\theta_1(t) \quad \dots \quad \theta_{n_\theta}(t)]$ and

$$A_i(\theta(t)) = \bar{A}_\iota + \sum_{j=1}^{n_\theta} \theta_j(t)\, \bar{A}_{ij}$$
$$B_i(\theta(t)) = \bar{B}_\iota + \sum_{j=1}^{n_\theta} \theta_j(t)\, \bar{B}_{ij} \quad (5.16)$$

According to the SNT [23, 51]and [68],each parameter $\theta_j(t)$is expressed as a function of its upper and lower bounds, respectively denoted $\theta_j^1$and θ_j^2such that:

$$\theta_j(t) = h_j^1\left(\theta_j(t)\right)\theta_j^1 + h_j^2\left(\theta_j(t)\right)\theta_j^2 \tag{5.17}$$

Where $h_j^1\left(\theta_j(t)\right)$ and $h_j^2\left(\theta_j(t)\right)$are defined by

$$\begin{aligned} h_j^1\left(\theta_j(t)\right) &= \frac{\theta_j(t)-\theta_j^2}{\theta_j^1-\theta_j^2} \\ h_j^2\left(\theta_j(t)\right) &= \frac{\theta_j^1-\theta_j(t)}{\theta_j^1-\theta_j^2} \end{aligned} \tag{5.18}$$

And satisfy the convex sum property :

$$\begin{gathered} h_j^1\left(\theta_j(t)\right) + h_j^2\left(\theta_j(t)\right) = 1 \\ 0 \le h_j^2\left(\theta_j(t)\right) \le 1 \end{gathered} \tag{5.19}$$

Replacing (5.17) and(5.18)in (5.16), it becomes:

$$\begin{cases} A_i\big(\theta(t)\big) = \bar{A}_{ci} + \sum_{j=1}^{n_\theta}\sum_{k=1}^{2} h_j^k\left(\theta_j(t)\right)\theta_j^k\bar{A}_{ij} \\ B_i\big(\theta(t)\big) = \bar{B}_{ci} + \sum_{j=1}^{n_\theta}\sum_{k=1}^{2} h_j^k\left(\theta_j(t)\right)\theta_j^k\bar{B}_{ij} \end{cases} \tag{5.20}$$

The time-varying matrices $A_i\big(\theta(t)\big)$and $B_i\big(\theta(t)\big)$can now be written as polytopic matrices, then (5.15) becomes:

$$\begin{aligned} \dot{e}_c(t) = \sum_{i=1}^{m=<n\times n}\sum_{j=1}^{n_\theta} \frac{\left(\overline{\delta}_i(\xi)+\underline{\delta}_i(\xi)\right)\left(\overline{h}_j(\theta)+\underline{h}_j(\theta)\right)}{m\times n_\theta} \Big\{\Big(\big(Ac - \mathrm{B}_0\mathrm{K}_0 + n_{\theta\times}\big(A\theta_j^1 + A\theta_j^2\big) + m \\ \times\left(Ax_{ci}^1 + Ax_{ci}^2\right) + m\times n_\theta \times (Ax\theta_{ij}^{11} + Ax\theta_{ij}^{12} + Ax\theta_{ij}^{21} + Ax\theta_{ij}^{22})\big)e_c(t) \\ + D_v v(t) - \dot{x}_c(t) + A_{ij}x_c(t)\Big)e_c(t) + D_v v(t) - I\dot{x}_c(t) + A_{ij}^{kl}x_c(t)\Big\} \end{aligned} \tag{5.21}$$

Such that:$A_{ij}^{kl} = Ac + n_\theta \times \left(A\theta_j^l\right) + m\times\left(Ax_{ci}^k\right) + m\times n_\theta \times (Ax\theta_{ij}^{kl})$

For k=1,2 and l=1,2.

Then (5.21)can be expressed as:

$$\dot{e}_c(t) = \sum_{i=1}^{m=<n\times n} \sum_{j=1}^{n_\theta} (h_{ij}^{kl}(\xi,\theta)\{(Ac - \mathrm{B_0K_0} + n_\theta \times (A\theta_j^l) + m \times (Ax_{ci}^k) + m \times n_\theta \times Ax\theta_{ij}^{kl})e_c(t) + D_v v(t) - \dot{x}_c(t) + A_{ij}^{kl} x_c(t)\} \tag{5.22}$$

Finally (5.22) is transformed to:

$$\dot{e}_c(t) = \sum_{i=1}^{m} \sum_{j=1}^{n_\theta} (h_{ij}^{kl}(\xi,\theta)\{(A_{ij}^{kl} - B_0K_0))e_c(t) + D_v v(t) - \dot{x}_c(t) + A_{ij}^{kl} x_c(t)\} \tag{5.23}$$

For k=1,2 and l=1,2.

5.3.1.1Stability analysis:

The stability analysis of the dynamic of the state error represented in (5.23) will be studied in using the quadratic Lyapunov function with common matrix as follows[51]:

$$W(e_c(t)) = {e_c}^T(t)Pe_c(t)\,, \quad P = P^T > 0 \tag{5.24}$$

The stability is checked when the derivative of the Lyapunov function (5.24) is less than zero

$$\dot{W}(e_c(t)) \leq 0 \tag{5.25}$$

The stability is related to the derivative of (5.23) based on [22, 54], so:

$$\dot{W}(e_c(t)) = {e_c}^T(t)\left(\left({A_{ij}^{kl}}^T P + PA_{ij}^{kl} - K_0^T B_0^T P - PB_0K_0\right)\right)e_c(t) \tag{5.26}$$

The stability of the estimation error dynamic is ensured if the time derivative of the Lyapunov equation (5.26) is negative definite, such that the following LMIs is with time-independent

$${A_{ij}^{kl}}^T P + PA_{ij}^{kl} - K_0^T B_0^T P - PB_0K_0 < 0 \tag{5.27}$$

To express the inequality (5.27) in term of LM I's, the change of variables$M = K_0P$ is used and the LMIs conditions are obtained as follows, with the addition of βrepresenting the rate of convergence, so:

$$A_{ij}^{kl^T}P + PA_{ij}^{kl^T} - M^T B_0^T - B_0 M + \beta P < 0 \tag{5.28}$$

Theorem5.1: The dynamics of the uncertain system (5.23) is asymptotically stable, if there exist $P = P^T > 0$ and $\beta > 0$such that:

$$A_{ij}^{kl^T}P + PA_{ij}^{kl} - M^T B_0^T - B_0 M + \beta P < 0 \tag{5.29}$$

$$With A_{ij}^{kl} = Ac + n_\theta \times \left(A\theta_j^l\right) + m \times \left(Ax_{ci}^k\right) + m \times n_\theta \times \left(Ax\theta_{ij}^{kl}\right).$$

Where

$A\theta_j^1 = \overline{\theta}_j . A\theta_j; A\theta_j^2 = \underline{\theta}_j . A\theta_j$ *and* $Ax_{ci}^1 = \overline{\xi}_i . Ax_{ci}; Ax_{ci}^2 = \underline{\xi}_i . Ax_{ci}$;

$Ax\theta_{ij}^{11} = \overline{\xi}_i\overline{\theta}_j . Ax\theta_{ij}$;,$Ax\theta_{ij}^{12} = \overline{\xi}_i\underline{\theta}_j . Ax\theta_{ij}$;$Ax\theta_{ij}^{21} = \underline{\xi}_i\overline{\theta}_j . Ax\theta_{ij}$;$Ax\theta_{ij}^{22} = \underline{\xi}_i\underline{\theta}_j . Ax\theta_{ij}$**(5.30)**

For $i = 1, \dots, m \le n \times n$, $j = 1, \dots, n_\theta$, ***k=1 ,2 and l=1,2.***

The controller gain is given by:

$$K_0 = MP^{-1}$$

5.3.2 MVT$-PI$-H$_\infty$ $-$Controller of NL uncertain systems time varying parameters:

To eliminate the effects of disturbance and the parametric uncertainty in the steady state, it is better to add an integral action, so the control is rewritten as :

$$u(t) = -[K_1 \quad K_2]\begin{bmatrix} e(t) \\ e_I(t) \end{bmatrix} = K_I \bar{e}(t) \tag{5.31}$$

Such as the error state bound, the integral action is:

$$e_I(t) = \int \big(x(t) - x_c(t)\big)dt \tag{5.32}$$

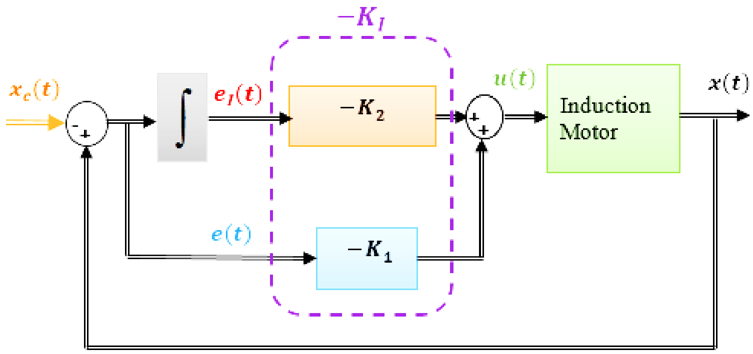


Figure 5.1 The MVT- PI –**H**∞ control design

The combination of the MVT theory with the sector nonlinearity approach allows getting the following dynamics of the augmented state control error with MVT-PI regulator:
The dynamics of the augmented state feedback error (5.32) is written as:

$$\dot{\bar{e}}(t) = \sum_{i=1}^{m}\sum_{j=1}^{n_\theta} h_{ij}^{kl}(\xi,\theta) * \left(\bar{S}_{ij}^{kl}\bar{e}(t) + \bar{D}\bar{w}(t)\right) \tag{5.33}$$

Where

$$\bar{S}_{ij}^{kl} = \bar{A}_{ij}^{kl} - \bar{B}K_I\,, \bar{A}_{ij}^{kl} = \begin{bmatrix} A_{ij}^{kl} & 0 \\ I & 0 \end{bmatrix}, \bar{B} = \begin{bmatrix} B_0 \\ 0 \end{bmatrix}, \bar{D} = \begin{bmatrix} A_{ij}^{kl} & -I & Dv \\ 0 & 0 & 0 \end{bmatrix}, \bar{w}(t) = \begin{bmatrix} x_c(t) \\ \dot{x}_c(t) \\ v(t) \end{bmatrix}$$

5.3.2.1 Synthesis for H_∞performance:

The existence of the disturbances $\bar{w}(t)$ will affect to the control performances. So as to minimize the effect of the disturbance $\bar{w}(t)$, the H_∞ performances has been taken into account [69].

$$\int_0^\infty \bar{e}^T(t)\,\bar{e}(t)dt \le \gamma^2 \int_0^\infty \bar{w}^T(t)\,\bar{w}(t)\,dt \tag{5.34}$$

Consider the quadratic Lyapunov function as:

$$V(\bar{e}(t)) = \bar{e}^T(t)P\bar{e}(t) \tag{5.35}$$

Where $P = P^T > 0$

We can use the same steps as in chapter four, then, we can obtain the following theorem:

Theorem 5.2: The dynamics of system (5.33) is asymptotically stable, if there exist $\boldsymbol{P = P^T > 0}$, and $\boldsymbol{\alpha > 0}$such that:

$$\begin{bmatrix} \overline{A_{ij}^{kl}}^T X + X\overline{A_{ij}^{kl}} - \bar{B}M - M^T\bar{B}^T + \alpha X & \bar{D} & X \\ \bar{D}^T & -\gamma^2 I & 0 \\ X & 0 & -I \end{bmatrix} < 0 \tag{5.36}$$

$$\boldsymbol{With \quad \bar{S}_{ij}^{kl} = \bar{A}_{ij}^{kl} - \bar{B}K_I and \bar{A}_{ij}^{kl} = \begin{bmatrix} A_{ij}^{kl} & 0 \\ I & 0 \end{bmatrix}, \bar{D} = \begin{bmatrix} A_{ij}^{kl} & -IDv \\ 0 & 0 \quad 0 \end{bmatrix}}$$

$\boldsymbol{With A_{ij}^{kl} = Ac + n_\theta \times (A\theta_j^l) + m \times (Ax_{ci}^k) + m \times n_\theta \times (Ax\theta_{ij}^{kl}).}$

And $\boldsymbol{A\theta_j^1 = \bar{\theta}_j . A\theta_j; A\theta_j^2 = \underline{\theta}_1 . A\theta_j}$ **and** $\boldsymbol{Ax_{ci}^1 = \bar{\xi}_i . Ax_{ci}; Ax_{ci}^2 = \underline{\xi}_i . Ax_{ci}}$;

$$\boldsymbol{Ax\theta_{ij}^{12} = \underline{\theta}_i\bar{\xi}_j . Ax\theta_{ij}; Ax\theta_{ij}^{21} = \underline{\xi}_i\bar{\theta}_j . Ax\theta_{ij}; Ax\theta_{ij}^{22} = \underline{\xi}_i\underline{\theta}_j . Ax\theta_{ij}}$$

For $\mathbf{i = 1, \dots, m \leq n \times n \ , j = 1, \dots, n_\theta}$

The controller gain is given as : $\boldsymbol{K_I = MP^{-1}}$**.**

5.3.3 FOC control using robust H_∞ PI controller applied to IM machine drive:

First, we should determine the uncertain model of the IM machine drives system in the synchronous d-q frame rotating with electromagnetic field-oriented[66].The principle behind field-oriented control is that the machine flux and torque are controlled independently, in a similar fashion to a separately exited DC machine. In consequently the rotor flux vector is (Ψrd, Ψrq) aligned to the d-axis and the following results can be obtained.

The design of proposed control law is implemented through an illustrative simulation test under the MATLAB/Simulink environment. The PI-robust control based on MVT will be applied to the IM machine which parameters are mentioned in Appendix A. The proposed MVT for the control law has been tested in simulation and results were presented.

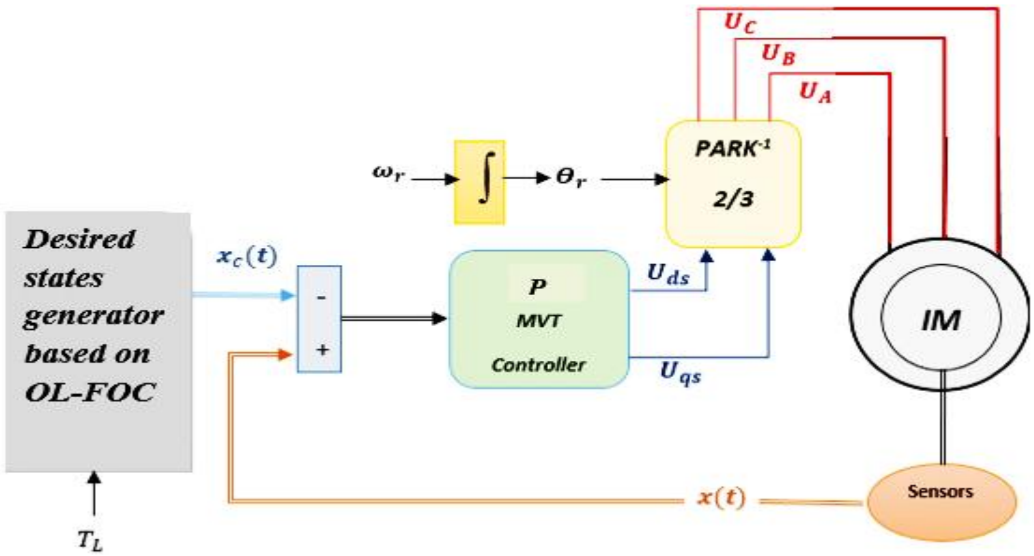


Figure 5.2 Global scheme of the **robust** $\boldsymbol{H_\infty - PI}$ control law of the IM based on MVT

Before going to the control and estimation, the uncertain model of the IM machine should be found with time varying parameters and will be represented according to (5.24) in the follwing steps :

- ✓ The, electrical speed of the stator defined in the synchronous d-q frame rotating with electromagnetic field-oriented is obtained and replaced with desired states *as* follows**:**

$$\omega_s = \left(n_p x_5 + \frac{M}{\tau_r\, \emptyset_{rdc}} x_2\right) \tag{5.37}$$

- ✓ One need to determine the gradient of $f(x(t), \theta(t))$, so the robust $H_\infty - P$-controller state error equation control can be found as:

$$\dot{e}_c(t) = \sum_{i=1}^{5=<n\times n} \sum_{j=1}^{n_\theta=3} (h_{ij}^{kl}(\xi,\theta)) \left\{ \left(Ac - \mathrm{B}_0\mathrm{K}_0 + n_\theta \times \left(A\theta_j^l\right) + m \times \left(Ax_{ci}^k\right) + m \times n_\theta \times \right.\right. \tag{5.38}$$

$Ax\theta ijklect+Dvvt-xct+Aijklxct$ With k=1,2 and l=1,2.

5.3.3.1 IM machine model with varying parameters:

To model the IM machines with varying parameters, we start with the nonlinear term $f(x(t),\theta(t))$:

$$f(x(t),\theta(t)) = \begin{bmatrix} -\gamma i_{sd} + \omega_s i_{sq} + \frac{k_s}{\tau_r}\emptyset_{rd} + k_s n_p \omega_r \emptyset_{rq} \\ -\omega_s i_{sd} - \gamma i_{sq} - k_s n_p \omega_r \emptyset_{rd} + \frac{k_s}{\tau_r}\emptyset_{rq} \\ \frac{M}{\tau_r} i_{sd} - \frac{1}{\tau_r}\emptyset_{rd} + \left(\omega_s - n_p\omega_r\right)\emptyset_{rq} \\ \frac{M}{\tau_r} i_{sq} - \left(\omega_s - n_p\omega_r\right)\emptyset_{rd} - \frac{1}{\tau_r}\emptyset_{rq} \\ \frac{n_p M}{J L_r}\left(\emptyset_{rd} i_{sq} - \emptyset_{rq} i_{sd}\right) - \frac{b}{J}\omega_r \end{bmatrix} \tag{5.39}$$

It could be written as:

$$A_x(x(t),\theta(t))x(t) = \begin{bmatrix} -\gamma & \omega_s & \frac{k_s}{\tau_r} & k_s n_p \omega_r & 0 \\ -\omega_s & -\gamma & -k_s n_p \omega_r & \frac{k_s}{\tau_r} & 0 \\ \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & \frac{M}{\tau_r \emptyset_r} i_{sq} & 0 \\ 0 & \frac{M}{\tau_r} & -\frac{M}{\tau_r \emptyset_r} i_{sq} & -\frac{1}{\tau_r} & 0 \\ 0 & 0 & \frac{n_p M}{J L_r} i_{sq} & -\frac{n_p M}{J L_r} i_{sd} & -\frac{b}{J} \end{bmatrix} x(t) \tag{5.40}$$

Therefore, the system (5.38) could be written in canonical form in order to apply the stability criteria for the uncertain systems in closed loop to obtain the gains of the controller.

If we replace, first, the electrical speed of the stator by the expression defined by (5.37) and the varying parameters in the nonlinear model (5.40) of the induction motor, so the gradient is rewritten as the following state space form:

$$\frac{\partial f}{\partial x}\big(\xi i, \theta(t)\big) =$$

$$\begin{bmatrix} -\gamma & \left(n_p x_5 + \frac{2M}{\tau_r\, \emptyset_{rdc}} x_2\right) & \frac{k_s}{\tau_r} & k_s\, n_p x_5 & (n_p x_2 + k_s\, n_p x_4) \\ -(n_p x_5 + \frac{M}{\tau_r\, \emptyset_{rdc}} x_2) & -\gamma - \frac{M}{\tau_r\, \emptyset_{rdc}} x_1 & -k_s\, n_p x_5 & \frac{k_s}{\tau_r} & \left(-k_s\, n_p x_3 - n_p x_1\right) \\ \frac{M}{\tau_r} & \frac{M}{\tau_r\, \emptyset_{rdc}} x_4 & -\frac{1}{\tau_r} & \frac{M}{\tau_r\, \emptyset_{rdc}} x_2 & 0 \\ 0 & \frac{M}{\tau_r} - \frac{M}{\tau_r\, \emptyset_{rdc}} x_3 & -\frac{M}{\tau_r\, \emptyset_{rdc}} x_2 & -\frac{1}{\tau_r} & 0 \\ -\frac{n_p M}{J L_r} x_4 & \frac{n_p M}{J L_r} x_3 & \frac{n_p M}{J L_r} x_2 & -\frac{n_p M}{J L_r} x_1 & -\frac{b}{J} \end{bmatrix} \quad (5.38)$$

Next, we plug the following parameters variations $\theta_1(t)$, $\theta_2(t)$ *and* $\theta_3(t)$ in (5.3) defined by these expressions:

$$\gamma = \left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma \tau_r}\right) = \gamma_n + \frac{\theta_1}{\sigma} + \frac{\theta_2(t)}{\sigma L_r}(1-\sigma),\ \gamma_n = \left(\frac{R_{sn}}{\sigma L_s} + \frac{1-\sigma}{\sigma \tau_r}\right) \text{ and} \frac{1}{\tau_r} = \frac{1}{\tau_{rn}} + \frac{\theta_{2(t)}}{L_r}$$

With $\begin{cases} R_s = R_{sn} + \theta_1 \\ R_r = R_{rn} + \theta_2 \\ b = b_n + \theta_3 \end{cases}$ and $\begin{cases} \theta_1 = \Delta R_s \\ \theta_2 = \Delta R_r \\ \theta_3 = \Delta b \end{cases}$

Then, the gradient becomes:

$$\frac{\partial f}{\partial x}\big(\xi i, \theta(t)\big)$$

$$= \begin{bmatrix} -\gamma_n - \frac{\theta_1(t)}{\sigma L_s} - \frac{\theta_2(t)}{\sigma L_r}(1-\sigma) & \left(n_p x_5 + \frac{2M}{\tau_r\,(\theta_2)\emptyset_{rdc}} x_2\right) & \frac{k_s}{\tau_r\,(\theta_2)} & k_s\,n_p x_5 & (n_p x_2 + k_s\,n_p x_4) \\ -(n_p x_5 + \frac{M}{\tau_r\,(\theta_2)\emptyset_{rdc}} x_2) & -\gamma_n - \frac{\theta_1(t)}{\sigma L_s} - \frac{\theta_2(t)}{\sigma L_r}(1-\sigma) - \frac{M}{\tau_r\,(\theta_2)\,\emptyset_{rdc}} x_1 & -k_s\,n_p x_5 & \frac{k_s}{\tau_r\,(\theta_2)} & \left(-k_s\,n_p x_3 - n_p x_1\right) \\ \frac{M}{\tau_r\,(\theta_2)} & \frac{M}{\tau_r\,(\theta_2)\emptyset_{rdc}} x_4 & -\frac{1}{\tau_r} & \frac{M}{\tau_r\,(\theta_2)\emptyset_{rdc}} x_2 & 0 \\ 0 & \frac{M}{\tau_r\,(\theta_2)} - \frac{M}{\tau_r\,(\theta_2)\emptyset_{rdc}} x_3 & -\frac{M}{\tau_r\,(\theta_2)\emptyset_r} x_2 & -\frac{1}{\tau_r\,(\theta_2)} & 0 \\ -\frac{n_p M}{J L_r} x_4 & \frac{n_p M}{J L_r} x_3 & \frac{n_p M}{J L_r} x_2 & -\frac{n_p M}{J L_r} x_1 & -\frac{1}{J} b_n + \theta_3(t)/J \end{bmatrix}$$

(5.39)

Finally, we have to arrange (5.39) according to the form of the state error equation, so

$$\frac{\partial f\left(\xi_i, \theta(t)\right)}{\partial x} =$$

$$\begin{bmatrix} -\gamma_n & 0 & \frac{k_s}{\tau_{rn}} & 0 & 0 \\ 0 & -\gamma_n & 0 & \frac{k_s}{\tau_{rn}} & 0 \\ \frac{M}{\tau_{r\,n}} & 0 & -\frac{1}{\tau_{rn}} & 0 & 0 \\ 0 & \frac{M}{\tau_{rn}} & 0 & -\frac{1}{\tau_{rn}} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{J} b_n \end{bmatrix} + \begin{bmatrix} -\frac{\theta_1(t)}{\sigma L_s} - \frac{\theta_2(t)}{\sigma L_r}(1-\sigma) & 0 & \frac{k_s\,\theta_2(t)}{L_r} & 0 & 0 \\ 0 & -\frac{\theta_1(t)}{\sigma L_3} - \frac{\theta_2(t)}{\sigma L_r}(1-\sigma) & 0 & \frac{k_s\,\theta_2(t)}{L_r} & 0 \\ \frac{M\theta_2(t)}{L_r} & 0 & -\frac{\theta_2(t)}{L_r} & 0 & 0 \\ 0 & \frac{M\theta_2(t)}{L_r} & 0 & -\frac{\theta_2(t)}{L_r} & 0 \\ 0 & 0 & 0 & 0 & -\frac{\theta_3(t)}{J} \end{bmatrix}$$

$$+x_1(t) \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{M\theta_2(t)}{0.85 L_r} - \frac{M}{0.85\tau_{rn}} & 0 & 0 & -n_p \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{n_p M}{J L_r} & 0 \end{bmatrix}$$

$$+x_2(t) \begin{bmatrix} 0 & 2M\frac{\theta_2(t)}{0.85 L_r} + \frac{2M}{0.85\tau_{rn}} & 0 & 0 & n_p \\ 0 & -\frac{M\theta_2(t)}{0.85 L_r} - \frac{M}{0.85\tau_{rn}} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{M\theta_2(t)}{0.85 L_r} + \frac{M}{0.85\tau_{rn}} & 0 \\ 0 & 0 & -\frac{M\theta_2(t)}{0.85 L_r} - \frac{M}{0.85\tau_{rn}} & 0 & 0 \\ 0 & 0 & +\frac{n_p M}{J L_r} & 0 & 0 \end{bmatrix}$$

$$+x_3(t)\begin{bmatrix}0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & -k_s n_p\\ 0 & 0 & 0 & 0 & 0\\ 0 & -\frac{M\theta_2(t)}{0.85L_r}-\frac{M}{0.85\tau_{rn}} & 0 & 0 & 0\\ 0 & \frac{n_pM}{JL_r} & 0 & 0 & 0\end{bmatrix}+x_4(t)\begin{bmatrix}0 & n_p & 0 & k_s n_p & 0\\ 0 & M\frac{\theta_2(t)}{0.85L_r}+\frac{M}{0.85\tau_{rn}} & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0\\ -\frac{n_pM}{JL_r} & 0 & 0 & 0 & 0\end{bmatrix}$$

$$+x_5(t)\begin{bmatrix}0 & n_p & 0 & k_s n_p & 0\\ -n_p & 0 & -k_s n_p & 0 & 0\\ 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0\end{bmatrix} \tag{5.40}$$

We can affect each matrix found in (5.40) by the following matrices, so, the gradient:

$$\begin{aligned}\frac{\partial f}{\partial x}\left(\xi_i,\theta(t)\right) &= A_c+\theta_1(t).A\theta_1+\theta_2(t).A\theta_2+\theta_3(t).A\theta_3+x_1(t).Ax_1(\theta_1,\theta_2,\theta_3)\\ &\quad +x_2(t).Ax_2(\theta_1,\theta_2,\theta_3)+x_3(t).Ax_3(\theta_1,\theta_2,\theta_3)+x_4(t).Ax_4(\theta_1,\theta_2,\theta_3)\\ &\quad +x_5(t).Ax_5(\theta_1,\theta_2,\theta_3)\end{aligned} \tag{5.41}$$

$$\begin{aligned}\frac{\partial f}{\partial x}\left(\xi_i,\theta(t)\right) &= A_c+\theta_1(t).A\theta_1+\theta_2(t).A\theta_2+\theta_3(t).A\theta_3+x_1(t).(Ax_{c1}+\theta_1.Ax\theta_{11}\\ &\quad +\theta_2.Ax\theta_{12}+\theta_3.Ax\theta_{13})+\cdots\dots\dots+x_5(t).(Ax_{c5}+\theta_1.Ax\theta_{51}\\ &\quad +\theta_2.Ax\theta_{52}+\theta_3.Ax\theta_{52}).\end{aligned} \tag{5.42}$$

First, we apply a sector nonlinear method to the premise variable ξ in (5.42):

$$\begin{aligned}\frac{\partial f}{\partial x}\left(\xi_i,\theta(t)\right) &= A_c+\theta_1(t).A\theta_1+\theta_2(t).A\theta_2+\theta_3(t).A\theta_3+\overline{\delta}_1(t)\overline{\xi}_1.(Ax_{c1}+\theta_1Ax\theta_{11}\\ &\quad +\theta_2Ax\theta_{12}+\theta_3Ax\theta_{13})+\underline{\delta}_1(t)\underline{\xi}_1.(Ax_{c1}+\theta_1.Ax\theta_{11}+\theta_2.Ax\theta_{12}\\ &\quad +\theta_3.Ax\theta_{13})\cdots\cdots\cdots+\overline{\delta}_5(t)\overline{\xi}_5.(Ax_{c5}+\theta_1.Ax\theta_{51}+\theta_2.Ax\theta_{52}\\ &\quad +\theta_3.Ax\theta_{53})+\underline{\delta}_5(t)\underline{\xi}_5(Ax_{c5}+\theta_1Ax\theta_{51}+\theta_2Ax\theta_{52}+\theta_3Ax\theta_{53}).\end{aligned} \tag{5.43}$$

Next, we continue to apply a sector nonlinear to the permissible variable θ_i and to make things more clear, we treat only two cases as an example, the first and the last term of (5.43)

At this stage, we use SNL to the varying parameters in (5.43), and then it becomes:

$$\begin{aligned}\frac{\partial f}{\partial x}(\xi i, \theta(t)) &= Ac + (\overline{h}_1(\theta_1(t))\overline{\theta}_1.A\theta_1 + \underline{h}_1(\theta_1(t))\underline{\theta}_1.A\theta_1) + \cdots \\ &+ \overline{\delta}_1(t)\overline{\xi}_1(Ax_{c1} + \overline{h}_1(\theta_1(t))\overline{\theta}_1.Ax\theta_{11} + \underline{h}_1(\theta_1(t))\underline{\theta}_1.Ax\theta_{11} \\ &+ \cdots \underline{h}_3(\theta_3(t))\underline{\theta}_3 .Ax\theta_{13}) \ldots \\ &+ \cdots \underline{\delta}_5(t)\underline{\xi}_5(Ax_{c5} + (Ax_{c1} + \overline{h}_1(\theta_1(t))\overline{\theta}_1.Ax\theta_{51} \ldots \ldots \overline{h}_3(\theta_3(t))\overline{\theta}_3.Ax\theta_{53} \\ &+ \underline{h}_3(t)\underline{\theta}_3.Ax\theta_{53}\end{aligned} \tag{5.44}$$

$$\begin{aligned}\frac{\partial f}{\partial x}(\xi i, \theta(t)) &= Ac + \overline{h}_1(\theta_1(t))\overline{\theta}_1.A\theta_1 + \underline{h}_1(\theta_1(t))\underline{\theta}_1.A\theta_1 \ldots + \overline{\delta}_1\left(\xi_1(t)\right).\overline{\xi}_1 .Ax_{c1} \\ &+ \overline{\delta}_1(\xi_1(t)).\overline{h}_1(\theta_1(t))\overline{\xi}_1\overline{\theta}_1.Ax\theta_{11} \\ &+ \overline{\delta}_1(\xi_1(t))\underline{h}_1(\theta_1(t))\underline{\theta}_1\overline{\xi}_1.Ax\theta_{11} \ldots. + \underline{\delta}_5\left(\xi_5(t)\right)\underline{\xi}_5.Ax_{c5} \\ &+ \underline{\delta}_5(\xi_5(t))\overline{h}_3(\theta_3(t))\underline{\xi}_5\overline{\theta}_3.Ax\theta_{53} + \underline{\delta}_5(\xi_1(t))\underline{h}_3(\theta_3(t))\underline{\xi}_5\underline{\theta}_3.Ax\theta_{53}\end{aligned} \tag{5.45}$$

If we replace (5.45) in the state error control equation (5.24), so

$$\begin{aligned}\dot{e}_c(t) = \Big(&-B_0K_0 + Ac + \overline{h}_1(\theta_1(t))\overline{\theta}_1.A\theta_1 + \underline{h}_1(t)\underline{\theta}_1.A\theta_1 + \cdots + \overline{\delta}_1(\xi_1(t))\overline{\xi}_1 .Ax_{c1} \\ &+ \overline{\delta}_1(\xi_1(t))\overline{h}_1(\theta_1(t))\overline{\theta}_1\overline{\xi}_1.Ax\theta_{11} + \overline{\delta}_1(\xi_1(t))\underline{h}_1(\xi_1)\underline{\theta}_1\overline{\xi}_1.Ax\theta_{11} \\ &+ \ldots\ldots + \underline{\delta}_5(\xi_5(t))\underline{\xi}_5.Ax_{c5}.\underline{\delta}_5(\xi_1(t))\overline{h}_3(\theta_3(t))\underline{\xi}_5\overline{\theta}_3.Ax\theta_{53} \\ &+ \underline{\delta}_5(\xi_1(t))\underline{h}_3(t)\underline{\xi}_5\underline{\theta}_3.Ax\theta_{53}\Big)e_c(t) + D_v v(t) - \dot{x}_c(t) + A_{ij}x_c(t)\end{aligned} \tag{5.46}$$

The (5.46) can be expressed in general form as follow:

$$\dot{e}_c(t) = \Bigg(Ac - B_0K_0 + \sum_{j=1}^{3} (\overline{h}_j\left(\theta_j(t)\right)\overline{\theta}_j.A\theta_j + \underline{h}_j(t)\underline{\theta}_j\,.A\theta_j)$$
$$+ \sum_{i=1}^{5} (\overline{\delta}_i(\xi_i)\overline{\xi}_i\,.Ax_{ci} + \underline{\delta}_i(\xi_i)\underline{\xi}_i.Ax_{ci})$$
$$+ \sum_{i=1}^{m=5} \sum_{j=1}^{n_{\theta=3}} (\,\overline{\delta}_i(\xi_i)\overline{h}_j\left(\theta_j(t)\right)\overline{\theta}_j\overline{\xi}_i.Ax\theta_{ij} + \overline{\delta}_i(\xi_i)\underline{h}_j(\theta_j(t))\underline{\theta}_1\overline{\xi}_j\,.Ax\theta_{ij}$$
$$+ \underline{\delta}_i(\xi_i)\overline{h}_j\left(\theta_j(t)\right)\underline{\xi}_i\overline{\theta}_j.Ax\theta_{ij} + \underline{\delta}_i(\xi_i)\underline{h}_j(\theta_j(t))\underline{\xi}_i\underline{\theta}_j\,.Ax\theta_{ij})\Bigg)e_c(t) + D_v v(t)$$
$$- \dot{x}_c(t) + A_{ij}x_c(t) \tag{5.47}$$

To simplify the form of the result (5.47), we need to scale to one all terms, so:

$$\sum_{i=1}^{m<n*n} (\overline{\delta}_i + \underline{\delta}_i) \sum_{j=1}^{n_\theta} (\overline{h}_j + \underline{h}_j) = m * n_\theta \tag{5.48}$$

Then, (5.47) becomes

$$\dot{e}_c(t) = \sum_{i=1}^{m=5<n\times n=25} \sum_{j=1}^{n_\theta=3} \frac{\left(\overline{\delta}_i(\xi) + \underline{\delta}_i(\xi)\right)\left(\overline{h}_j(\theta) + \underline{h}_j(\theta)\right)}{m \times n_\theta} \Big\{\Big(Ac - B_0K_0 + n_\theta$$
$$* \left(\overline{\theta}_j.A\theta_j + \underline{\theta}_j.A\theta_j\right) + m * \left(\overline{\xi}_i\,.Ax_{ci} + \underline{\xi}_i.Ax_{ci}\right) + m * n_\theta(\overline{\theta}_j\overline{\xi}_i.Ax\theta_{ij}$$
$$+ \underline{\theta}_1\overline{\xi}_j.Ax\theta_{ij} + \underline{\xi}_i\overline{\theta}_j.Ax\theta_{ij} + \underline{\xi}_i\underline{\theta}_j.Ax\theta_{ij})\Big) e_c(t) + D_v v(t) - \dot{x}_c(t)$$
$$+ A_{ij}x_c(t)\Big\} \tag{5.49}$$

And if we attribute

$$A\theta_j^1 = \overline{\theta}_j.A\theta_j, A\theta_j^2 = \underline{\theta}_1.A\theta_j \quad \text{and} \quad Ax_{ci}^1 = \overline{\xi}_i\,.Ax_{ci}, Ax_{ci}^2 = \underline{\xi}_i\,.Ax_{ci}\,;$$
$$Ax\theta_{ij}^{11} = \overline{\theta}_j\overline{\xi}_i.Ax\theta_{ij}Ax\theta_{ij}^{12} = \underline{\theta}_1\overline{\xi}_j.Ax\theta_{ij}, Ax\theta_{ij}^{21} = \underline{\xi}_i\overline{\theta}_j.Ax\theta_{ij},$$
$$Ax\theta_{ij}^{22} = \underline{\xi}_i\underline{\theta}_j.Ax\theta_{ij} \tag{5.50}$$

$$A_{ij} = Ac + n_\theta * \left(\overline{\theta}_j . A\theta_j + \underline{\theta}_j . A\theta_j\right) + \ m * \left(\overline{\xi}_i . Ax_{ci} + \underline{\xi}_i . Ax_{ci}\right) + m * n_\theta(\overline{\theta}_j \overline{\xi}_i . Ax\theta_{ij}$$
$$+ \underline{\theta}_1 \overline{\xi}_j . Ax\theta_{ij} + \underline{\xi}_i \overline{\theta}_j . Ax\theta_{ij} + \underline{\xi}_i \underline{\theta}_j . Ax\theta_{ij})$$

(5.49) becomes

$$\dot{e}_c(t) = \sum_{i=1}^{5=<n\times n} \sum_{j=1}^{n_\theta=3} (h_{ij}^{kl}(\xi,\theta)) \{ (Ac - \mathrm{B}_0\mathrm{K}_0 + n_\theta \times (A\theta_j^l) + m \times (Ax_{ci}^k) + m \times n_\theta \times$$
(Axθijkl)ect+Dvvt−xct+(Aijkl)xct With k=1,2 and l=1,2. (5.51)

With the new following designation

$$h_{11}^{11}(\xi,\theta) = \frac{\overline{\delta}_1(\xi_1)\overline{h}_1(\theta_1(t)}{5\times 3} \; ; h_{11}^{12}(\xi,\theta) = \frac{\overline{\delta}_1(\xi_1)\underline{h_1}(\theta_1(t))}{5\times 3}; \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.; \quad (5.52)$$
$$h_{53}^{22}(\xi,\theta) = \frac{\underline{\delta}_5(\xi_5)\underline{h}_3(\theta_3(t))}{5\times 3}.$$

Then the final state error equation control (5.51) can be expressed as it is expected:

$$\dot{e}_c(t) = \sum_{i=1}^{m=<n\times n} \sum_{j=1}^{n_\theta} h_{ij}^{kl}(\xi,\theta) \left\{ \left(A_{ij}^{kl} - B_0K_0\right)e_c(t) + D_v v(t) - \dot{x}_c(t) + A_{ij}^{kl} x_c(t) \right\} \quad (5.53)$$

With k = 1,2 and l = 1,2 and

$$A_{ij}^{kl} = \left(Ac + n_\theta \times (A\theta_j^l) + m \times (Ax_{ci}^k) + m \times n_\theta \times (Ax\theta_{ij}^{kl})\right) \quad (5.54)$$

5.3.3.2 Simulation results for closed loop FOC:

A rotor speed reference of 180 rad/s is chosen for the high-speed test that started from t = 0s and ends at t = 3sec. While for the medium-speed test, a speed value of 120 rad/sec is applied between the instant t=3sec and t = 6s. In order to obtain the FOC conditions, the q-axis rotor flux reference remain at zero Wb in all simulation time and the rotor flux reference at the value of 0.851Wb which is oriented along the d-axis as in chapter four. For proving the robustness of the proposed approach, three disturbances are taken into consideration those are the load torque and variations of the stator resistance, rotor resistance and friction coefficient b.

Initially, the motor is unloaded, after that, a load torque of 4 N.m is applied to the IM's machine from t = 2sec and degraded to 2N.m s at t=4sec until the end of the simulation time.

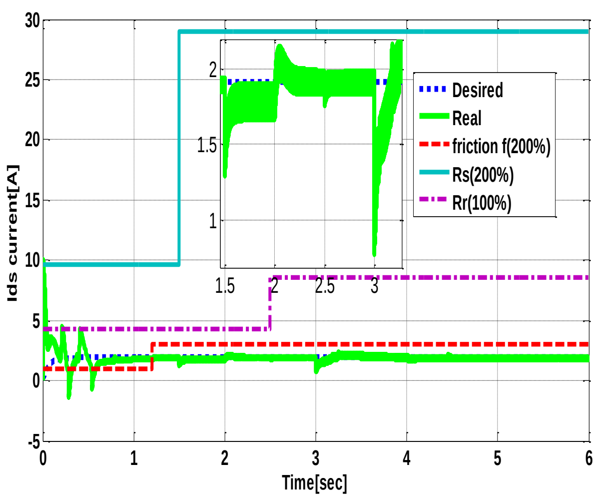
For the parameters variations test, we took the following variations:

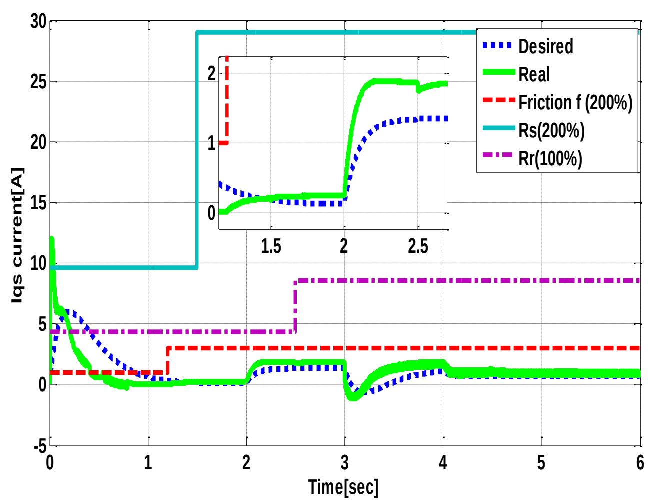
- ✓ Variation of R_r is considered to be 100% from the nominal value and at t= 1.5sec
- ✓ $R_s$is increased to 200% of the nominal value at t= 2.5sec
- ✓ The friction coefficient b is increased 200% at t=1.2sec.

The exploitation of the YALMIP software computer allows finding the PI-controller gainK_I:

$$K_1 = \begin{bmatrix} 0.209 & 1650 & -0.742 & 0.511 & 0.281 \\ 17.322 & 1.714 & 5.202 & -908.445 & -3.121 \end{bmatrix};$$

$$K_2 = \begin{bmatrix} 21.501 & -1.150 & 0.321 & 0.0251 & -0.232 \\ -270.305 & 11.270 & 241.152 & -1508.120 & 23.129 \end{bmatrix}$$





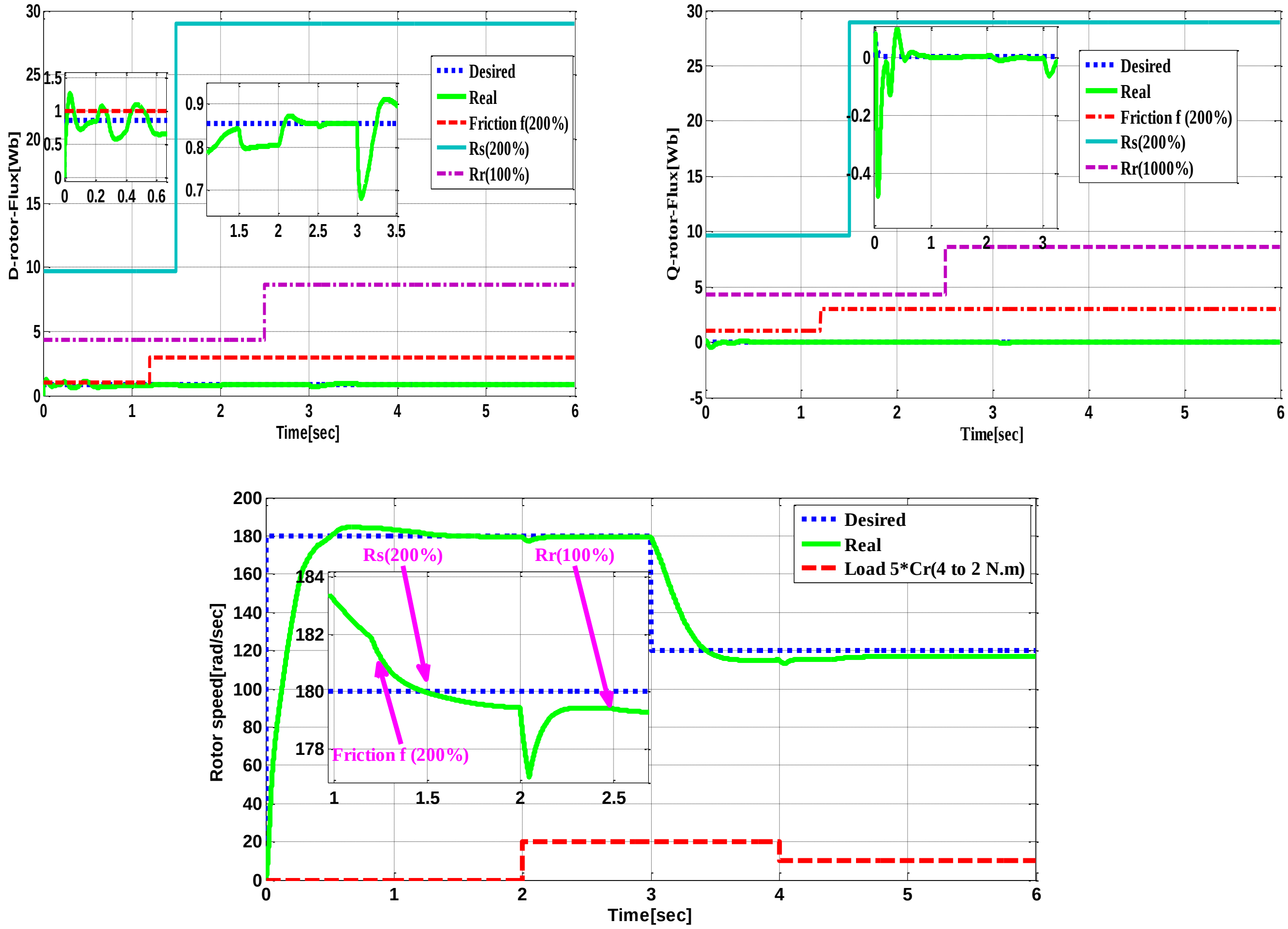


Figure 5.3 Robust $H_{\infty} - PI$ controller of the IM machine under FOC states responses.

The simulation results of the MVT robust control based H_{∞} concept mentioned above show the effectiveness of this technic. For all the IM states, it is clear that the real states still closer to their desired values with a minimum errors. The rotor speed is close to its desired value with a minimum effect of the load torque and the parameters variations to the tracking error as indicated in figure 5.3. However of the high parameters variation of the rotor and stator resistances, the tracking error is approximately not considerable for all the IM states, this due to the independency between the controller gain and the IM states and the also to the missing of the decoupling block which is considered depend to the IM parameters in other methods of control. From the figure, we can note that the impact of the based *PI-MVT* controller when load torque is applied to the IM's machine an important reduction of the rotor speed error which shows the robustness of the proposed controller. We can notice also the d-axis stator flux remain near its value ($0.851Wb$), while the q-flux remains closer to zero Wb (=0Wb) in all conditions which demonstrates the decoupling and assure the field oriented control conditions. This shows also the efficiency of the proposed controller.

These simulation results prove and affirm the high effectiveness of the suggested robust PI-MVT controller. The rotor speed and the stator currents track the reference signals, which affirm the robustness of the proposed algorithm for load torque and parameters variations.

5.4 H_∞Extended MVT observer design for uncertain nonlinear systems:

Reconsidering the obtained uncertain nonlinear model with bounded varying parameters:

$$\begin{cases} \dot{x}(t) = A_0 x(t) + B_0 u(t) + \Phi\big(x(t), \theta(t)\big) + D_v v(t) \\ y(t) = C_0 x(t) \end{cases} \tag{5.55}$$

Where A_0 andB_0 are defined as the nominal matrices with $\Phi(x(t), \theta) = f(x(t), \theta) - A_0 x(t)$which depends on the system state x(t) and the parameter θ(t), an extended state and parameter observer may be designed and implemented. An $\boldsymbol{L_2}$ attenuation approach is proposed to minimize the effect of the time-varying parameters on the state and parameter error estimations.

The proposed extended state and parameter observer of system (5.55) is taken inspired from the TS uncertain model representation of [23-25]:

$$\begin{cases} \dot{\hat{x}}(t) = A_0 \hat{x}(t) + B_0 u(t) + \Phi\left(\hat{x}(t), \hat{\theta}(t)\right) + L_1(y - \hat{y}) \\ \dot{\hat{\theta}}(t) = L_2 \hat{\theta} + L_3(y - \hat{y}) \end{cases} \tag{5.56}$$

Where $L_1 \in R^{n\times n}, L_2 \in R^{n_\theta \times n_\theta} and\ L_3 \in R^{n_\theta \times ny}$are the gains to be determined such that the estimated state and parameter converge to the actual system state and parameters.

The state estimation error$e_x$and $e_\theta$are defined as

$$e_x(t) = x(t) - \hat{x}(t) \tag{5.57}$$

$$e_\theta(t) = \theta(t) - \hat{\theta}(t) \tag{5.58}$$

We replace (5.57) and (5.58) in the equation of (5.56), the combined state and the parameter error equation becomes using MVT theorem, so:

$$\begin{cases} \dot{e_x}(t) = A_0 e_x(t) + \Big(\varphi\big(x(t), \theta(t)\big) - \hat{\varphi}\big(\hat{x}(t), \hat{\theta}(t)\big)\Big) - L_1 C_0\, e_x(t) + D_v v(t) \\ \dot{e}_\theta(t) = L_2 e_\theta(t) - L_3 C_0\, e_x(t) - L_2 \theta + \dot{\theta} \end{cases} \tag{5.59}$$

Then, the first equation of (5.59) can be transformed to

$$\dot{e_x}(t) = \left(A_0 + \sum_{i=1}^{n}\sum_{j=1}^{n} e_n(i)\, e_n^T(j) \frac{\partial \varphi_i}{\partial x_j}(\xi_i) \right) e_x(t) + \sum_{i=1}^{n}\sum_{j=1}^{n\theta} e_n(i)\, e_n^T(j) \frac{\partial \varphi_i}{\partial \theta_j}(\zeta^i) e_\theta(t) - L_1 C_0 C e_x(t) + D_v v(t) \tag{5.60}$$

With:

$$\dot{e_x}(t) = \dot{x}(t) - \dot{\hat{x}}(t) \tag{5.61}$$

$$\dot{e}_\theta(t) = \dot{\theta}(t) - \dot{\hat{\theta}}(t) \tag{5.62}$$

At this stage, one need to develop and determine the extended observer gains $L_1, L_2\ and\ L_3$ based on the combined state and the parameter error equations which is given in a compact form as:

$$\begin{pmatrix} \dot{e_x} \\ \dot{e}_\theta \end{pmatrix} = \sum_{i=1}^{2p} \grave{h}_i(\zeta) \begin{pmatrix} A_{cx} - L_1 C_0 + (p * \zeta_i * Ax_i) A_{c\theta} + (p * \zeta_i * A\theta_i) \\ - L_3 C_0 L_2 \end{pmatrix} \begin{pmatrix} e_x \\ e_\theta \end{pmatrix} + \begin{bmatrix} D_v & 0 & 0 \\ 0 & -L_2 & I \end{bmatrix} \overline{w}(t) \tag{5.63}$$

With

$$\bar{w}(t) = \begin{bmatrix} v(t) \\ \theta(t) \\ \dot{\theta}(t) \end{bmatrix}; D_w = \begin{bmatrix} D_v & 0 & 0 \\ 0 & -L_2 I \end{bmatrix} \tag{5.64}$$

If we take

$$S_i = \begin{bmatrix} A_{cx} - L_1 C_0 + \left(p * \zeta_i * Ax_i\right) A_{c\theta} + (p * \zeta_i * A\theta_i) \\ - L_3 C_0 L_2 \end{bmatrix} \tag{5.65}$$

Then,(5.63) becomes

$$\dot{z}(t) = \sum_{i=1}^{2p} \grave{h}_i(\zeta) * S_i z(t) + D_w \bar{w}(t) \tag{5.66}$$

Such that $z(t) = \begin{pmatrix} e_x \\ e_\theta \end{pmatrix}$ with$p = (n_\theta + m)$ whichrepresents the total number of the states and parameters together of the IM's machine model.

Therefore, our objective is to design the extended state and parameter observer with a minimal $z(t)$ withL_2gain of the transfer from $\bar{w}(t)$to $z(t)$.The computation of the observer gains is detailed in the next theorem.

Theorem 5. 3: There exists a robust extended state and parameter observer (5.63) for a nonlinear time-varying parameter system (5.23) with an L2 gains from $\mathbf{\overline{w}(t)}$to $\mathbf{z(t)}$bounded if there exists symmetric positive definite matrices $\mathbf{P_1}$, $\mathbf{P_2}$and a positive scalar $\beta = \boldsymbol{\gamma}^2$solutions of the optimization problem under the following constraints for i = 1, . . . , p :

$$\begin{pmatrix} \begin{bmatrix} AAx_i^T P_1 + P_1 AAx_i - C_0{}^T M - MC_0 & -C_0{}^T R^T + P_1 AA\theta_i \\ -RC_0 + AA\theta_i^T P_1 & -N^T - N \end{bmatrix} & \begin{bmatrix} P_1 D_v & 0 & 0 \\ 0 & N & P_2 \end{bmatrix} & [I_0] \\ \begin{bmatrix} D_v{}^T P_1 & 0 \\ 0 & N^T \\ 0 & P_2 \end{bmatrix} & -\gamma^2 I & 0 \\ [I_0] & 0 & -[I_0] \end{pmatrix} < 0$$

(5.67)

Where

$$\boldsymbol{AAx_i = \left(A_{cx} + (p * \zeta_i * Ax_i)\right)} \textbf{\textit{ and }} \boldsymbol{AA\theta_i = \left(A_{c\theta} + (p * \zeta_i * A\theta_i)\right)}$$

The observer gains are$L_1 = P_1^{-1} M L_2 = P_2^{-1} N$ ***and*** $L_3 = P_2^{-1} R$.

Where $\boldsymbol{L_1 \in R^{nxn}, L_2 \in R^{n_\theta \times n_\theta}}$ ***and*** $\boldsymbol{L_3 \in R^{n_\theta \times ny}}$.

5.4.1 Proof of the theorem5.3:

The existence of the disturbances $\overline{w}(t)$ will affect the estimator performances, so as to minimize the effect of the disturbance $\overline{w}(t)$, the H_∞ performances has been taken into account [69].Such that:

$$\int_0^\infty z^T(t) z(t)\, dt \le \gamma^2 \int_0^\infty \overline{w}^T(t)\, \overline{w}(t)\, dt \tag{5.68}$$

Consider the quadratic Lyapunov function as:

$$V\big(z(t)\big) = z^T(t)Pz(t) \tag{5.69}$$

Using (5.69), its time derivative is given by

$$\dot{V}\big(z(t)\big) = \dot{z}^T(t)Pz(t) + z^T(t)P\dot{z}(t) \tag{5.70}$$

Where $P = P^T > 0$

To develop the asymptotic stability of (5.63) and attain the H_∞ performance of the state and parameter estimation errors, it is known that z(t) is asymptotically converges toward zero and the *L2* gain from $\overline{w}(t)$ to $z(t)$ is bounded by β= γ^2 if the following inequality holds

$$\dot{V}\big(z(t)\big) + z^T(t)z(t) - \gamma^2\overline{w}^T(t)\overline{w}(t) < 0 \tag{5.71}$$

The previous equation becomes an LMI's form as next:

$$\dot{z}^T(t)Pz(t) + z(t)^T P\dot{z}(t) + z^T(t)z(t) - \gamma^2\overline{w}^T(t)\overline{w}(t) < 0 \tag{5.72}$$

This is equivalent to:

$$\sum_{i=1}^{2p} h_i(\xi,\theta)\, z^T(t)\big[S_i{}^T P + PS_i + I_0\big]z(t) + \overline{w}^T(t)\big[D_w{}^T P\big]z(t) + z^T(t)[PD_w]\overline{w}(t) - \gamma^2\overline{w}^T(t)\overline{w}(t) < 0 \tag{5.73}$$

Then, it is possible to present the last equation as:

$$\sum_{i=1}^{2p} h_i(\xi,\theta)\,[z^T(t) \quad \overline{w}^T(t)]\begin{bmatrix}\big[S_i{}^T P + P\bar{S}_i + I_0\big] & PD_w \\ D_w{}^T P & -\gamma^2 I\end{bmatrix}\begin{bmatrix} z(t) \\ \overline{w}(t)\end{bmatrix} < 0 \tag{5.74}$$

$$\dim\ I_0 = (m + n_\theta) \times (m + n_\theta), dim(I) = (n_\theta + m + m) \times (n_\theta + m + m) \tag{5.75}$$

The stability is considered in the following part:

$$\sum_{i=1}^{2p} h_i(\xi,\theta)\begin{bmatrix}[S_i{}^T P + PS_i] + I_0 & PD_w \\ D_w{}^T P & -\gamma^2 I\end{bmatrix} < 0 \tag{5.76}$$

After, we arrange (5.76), firstly as:

$$\sum_{i=1}^{2p} h_i(\xi,\theta)\begin{bmatrix}[S_i{}^T P + PS_i] & PD_w \\ D_w{}^T P & -\gamma^2 I\end{bmatrix} + \begin{bmatrix}I_0 & 0 \\ 0 & 0\end{bmatrix} < 0 \tag{5.77}$$

And secondly:

$$\sum_{i=1}^{2p} h_i(\xi,\theta)\begin{bmatrix}[S_i{}^T P + PS_i] & PD_w \\ D_w{}^T P & -\gamma^2 I\end{bmatrix} + \begin{bmatrix}I_0 \\ 0\end{bmatrix}[I_0 \quad 0] < 0 \tag{5.78}$$

Using Schur's complement, (5.77) becomes as follow:

$$\sum_{i=1}^{2p} h_i(\xi,\theta)\begin{bmatrix}[S_i{}^T P + PS_i] & PD_w & I_0 \\ D_w{}^T P & -\gamma^2 I & 0 \\ I_0 & 0 & -I_0\end{bmatrix} < 0 \tag{5.79}$$

The stability depends only upon the following matrix:

$$\begin{bmatrix}S_i{}^T P + PS_i & PD_w & I_0 \\ D_w{}^T P & -\gamma^2 I & 0 \\ I_0 & 0 & -I_0\end{bmatrix} < 0 \tag{5.80}$$

For that purpose, a block diagonal structure for the Lyapunov matrices P is considered which is defined by:$P = diag(P1, P2)$:

And ,if we take $Q = \begin{bmatrix}S_i{}^T P + PS_i & PD_w & I_0 \\ D_w{}^T P & -\gamma^2 I & 0 \\ I_0 & 0 & -I_0\end{bmatrix} < 0$ (5.81)

Next, we start to evaluate each components in Q matrix:$AAx_i = \left(A_{cx} + (p * \zeta_i * Ax_i)\right)$ and $AA\theta_i = \left(A_{c\theta} + (p * \zeta_i * A\theta_i)\right)$

With$S_i = \begin{bmatrix}A_{cx} + (p * \zeta_i * Ax_i) - L_1 C_0 & A_{c\theta} + (p * \zeta_i * A\theta_i) \\ -L_3 C_0 & L_2\end{bmatrix}$; so

$$✓\quad {S_i}^T P = \begin{bmatrix} A_{cx} + (p * \zeta_i * Ax_i) - L_1 C_0 & A_{c\theta} + (p * \zeta_i * A\theta_i) \\ - L_3 C_0 & L_2 \end{bmatrix}^T \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix}$$

$$= \begin{bmatrix} [(A_{cx} + (p * \zeta_i * Ax_i) - L_1 C_0]^T P_1 & -[L_3 C_0]^T P_2 \\ [(A_{c\theta} + (p * \zeta_i * A\theta_i)]^T P_1 & -[L_2]^T P_2 \end{bmatrix} \tag{5.82}$$

$$✓\quad PS_i = \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} \begin{pmatrix} A_{cx} - L_1 C_0 + Ax_i A_{c\theta} + (p * \zeta_i * A\theta_i) \\ - L_3 C_0 L_2 \end{pmatrix}$$

$$= \begin{bmatrix} P_1(A_{cx} - L_1 C_0 + (p * \zeta_i * Ax_i)) & P_1(A_{c\theta} + (p * \zeta_i * A\theta_i)) \\ -P_2 L_3 C_0 P_2 L_2 & \end{bmatrix} \tag{5.83}$$

The combination of the two previous equations, which can be developed to:

$$✓\quad {S_i}^T P + PS_i = \begin{bmatrix} [(A_{cx} + (p * \zeta_i * Ax_i) - L_1 C_0]^T P_1 & -[L_3 C_0]^T P_2 \\ [(A_{c\theta} + (p * \zeta_i * A\theta_i)]^T P_1 & [L_2]^T P_2 \end{bmatrix} + \tag{5.84}$$

$$\begin{bmatrix} P_1(A_{cx} - L_1 C_0 + (p * \zeta_i * Ax_i)) & P_1(A_{c\theta} + (p * \zeta_i * A\theta_i)) \\ -P_2 L_3 C_0 P_2 L_2 & \end{bmatrix}.$$

Next, the term:

$$✓\quad PD_w = \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} \begin{bmatrix} D_v & 0 & 0 \\ 0 & L_2 & I \end{bmatrix} = \begin{bmatrix} P_1 D_v & 0 & 0 \\ 0 & P_2 L_2 & P_2 I \end{bmatrix} \tag{5.85}$$

And

$$✓\quad {D_w}^T P = \begin{bmatrix} D_v & 0 & 0 \\ 0 & L_2 & I \end{bmatrix}^T \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} = \begin{bmatrix} {D_v}^T P_1 & 0 \\ 0 & {L_2}^T P_2 \\ 0 & P_2 \end{bmatrix} \tag{5.86}$$

Finally, the Q matrix is obtained if we take:

$AAx_i = \left(A_{cx} + (p * \zeta_i * Ax_i)\right)$ and $AA\theta_i = \left(A_{c\theta} + (p * \zeta_i * A\theta_i)\right)$ with the following designation of these matrices in (5.86) :

$$\begin{bmatrix} \begin{bmatrix} [AAx_i - L_1 C_0]^T P_1 & -[L_3 C_0]^T P_2 \\ [AA\theta_i]^T P_1 & [L_2]^T P_2 \end{bmatrix} + \begin{bmatrix} (P_1 AAx_i - L_1 C_0 P_1 AA\theta_i) \\ -P_2 L_3 C_0 P_2 L_2 \end{bmatrix} & \begin{bmatrix} P_1 D_v & 0 & 0 \\ 0 & P_2 L_2 & P_2 I \end{bmatrix} & [I_0] \\ \begin{bmatrix} {D_v}^T P_1 & 0 \\ 0 & {L_2}^T P_2 \\ 0 & P_2 \end{bmatrix} & -\gamma^2 I & 0 \\ [I_0] & 0 & -[I_0] \end{bmatrix} \tag{5.87}$$

With the following designation of these matrices to:

$$M = P_1 L_1 \quad , \quad N = P_1 L_2 \ \text{ and } \ R = P_2 L_3 \tag{5.88}$$

Then, based on (5.87) and (5.88) , the time-varying term can be expressed in the final form of the LMI's that is written in the following form as expected which is stating the following sufficient condition for quadratic stability in the context of LMI formulation:

$$\begin{pmatrix} \begin{bmatrix} AAx_i^T P_1 + P_1 AAx_i - C_0{}^T M - MC_0 & -C_0{}^T R^T + P_1 AA\theta_i \\ -RC_0 + AA\theta_i^T P_1 & N^T + N \end{bmatrix} & \begin{bmatrix} P_1 D_v & 0 & 0 \\ 0 & N & P_2 \end{bmatrix} & [I_0] \\ \begin{bmatrix} D_v{}^T P_1 & 0 \\ 0 & N^T \\ 0 & P_2 \end{bmatrix} & -\gamma^2 I & 0 \\ [I_0] & 0 & -[I_0] \end{pmatrix} < 0 \qquad (5.89)$$

$$i, = 1, \dots, \mathrm{p}$$

And the gains can be found :

$L_1 = P_1^{-1} M \quad , L_2 = P_2^{-1} N$ and $L_3 = P_2^{-1} R$

5.5 Robust PI controller based extended observer design based on the MVT approach for the IM- FOC with uncertain parameters:

The proposed extended $H\infty$ observer design is applied to the IM's machine drives to estimate all the ordinary IM states (i_{ds}, i_{qs}, $\emptyset_{rd}$, $\emptyset_{rq}$ and ω_r) and the varying parameters $\Theta_i(t)$ where the global scheme of the proposed extended observer is presented in figure 5.4. In figures 5.5, the real states have the red line, while the dashed green line indicates the estimated states and parameters. Initially, the motor is unloaded, after that, a load torque of 4N.m is applied to the IM machine at t = 2sec that is given in figure 5.5. To show the effectiveness of the robust extended MVT observer, firstly, a reference speed is chosen 180 rad/sec for the first three seconds, and then it has increased to the nominal speed (120 rad/sec) from 3sec to 6sec. Secondly, the initial estimated states are taken as:

$[-2 \quad 4 \quad -0.4 \quad 0.2 \quad 20 \quad 4 \quad 8 \quad 1.2e-4]$.

The design of the MVT robust PI controller based robust extended observer approach for IM control strategy, which has been previously presented in figure 5.4 with uncertain parameters. The desired states and parameters are generated based on FOC conditions ($\emptyset_{rq}$=0) where the references generator should has the load torque as well as it is presented in sub-section 4.3.1. The MVT control approach are compared in this case, the control and estimation are presented in (a) and (b) respectively in the next figures in order to show the effectiveness of the MVT concept. The reference of the rotor speed is firstly chosen 180rad/sec for high speed test, whereas a reference of 120rad/sec is taken for the medium speed test at t=3sec. The IM motor is unloaded firstly, then a nominal load torque of 4 to 2 N.m is applied to the IM at t=2sec and t=4sec respectively. In this simulation test, it considered that the variations of the parameters are happened as follow:

$$\text{Parameters variations:} \begin{cases} Friction\ coefficent\ b\ (200\%)\ at\ t = 1.2sec \\ Rs(200\%)\ at\ t = 1.5sec \\ Rr\ (100\%)\ at\ t = 2.5sec \end{cases}$$

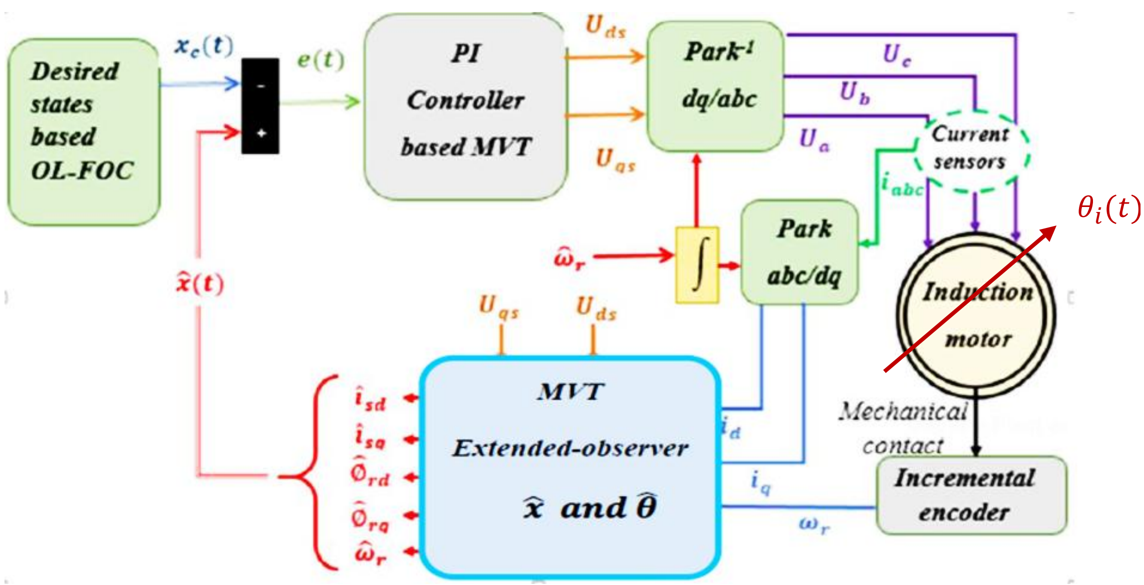


Figure5.4 PI- $H\infty$ controller based $H\infty$ MVT observer applied to the IM machine

Based on the general form of the extended observer, first, one should determine all the matrices components in the following states equation:

$$\begin{pmatrix} \dot{e_x} \\ \dot{e}_\theta \end{pmatrix} = \sum_{i=1}^{2p} h_i\,(\xi, \theta) \begin{pmatrix} A_{cx} - L_1\,C_0 + (\mathrm{p} * \zeta_i * Ax_i) & A_{c\theta} + (\mathrm{p} * \zeta_i * A\theta_i) \\ - L_3 C_0 & L_2 \end{pmatrix} \begin{pmatrix} e_x \\ e_\theta \end{pmatrix} + \begin{bmatrix} D_v & 0 & 0 \\ 0 & L_2 & I \end{bmatrix} \overline{w}(t) \tag{5.90}$$

With

$$\overline{w}(t) = \begin{bmatrix} v(t) \\ \theta(t) \\ \dot{\theta}(t) \end{bmatrix}, \quad \text{and } S_i = \begin{bmatrix} A_{cx} + \left(p * \zeta_i * Ax_i\right) - L_1\,C_0 & A_{c\theta} + (p * \zeta_i * A\theta_i) \\ - L_3 C_0 & L_2 \end{bmatrix}$$

Secondly, we will determine all components of the main matrix S_i if we treat only two parameters variations $\theta_1(t)$ and $\theta_2(t)$ as an example in order to clarify the application of the theorem.

So, the gradient becomes:

$$\frac{\partial f}{\partial x}(x_i, \theta(t)) = \begin{bmatrix} -\left(\gamma_n + \theta_1(t)/\sigma L_s\right) & \left(n_p x_5 + \frac{2M}{\tau_r\,\emptyset_{rdc}} x_2\right) & \frac{k_s}{\tau_r} & k_s\,n_p x_5 & (n_p x_2 + k_s\,n_p x_4) \\ -(n_p x_5 + \frac{2M}{\tau_r\,\emptyset_{rdc}} x_2) & -\left(\gamma_n + \theta_1(t)/\sigma L_s\right) - \frac{M}{\tau_r\,\emptyset_{rdc}} x_1 & -k_s\,n_p x_5 & \frac{k_s}{\tau_r} & \left(-k_s\,n_p x_3 - n_p x_1\right) \\ \frac{M}{\tau_r} & \frac{M}{\tau_r\,\emptyset_{rdc}} x_4 & -\frac{1}{\tau_r} & \frac{M}{\tau_r\,\emptyset_{rdc}} x_2 & 0 \\ 0 & \frac{M}{\tau_r} - \frac{M}{\tau_r\,\emptyset_{rdc}} x_3 & -\frac{M}{\tau_r\,\emptyset_r} x_2 & -\frac{1}{\tau_r} & 0 \\ -\frac{n_p M}{J L_r} x_4 & \frac{n_p M}{J L_r} x_3 & \frac{n_p M}{J L_r} x_2 & -\frac{n_p M}{J L_r} x_1 & -\frac{1}{J} b_n + \theta_2(t)/J \end{bmatrix} \tag{5.91}$$

We adjust (5.91) to

$$\frac{\partial f}{\partial x}(x_i,\theta(t)) = \begin{bmatrix} -\gamma_n & 0 & \frac{k_s}{\tau_r} & 0 & 0 \\ 0 & -\gamma_n & 0 & \frac{k_s}{\tau_r} & 0 \\ \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & 0 & 0 \\ 0 & \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{J}b_n \end{bmatrix} \tag{5.92}$$

$$+\begin{bmatrix} -\frac{\theta_1(t)}{\sigma L_s} & \left(n_p x_5 + \frac{2M}{\tau_r \emptyset_{rdc}}x_2\right) & 0 & k_s n_p x_5 & (n_p x_2 + k_s n_p x_4) \\ -(n_p x_5 + \frac{2M}{\tau_r \emptyset_{rdc}}x_2) & -\frac{\theta_1(t)}{\sigma L_s} - \frac{M}{\tau_r \emptyset_{rdc}}x_1 & -k_s n_p x_5 & 0 & (-k_s n_p x_3 - n_p x_1) \\ 0 & \frac{M}{\tau_r \emptyset_{rdc}}x_4 & 0 & \frac{M}{\tau_r \emptyset_{rdc}}x_2 & 0 \\ 0 & -\frac{M}{\tau_r \emptyset_{rdc}}x_3 & -\frac{M}{\tau_r \emptyset_{rdc}}x_2 & 0 & 0 \\ -\frac{n_p M}{J L_r}x_4 & \frac{n_p M}{J L_r}x_3 & \frac{n_p M}{J L_r}x_2 & -\frac{n_p M}{J L_r}x_1 & \frac{\theta_2(t)}{J} \end{bmatrix}$$

Next, we search all permissible vectors to put them in a normalized form

$$\frac{\partial f}{\partial x}\big(x(t),\theta(t)\big) =$$

$$\begin{bmatrix} -\gamma_n & 0 & \frac{k_s}{\tau_r} & 0 & 0 \\ 0 & -\gamma_n & 0 & \frac{k_s}{\tau_r} & 0 \\ \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & 0 & 0 \\ 0 & \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{J}b_n \end{bmatrix} + x_1(t)\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{M}{\tau_r \emptyset_{rdc}} & 0 & 0 & -n_p \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{\mathrm{n_p M}}{\mathrm{JL_r}} & 0 \end{bmatrix}$$

$$+x_2(t)\begin{bmatrix} 0 & \frac{2M}{0.85L_r} & 0 & 0 & n_p \\ -\frac{2M}{0.85\tau_r} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{M}{0.85\tau_r} & 0 \\ 0 & 0 & -\frac{M}{0.85\tau_r} & 0 & 0 \\ 0 & 0 & \frac{n_pM}{JL_r} & 0 & 0 \end{bmatrix} + \ldots + x_5(t)\begin{bmatrix} 0 & n_p & 0 & k_s n_p & 0 \\ -n_p & 0 & -k_s n_p & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$+\theta_1(t)\begin{bmatrix} -1/\sigma L_s & 0 & 0 & 0 & 0 \\ 0 & -1/\sigma L_s & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} + \theta_2(t)\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{J} \end{bmatrix} \tag{5.93}$$

So, in standard form, the gradient (5.93) is expressed as:

$$\frac{\partial f}{\partial x}\big(x(t), \theta(t)\big) = A_{cx} + x_1(t).Ax_1 + x_2(t).Ax_2 + x_3(t).Ax_3 + x_4(t).Ax_4 + x_5(t).Ax_5 + \theta_1(t)Ax_6 + \theta_2(t)Ax_7 \tag{5.94}$$

Next, we define

$$\frac{\partial f}{\partial \theta}\big(x(t), \theta(t)\big) = \begin{bmatrix} -x_1(t)/\sigma L_s & 0 \\ -x_2(t)/\sigma L_s & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & -\frac{x_5(t)}{J} \end{bmatrix} = x_1(t).A\theta_1 + x_2(t).A\theta_2 + x_5(t).A\theta_5 \tag{5.95}$$

Such that

$$A\theta_1 = \begin{bmatrix} -1/\sigma L_s & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}; A\theta_2 = \begin{bmatrix} 0 & 0 \\ -1/\sigma L_s & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \text{ And } A\theta_5 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & -\frac{1}{J} \end{bmatrix}$$

We apply the sector nonlinearities to the new defined augmented premise variable $\zeta = (\xi, \theta)$,

so (5. 94) and (5.95) became as

$$\frac{\partial f}{\partial x}(\zeta) = A_{cx} + \overline{\delta}_1(t)\overline{\zeta}_1 . Ax_1 + \underline{\delta}_1(t)\underline{\zeta}_1 Ax_1 + \cdots .. + \overline{\delta}_7(t)\overline{\zeta}_7 . Ax_7 + \underline{\delta}_7(t)\underline{\zeta}_7 Ax_7 \quad (5.96)$$

$$\frac{\partial f}{\partial \theta}(\zeta) = \zeta_1(t) . A\theta_1 + \zeta_2(t) . A\theta_{2+}\zeta_5(t) . A\theta_5 \quad (5.97)$$

$$= \overline{\delta}_1(t)\overline{\zeta}_1 . A\theta_1 + \underline{\delta}_1(t)\underline{\zeta}_1 A\theta_1 + \overline{\delta}_2(t)\overline{\zeta}_2 . A\theta_2 + \underline{\delta}_2(t)\underline{\zeta}_2 A\theta_1 + \overline{\delta}_5(t)\overline{\zeta}_5 . A\theta_5 + \underline{\delta}_5(t)\underline{\zeta}_5 A\theta_5$$

We replace (5.96) and (5.97) in the state error estimation equation, so:

$$\begin{pmatrix} \dot{e_x} \\ \dot{e_\theta} \end{pmatrix} = \begin{pmatrix} A_{cx} - L_1\, C_0 + \sum_{i=1}^{7*2\leq 2*p} h_i(\zeta)(\zeta_i * Ax_i)\, A_{c\theta} + \sum_{i=1}^{7*2\leq 2*p} h_i(\zeta)(\zeta_i * A\theta_i) \\ -L_3 C_0\, L_2 \end{pmatrix} \begin{pmatrix} e_x \\ e_\theta \end{pmatrix} + \begin{bmatrix} D_v & 0 & 0 \\ 0 & & L_2\, I \end{bmatrix} \overline{w}(t) \quad (5.98)$$

$$\begin{pmatrix} \dot{e_x} \\ \dot{e_\theta} \end{pmatrix} = \sum_{i=1}^{7*2\leq 2*\mathrm{p}} \grave{h_\iota}(\zeta) \begin{pmatrix} A_{cx} - L_1\, C_0 + (\mathrm{p} * \zeta_i * Ax_i) A_{c\theta} + (\mathrm{p} * \zeta_i * A\theta_i) \\ -L_3 C_0\, L_2 \end{pmatrix} \begin{pmatrix} e_x \\ e_\theta \end{pmatrix} + \begin{bmatrix} D_v & 0 & 0 \\ 0 & & L_2\, I \end{bmatrix} \overline{w}(t) \quad (5.99)$$

Such that:

$$\grave{h}_i(\zeta) = \frac{h_i(\zeta)}{\mathrm{p}}$$

$h_1(\zeta) = \overline{\delta}_1(\zeta)\,; h_2(\zeta) = \underline{\delta}_1(\zeta)$----------- $; h_{14}(\zeta) = \underline{\delta}_7(\zeta).$ (5.100)

With

$$\zeta = [\zeta_1\zeta_2 \dots \dots \dots \zeta_{2p}] = [\overline{\xi}_1\underline{\xi}_1 \dots \dots .. \overline{\xi}_5\underline{\xi}_5\overline{\theta}_1\underline{\theta}_1\overline{\theta}_2\underline{\theta}_2\,]$$

And

$D_v = -\frac{1}{J}$; $dim\, L_1 = 5 * 3$; $dim L_2 = 2 * 2$; $dim\, L_3 = 2 * 3$ and $dim\, I = 2 * 2$ (5.101)

The equation (5.99) could be written as in the following compact form:

$$\dot{z}(t) = \sum_{i=1}^{14} \grave{h}_i(\zeta) * S_i z(t) + D_w \overline{w}(t) \tag{5.102}$$

Such that

$$S_i = \begin{pmatrix} A_{cx} - L_1 C_0 + (\mathrm{p} * \zeta_i * Ax_i)A_{c\theta} + (\mathrm{p} * \zeta_i * A\theta_i) \\ - L_3 C_0 L_2 \end{pmatrix} \tag{5.103}$$

With $z(t) = \begin{pmatrix} e_x \\ e_\theta \end{pmatrix}$.

5.5.1Simulation results and discussions:

In this part we will simulate and present a results of a robust PI controller based robust extended observer using the MVT theory which is applied to the IM drive considered as uncertain system with varying parameters where the goals first ,is to get the controller and the observer gains from the two previous theorems.

The exploitation of the YALMIP software computer allows finding the controller and extended observer gains respectively:

$$K_1 = \begin{bmatrix} 0.209 & 1650 & -0.742 & 0.511 & 0.281 \\ 17.322 & 1.714 & 5.202 & -908.445 & -3.121 \end{bmatrix};$$

$$K_2 = \begin{bmatrix} 21.501 & -1.150 & 0.321 & 0.0251 & -0.232 \\ -270.305 & 11.270 & 241.152 & -1508.120 & 23.129 \end{bmatrix}$$

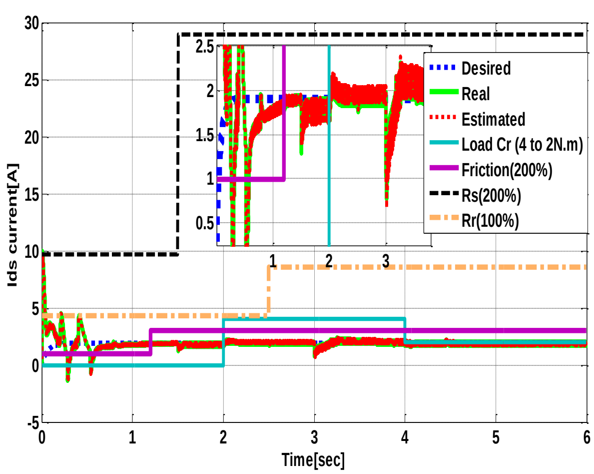
And $$L_1 = \begin{bmatrix} -2.4888 & 3.1130 & 2.4096^{-6} \\ -9.8266^{-5} & 1.3428 & 12.7270 \\ 0.0029 & 71.1755 & 3400.5 \\ -5.2944^{-5} & -1.3145 & -31.1879 \\ 0.001 & -6.5673^{-6} & 0.9999 \end{bmatrix};$$

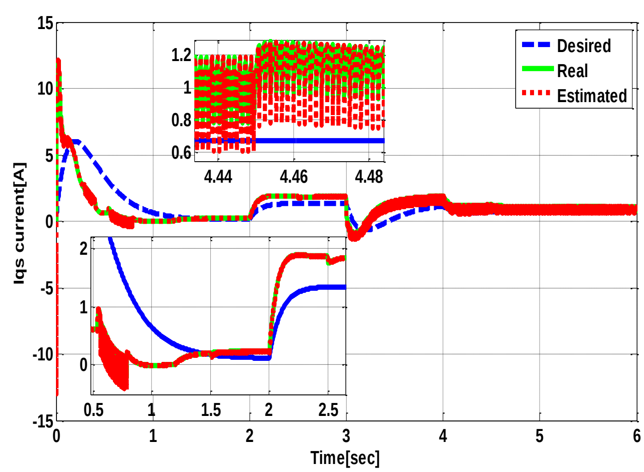
$$L_2 = 10^3 \begin{bmatrix} 0.0544 & 1.2789 & 12.025 \\ -0.002 & 0.0072 & -1.004 \\ -1.3145 & 0.950 & 6.005 \end{bmatrix};$$

$$L_3 = 10^2 \begin{bmatrix} 3.442 & -25.029 & 22.071 \\ -0.102 & 0.892 & -8.045 \\ -3.045 & 0.215 & -56.005 \end{bmatrix}$$

The resulting responses of all states and parameters of the IM machine under field-oriented control were given in Figure 5.5 The real q-axis stator current tracks its desired at the same time where the estimated state does the same, it is clear that the q-axis stator current is all a reproduction of the electromagnetic torque that proves that the FOC is assured. The estimated d-axis stator current follows its real where they track the desired value. It was also observed that the real and the estimated states of q-axis rotor flux stayed near zero ($\emptyset_{rq} = 0$), whereas its d-axis is around the rated rotor flux reference (0.851 Wb) which shows that the FOC is assured at the instant where the estimation errors is approximately zero. In addition, it has been observed that the estimated and the real states of the rotor speed are in closer proximity to its desired values. In despite of the application of the nominal load torque and parameter variations, all states subject to the control and the estimation conditions are not affected considerably, but only with a minimum effects on these conditions. The estimated states are closer to their real values despite the fact that the starting conditions of the estimated states are not zeros.

Through the simulation results given above, there is guaranteed success for the proposed robust PI-MVT controller-based robust extended observer and it can replace the other technics (adaptive control such as back stepping, sliding mode, nonlinear control ...etc.) in the industrial applications due to its effectiveness, simplicity, and low cost.





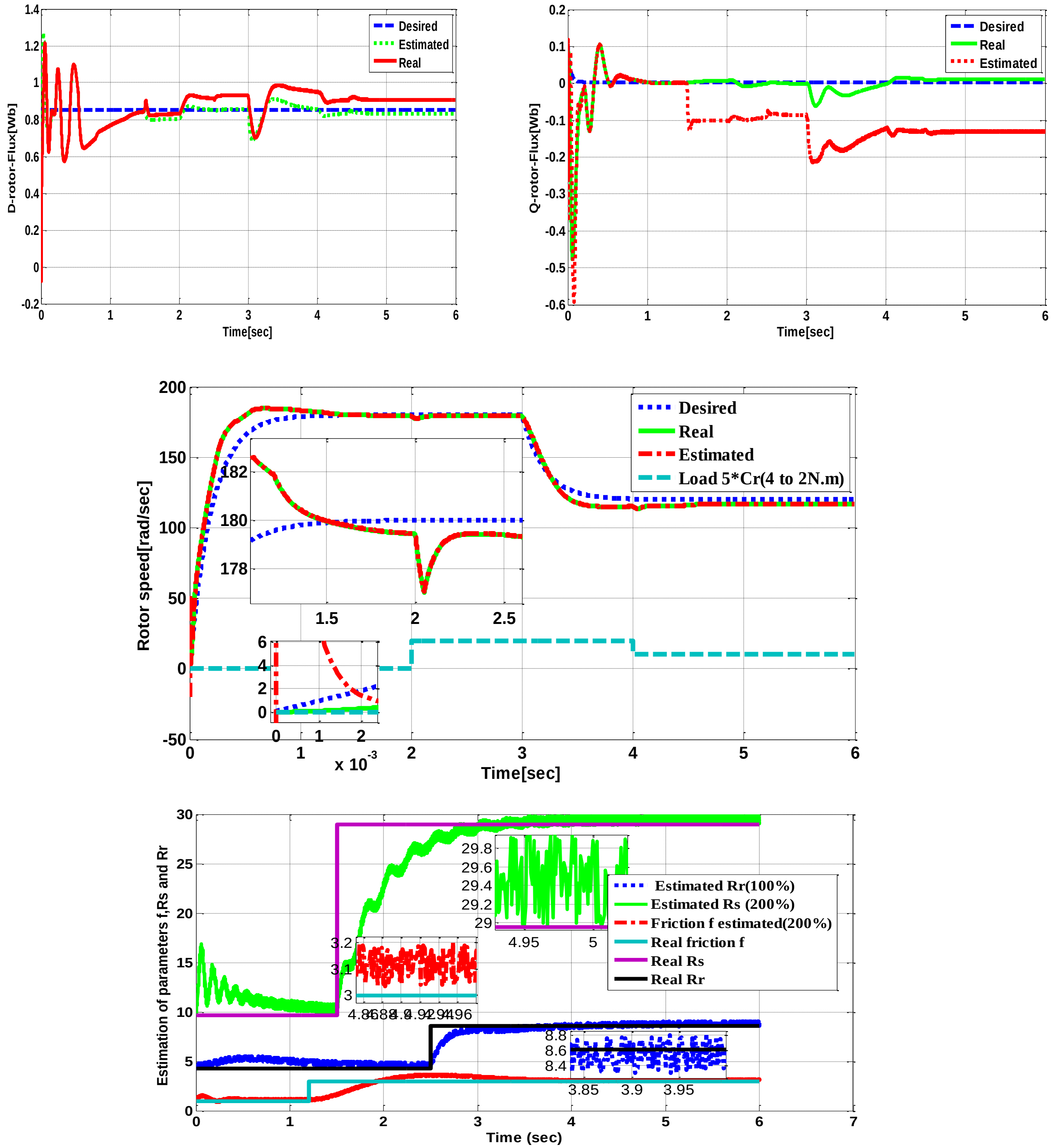


Figure 5.5states responses versus the load torque and parameters variations **(Rs ,Rr and f).**

Based on figure 5.5, the d and q axis stator currents are tracking their desired values with a minimum error approximately zero in all simulation time even in the application of the nominal load torque and varying parameters. The robust H_∞ control also show a minimum tracking error for the null speed test except for the rotor fluxes as presented in figures with a minimum errors. The effect of the load torque is not observable for the robust control where the speed decrease by 3rad/sec at the instant of application of the load torque for the normal control as indicated in the figures.

It is clear from the previous simulated results that the success of the robust control against the normal one that is very acceptable. However the MVT approach is simple to implement, these results show the effectiveness of the MVT approach, which can replace the previous complex technics.

The estimation error of d and q axis stator currents is approximately zero in the steady state, where the real and estimated states were around the desired states as proposed in figure 5.5. A maximum tracking error of 0.009Wb for the d-axis rotor flux, where it does not exceed 0.03Wb for the q-axis rotor flux. The success of the robust PI control based extended observer based on the MVT with a minimum effect of the load torque to the control and estimation errors and a minimum effect of them against different speeds tests.

The MVT approach for control based observer not only has a systematic and proven methodology, the gains of the controller and observer have been calculated separately and don't depend on the IM states, but also has good performances and efficiency as the previous results . These advantages of the MVT could allowing the exploitation of this strategy in many technical are as and industrial applications.

5.6 Conclusion:

In this chapter, we have firstly modeled the IM drive system with varying parameters as an uncertain system. A results of a robust PI controller based robust extended observer using the MVT theory was found which is applied to the IM drive considered as uncertain system with varying parameters where the goals first ,is to get the controller and the observer gains from a new two theorems which represent the main contribution of our work.

Then, the design and simulation of the robust control based H_∞ performance based on the MVT approach to the IM drive through the MATLAB/Simulink environment were carried out. In order to show the efficiency of this robust control, a comparison with a robust control and PI robust control-based observer has been presented. Based on the obtained simulated results mentioned above, it is clear that the effectiveness of the robust H_∞ MVT controller gave a high robustness on the tracking error even during an unpredictable load torque and parameters variations. Although, the controller based on MVT theory conducted to a good performance results due its simplicity, low cost implementation, consuming computation time even with a simple microcontroller showing no dependency between the controller parameters and the IM states in the implementation of the controller design. The main goals of this research work convinced us that theoretical results leading to a general and systematic methodology for proving the stability and determining the off line gains of the controller and observer as it was clarified compared to other technics when it is applied to uncertain nonlinear systems. These major advantages of the MVT approach could be a candidate in replacing all the previous control methods in the industrial applications. These algorithms which are taking into a count of parametric uncertainties that will be developed and proved and can be applied to the tolerant fault control and diagnosis systems. The implementation of the uncertain MVT controllers and observer design will be applied in to the IM drive in real experimental tests in order to confirm the agreement with the theoretical results.

Conclusions and future works

Conclusions

In the present work, a new systematic procedure is presented to deal with a new type of controller, which compensate the effect of parameters variation in the system and the estimation of state and parameter for nonlinear time-varying systems. It consists in transforming the combined control and estimation (states and parameters) errors dynamic system into a MVT model based on the sector non linearity approach and the convex polytopic transformation. This transformation has the advantage interest to represent exactly the uncertain system without any loss of information. A new parameter and state observer for the time-varying with unmeasured premise variables is proposed based on the L2 approach. The proposed controller and observer are then synthetized by solving the LMI optimization problem. The IM’s machine drives control is studied (function of a time-varying parameter). It was clearly shown that the variation of the rotor and stator resistances has a significant reduction effect on most of the system variables when the IM’s machine is implemented with these new controllers and observers.

From this observation, one can easily agree with the need for extended parameter and state estimation. The obtained results from the application example illustrate clearly the proposed approach performance. Therefore, as a future work, the authors intend to apply this procedure for fault detection and estimation and use the results for a Fault Tolerant Control (FTC) synthesis.

The work presented in this theses have the aim to show that the algorithms based on the nonlinear MVT theory and sector non-linearity must be used to the dynamics model of the nonlinear systems and to design stable and robust structures controllers and observers. The main contributions of this study lie with two topics. Firstly, the development of control methodologies based on the MVT approach essentially on the control of a three-phase IM's machine drives where the influence of the parameters uncertainties and/or disturbances on the performances command is taken into account. Secondly, a robust tracking control based on a robust extended observer scheme was proposed for the IM'machine drives as an uncertain nonlinear system affected only by load torque disturbance.

Indeed, the methods of robust and sensor-less control based on other techniques generally suffer from a limited area of convergence and a relatively high sensitivity vis-à-vis uncertainties and/or disturbances but also robustness in the presence of a parameters variation. We have tried to make both educational and practical manual that should allow the designer to deal with the control of electrical drives and have combining theory to implement practical and many applications of three-phase IM's machine control techniques which can be realized in many industrial domains.

Representation, synthesis and analysis tools such as MVT theory and convex transformations are necessary to implement the developed control techniques. These tools are summarized in chapters two. In chapter three, we are particularly interested in the modeling and using state feedback classical techniques of control and estimation of the IM synchronous machine by the MVT theory and SNL. Numerical simulation and practical tests were carried out to validate the feasibility of the used techniques.

In order to evaluate our contribution in relation to existing works, a state of the art was presented in the fifth chapter that illustrates the application of the results mentioned above, after a presentation of the IM machine as uncertain nonlinear system. We presented the different steps in order to obtain the final non-linear model of the IM's machine in the two axes rotating frame (d,q) with varying parameters. Three applications based on the MVT theory are designed for the IM's machine; first application concerns the robust controller of the IM states with varying parameters, the second application concerns of a robust PI control of IM's machine associated with the extended observer. These applications of these algorithms (controller and observer) are proven through simulations tests and showing their effectiveness

Future works

The work presented in this thesis opens a number of perspectives. In the short term, we intend to apply the analytical approach of the control and the observation used in this thesis to other types of electrical machines (synchronous machines, double fed IM,…etc.).We are convinced that such a study could improve the performance of the control and the state's estimation of electrical machines with or without a mechanical sensor in low speed or in pulsed torques.

In long term, the design of the robust state feedback-tracking controller approach for non-linear systems with varying parameters described by the MVT theory for faults and in degrade modes can now be extended and applied. The stability analysis can be enhanced with the Ricatti equation and other methods instead of the Lyapunov function.

We have shown the efficiency of this approach with simulations where the machine has undergone a load torque and important parametric variations, this work can be considered in the industrial application in the future and should checked through experimental tests. Nevertheless, a study of the loss of observability must be carried out because during the implementation we have assumed that the states of the IM are observable at every moment.

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Appendix A:

Induction motor for simulation

Parameter name	Parameter symbol	Parameter value	Parameter unit
Nominal power	P_n	1.1	Kw
Pole pair number	n_p	2	/
Rotor inductance	L_r	0.4718	Henry
Stator inductance	L_s	0.4718	Henry
Rotor resistance	R_r	4.3047	Ohm
Stator resistance	R_s	9.65	Ohm
Mutual inductance	M	0.4475	Henry
Moment of inertia	J	0.0293	Kg/m^2
Friction coefficient	b	9.9913e-4	Nm/rad/s

Appendix B:

Induction motor(used for experimental tests)

Parameter name	Parameter symbol	Parameter value	Parameter unit
Nominal power	P_n	186.5	Watt
Pole pair number	n_p	2	/
Rotor inductance	L_r	0.281	Henry
Stator inductance	L_s	0281	Henry
Rotor resistance	R_r	3.21	Ohm
Stator resistance	R_s	13.8	Ohm
Mutual inductance	M	0.257	Henry
Moment of inertia	J	0.001875	Kg/m^2
Friction coefficient	b	0.00052	Nm/rad/s

Figure A.1The nameplate of the used IM