Fuzzy Control System Review

Abdullah J. H. Al Gizi*, M.W. Mustafa, Malik A. Alsaedi, N. Zreen

Abstract— Overall intelligent control system which runs on fuzzy, genetic and neural algorithm is a promising engine for large –scale development of control systems . Its development relies on creating environments where anthropomorphic tasks can be performed autonomously or proactively with a human operator. Certainly, the ability to control processes with a degree of autonomy is depended on the quality of an intelligent control system envisioned. In this paper, a summary of published techniques for intelligent fuzzy control system is presented to enable a design engineer choose architecture for his particular purpose. Published concepts are grouped according to their functionality. Their respective performances are compared. The various fuzzy techniques are analyzed in terms of their complexity, efficiency, flexibility, start-up behavior and utilization of the controller with reference to an optimum control system condition.

Index Terms— Fuzzy, Intelligent Control System

1 Introduction RESERCH BACKGROUND

An intelligent system has the ability to act logically in an uncertain environment to achieve certain behavioral sub goals which support the system's ultimate goal. Control systems are a key enabling technology for the increase in functionality and safety of many critical applications such as transportation systems, manufacturing systems, medical devices, and networked embedded systems . Modern power systems are non-linear and behave in a highly complex manner with continuous extensive variations in their operating conditions. Design of this type of systems requires knowledge in many multi-disciplines. The most popular technique is to use Fuzzy controller in which expert knowledge can be incorporated into the design. Most of Fuzzy controllers which are used in industry have the same structure as incremental PD or PID controllers. Controller design using Genetic Algorithm and neural network has been combined with Fuzzy controller to form an intelligent control scheme. The first feedback device on record was the water clock invented by the Greek Ktesibios in Alexandria Egypt around the 3rd century B.C . [2] . This was certainly a successful device as water clocks of similar design were still being made in Baghdad when the Mongols captured that city in 1258 A.D. The first mathematical model to describe plant behavior for control purposes is attributed to J.C. Maxwell who in 1868 used differential equations to explain instability problems encountered with James Watt's flyball governor; the governor was introduced in 1769 to regulate the speed of steam engine vehicles.[1] . When J.C. Maxwell used mathematical modeling and methods to explain instability problems encountered with James Watt's flyball governor, it demonstrated the importance and usefulness of mathematical models and methods in understanding complex phenomena and signaled the beginning of mathematical system and control theory. It also signaled the end of the era of intuitive inventions. Control theory made significant strides in the past 120 years, with the use of frequency domain methods and Laplace transforms in the 1930s and 1940s and the development of optimal control methods and state space analysis in the 1950s and 1960s. Ideas such as optimal control (in the 1950s and 1960s) and stochastic, robust, adaptive and nonlinear control methods (in the 1960s till today), have made it possible to control complex dynamical systems more accurately than the original flyball governor.

A. Scope of this review

Owing to recent rising interest in intelligent control systems , it has been necessary to collect and classify these control systems and explain how their control techniques were developed. Despite the increase in the number of papers describing intelligent control techniques, understanding of the application of these techniques among the community of practice is somewhat sketchy. This is because those papers specifically deal only with research works which are aimed at achieving overall intelligent control using the techniques of fuzzy logic.This paper will attempt at classifying intelligent fuzzy control systems according to the control techniques used. There will be a discussion on how their intelligent control can be improved.

2 Fuzzy logic controllers

There are two main types of fuzzy logic based controller [5-12]. The first is the madman type fuzzy logic controller which is adaptive and where the system to be controlled is not explicitly identified. The second is the Takagi-surgeon type fuzzy logic controller (FLC) which is indirectly adaptive and where the system to be controlled is identified using T-S fuzzy model . The controller is designed based on the identified model.

Rule base approach provides a useful framework for the definition of different methods of logic control [13-15]. Controller design using the rule based approach would assemble three component implementation phases. These are the knowledge acquisition phase, the model development phase and the model testing phase Examples of rule base

• This work was supported in part by the Universiti Teknologi Malaysia, under MOHE Scheme, GUP Grant No. 01H80
• Mohd Wazir Bin Mustafa is with the Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor, Malaysia (e-mail: wazir@fke.utm.my).
• Abdullah J. H. Al Gizi is with the Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor, Malaysia (corresponding author 0060102831074; e-mail: abdullh969@ yahoo.com).

structure can be found in Fuzzy PI/PD/PID controllers, Fuzzy Lyapunov controllers and Self organizing rule controllers.

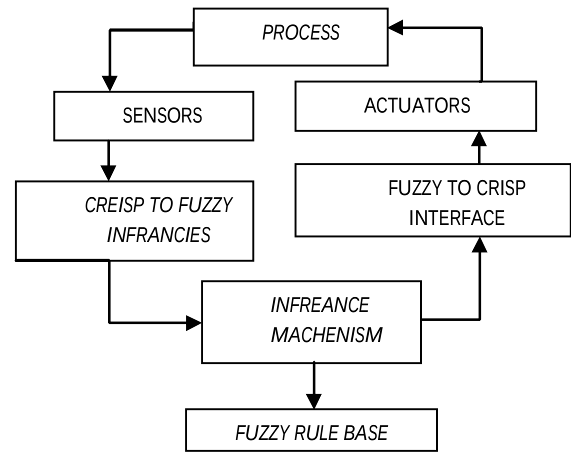

Fig.1 Mamdan type of fuzzy logic controller

Fuzzy rule base is normally run from statements containing fuzzy IF-THEN rules to derive the linguistic values for the intermediate and output linguistic variables

Let us denote the error and change of error as e and $\dot{e}$ and control input as u respectively .Looking at the output response curve the following rules can be formed: PD, PID

I. IF e is LE and $\dot{e}$ is SE/ME.THEN u is LARGE
II. IF e is ME and $\dot{e}$ is ME.THEN u is MEDIUM
III. IF e is SE and $\dot{e}$ is LE.THEN u is NEGATIVE SMALL

Fuzzy PI/ PID controllers provide the rules base that gives the change in controller output, i.e. $u(t+1)=u(t)+\Delta u$ where Δu can be found from the fuzzy rule base, and Fuzzy PD controller is the control input u is directly computed from the rule base. Fuzzy PI/PD/PID controller rule base is illustrated as follows:

2. 1 Fuzzy PD/ PID/PI controller

In a general FLC the control objective is to design a fuzzy controller using information based on some physical intuition event if the exact system dynamic is not known but the main problem is constructing the rule base for the controller .In a typical mamdani type FLC, the rule base is obtained using the notion of classical PD ,PI, or PID controller in Fuzzy Lyapunov control environment. The rule base is formed using the notion of Lyapunov Stability Theory for which $V(x)$ represents a general single input single output nonlinear system. The value $\dot{x}=f(x,u)$ is considered Lyapunov stable around the operating point $x=0$.

There exists a continuously differentiable function $V(x)$, known as Lyapunov function where $V(x)$ is positive definite in the neighborhood of 0 and $\dot{V}(x)$ is negative definite in the neighborhood of 0. Fuzzy Lyapunov controller, assumes prior knowledge of the system model. Under normal circumstances, only some partial knowledge about the system is known. Hence, it will be necessary to treat FLC as a classical case where a Lyapunove function candidate V is considered . The derivative of V (which is is $\dot{V}$) is then calculated and used to obtain the fuzzy rule base for the control input u as long as $\dot{V}$ is negative definite . According to the rule base , a fuzzy controller u is obtained using general inference mechanism and defuzzifiction method.FLC structure. That is with the rule base it will be possible to formulate the resulting conditions in the form of rules in one of two possible representations. That is

1: IF x1 is A1 and /or x2is A2 ….and/or xn is An THEN u is B, where Ai and B are linguistic variables (e.g. large .small).Representation

2: IF x1 is A1 and /or x2is A2 ….and/or xn is An THEN u is $f(x_1,x_2..............x_n)$ where $f(i)$ is a linear function.

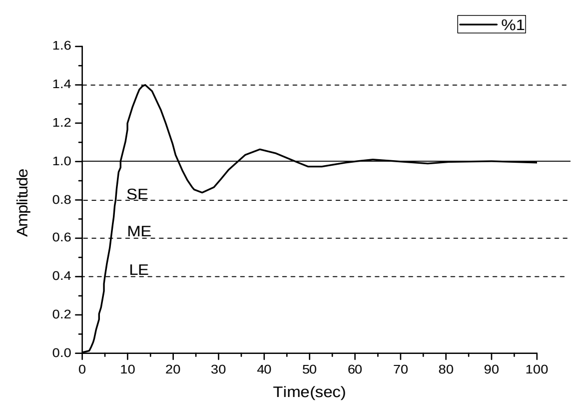

Fig.2.Looking at the general characteristics of PI/PD/PID response the rule base is formed LE, ME and SE denotes LARGE, MEDIUM and SMALL error respectively.

2. 2 Fuzzy Lyapunov Controller

To understand the use of FLC, it is useful to see how it is used on a Single Linked Manipulator (SLM): which is normally considered as a dynamic model described by the equation

$ml^2\ddot{\theta}+mgl\sin\theta=\tau$,

Where $m=1kg$, $g=\frac{9.81kg}{meter^2}$, $x_1=\theta, x_2=\dot{\theta}$ {afferent knowledge} $\tau\alpha\ddot{\theta}$, $\tau\alpha\dot{\theta}$.

Fuzzy Lyapunov controller:

SLM Without knowing the complete dynamics of the system, the following statements can be made: S-1 the relevant state variables are $x_1=\theta$ and $x_2=\dot{\theta}$,S-2, $\dot{x}$ is proportional to τ

,Let us take a lyapunov function candidate

$$V = 1/2(x_1^2 + x_2^2).$$

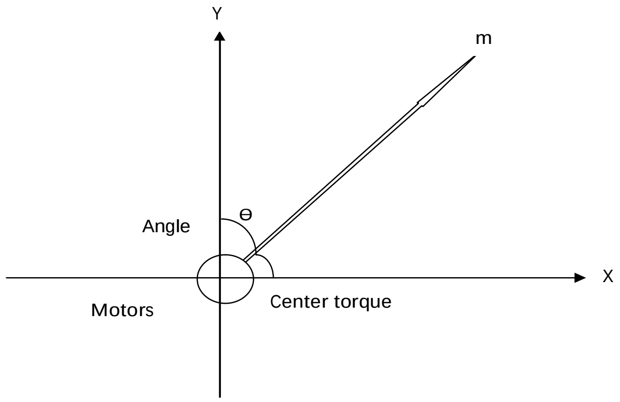

Fig.3. Single Link manipulator

The time derivative of V is: $\dot{V} = (x_1\dot{x}_1 + x_2\dot{x}_2)$

Where $\dot{x}_1 = x_1, x_2\alpha\tau$,Using S-1 and S-2. $\dot{V} = (x_1x_2 + x_2\tau)$ .Find FLC rule such that $\dot{v}$ qualitatively negative definite, $\dot{V} = (x_1x_2 + x_2\tau)$, Can make negative definite if the rule base is formed as follows:

IF x_1 is negative AND x_2 is negative, THEN τ is positive big

IF x_1 is positive AND x_2 is positive, THEN τ is negative big

IF x_1 is negative AND x_2 is positive, THEN τ is zero

IF x_1 is positive AND x_2 is negative, THEN τ is zero

2. 3 Takuge _Sugeno Type Fuzzy logic controller

In general (FLC using TS fuzzy model)Takuge-sugeno type fuzzy logic controller is an example of indirect adaptive control .The main steps are identifying the nonlinear system in terms of T-S fuzzy model and designing the controller based on the identified T-S fuzzy model .There are three different control structures using T-S fuzzy model. The first controller is designed with common input matrix ,the second linear controller is designed using robust control approach and the third controller is designed using LMI techniques.

Many important research work in this field have been carried out by several researchers. T.Takage and M .Sugeno approached Fuzzy identification from the coition of system when applied to modeling and control[17]. P.I.Kar ,Prnam Karmer and L. Bahera performed identification and stabilization of nonlinear plants using Fuzzy neural networks [18]. They also suggested a workable variable gain controllers for nonlinear systems using T-S Fuzzy model [20]. S.H.Zak proposed stabilizing fuzzy system models using linear controllers [19]. K.Tanaka proposed a novel fuzzy –neural-linear control systems with desirable stability and stabilizability [7]. H .K.Lam , F.H.F.Leung and Peter K.S.Tam proposed a linear matrix inequity approach for the control of Uncertain Fuzzy systems[21].

Type-1 and Type-2 FLSs (fuzzy logic system) have received increasing attention recently [22]. Type-2 (T2) FLSs have been applied in many engineering areas, demonstrating their ability to outperform Type-1 (T1) FLSs mainly in the presence of dynamic uncertainties [23]-[24]. The major difference between T1 and T2 FLSs is in the model of individual Fuzzy Sets (FSs) which use membership degrees that are themselves FSs. The most commonly used kind of T2 FLS is the Interval T2 (IT2) FLS, which uses interval membership degrees. Many researchers argue in favor of IT2 FLSs because of their potential to model and minimize the effects of dynamic uncertainties [25]. Typically, the performance of IT2 FLSs in various applications is compared to their T1 counterparts demonstrating improvements when noise and uncertainty are introduced into the system. Many researchers associate the geometrical properties of the interval centered with the uncertainty about the system's output [26,27].whereas, a method for incorporating the experimentally measured input uncertainty into the design of the IT2 FLS was proposed [28]. Interval type-2 fuzzy logic controllers (IT2 FLCs) have been attracting great interests recently. Many reported results have shown that IT2 FLCs are better able to handle uncertainties than their type-1 (T1) counterparts [29], [30], [32], [33].Wu and Tan [31], [32],[33] showed through both simulations and experiments that IT2 FLCs are better able to cope with modeling uncertainties, and hence IT2 FLCs optimized from simulations are more likely to perform well on the actual plant than T1 FLCs. Dongrui Wu, [34] explains that the two fundamental differences between IT2 and T1 FLCs are: 1) Addictiveness, meaning that the embedded T1 fuzzy sets used to compute the bounds of the type-reduced interval change as input changes; and, 2) Novelty, meaning that the upper and lower membership functions of the same IT2 fuzzy set may be used simultaneously in computing each bound of the type reduced interval. T1 FLCs do not have these properties; thus, a T1 FLC cannot implement the complex control surface of an IT2 FLC given the same rule base.

2. 4 Representation of a Nonlinear system

Let us consider a class of discrete nonlinear dynamical systems described by the vector equation

$$x(k+1) = f(x(k), u(k))$$

$$y(k) = h(y(k), u(k))$$

x is a one-dimensional state vector , u is a p-dimensional input vector and y is an m-dimensional output vector. The above system can be effectively modeled by fuzzy merging of equivalent linear systems in different operating regions using Takuge_sugeno (T-S) fuzzy model.

T-S Fuzzy model

A T-S Fuzzy model is composed of r rules where j^{th} rule have the following form.

Rule: IF $x_1(k)$ is F_1^j AND ….AND x_n (k) is F_n^j THEN

$x(k+1)=A_j x(k)+B_j u(k)$, $y(k)=C_j x(k)+D_j u(k)$, Where $x=[x_1,x_2,..........x_n]^T$ $j=1..............r$ .Given a current state vector $x(k)$ and a input vector $u(k)$,the T-S fuzzy model inters $x(k+1)$ as $x(k+1)=\frac{\sum_{j=1}^{r}\mu_j(A_j x(k))+B_j u(k)}{\sum_{j=1}^{r}\mu_j}$,

$$y(k)=\frac{\sum_{j=1}^{r}\mu_j(C_j x(k))+D_j u(k)}{\sum_{j=1}^{r}\mu_j},$$

Where $\mu_j=\prod_{j=1}^{r}\mu_j^i(x_i)$, $\mu_j^i(x_i)$ is the membership function of the fuzzy term F_j^n $j=1,2.............r$.

The overall fuzzy system can be simplified into $x(k+1)=\overline{A}_j x(k)+\overline{B}_j u(k)$, $y(k)=\overline{C}_j x(k)+\overline{D}_j u(k)$ the Nonlinear system $x(k+1)=f(x(k)yu(k)),\ y(k)=h(x(k)yu(k))$ where

$$\overline{A}=\sum_{j=1}^{r}\delta_j A_j,\overline{B}=\sum_{j=1}^{r}\delta_j B_j,\overline{C}=\sum_{j=1}^{r}\delta_j C_j,\overline{D}=\sum_{j=1}^{r}\delta_j D_j$$

$$,\delta_j=\frac{\mu_j}{\sum_{j=1}^{r}\mu_j}K\sum_{k=1}^{r}\delta_j=1$$

The overall system is nonlinear since $\overline{A}$ is a function of δ_j and δ_j is a function of $x(k)$

2. 5 Continous time T-S fuzzy model

"Continuous time counterpart of the overall fuzzy system is $\dot{x}=\overline{A}x+\overline{B}u$, $y=\overline{C}x+\overline{D}u$ where

$$\dot{x}=\sum_{j=1}^{r}\delta_j(A_j x+B_j u)\ ,\overline{A}=\sum_{j=1}^{r}\delta_j A_j,$$

$$\overline{B}=\sum_{j=1}^{r}\delta_j B_j,\overline{C}=\sum_{j=1}^{r}\delta_j C_j,\overline{D}=\sum_{j=1}^{r}\delta_j D_j$$

Identifying the linear model parameters .The parameters Aj and Bj can be found

- By linear zing the nonlinear system dynamics

Example: suppose the nonlinear dynamic is $\dot{x}=F(x,u)=(x+x^2)+u$ the sum is to find A and B such that in u neighborhood of a operating point $F(x,u)=(Ax+Bu)$

- When $x_0=0, A=\frac{\partial f}{\partial x}, B=\frac{\partial f}{\partial u}$ (Using Taylor 's series expiration)
- When $x_0\neq 0, A$ and $, B$ can be found out for affine type systems ie. $\dot{x}=f(x)+g(x)u$ in that case ,if a_i^T denote the i the row of A.

Then $a^2=\frac{\partial f}{\partial x}+\frac{linear\,\partial f}{\sum\partial u},\ B=g(xu)$ [reference system and control .H.Zak] .Thus two rules of T-S fuzzy model parameters are B_j

- R1:If $x=0,\dot{x}=x+u,A_1=1,B_1=1$
- R1:If $x=1,\dot{x}=2x+u,A_2=2,B_2=1$

The linear model parameters $A_j s'$ and $B_j s'$ also be identification

- From the input –output data of the system using a fuzzy neural network(FNN)
- When using a FNN the elements of A_j and B_j are the weights of the neural network
- Least square cast function is used to find the proper weights.
- Weights are updated using the standard gradient descent algorithm.

T-S fuzzy model with a common input matrix

- Discrete time T-S fuzzy model $x(k+1)=\overline{A}x+\overline{B}u(k)$
- Continuous time T-S fuzzy model $x=\overline{A}x+\overline{B}u$

Where $\overline{A}=\sum_{j=1}^{r}\delta_j A_j$,$\overline{B}=\sum_{j=1}^{r}\delta_j B_j$ the system will have a common input matrix when $B_j=BYJB$ is a constant matrix. Utility of common input matrix. Suppose we design individual linear controller for individual subsystems .This control action corresponding to jth subsystems is denoted by uj(k).If all linear subsystems have a common input matrix B than an overall control input of the from $u(k)=\sum_{j=1}^{r}\delta_j u_j(k)$ will curry than the individual subsystem are excised by inspective control inputs.

Controller design with common input matrix

Many researchers have made the system stable by using input data matrix which can be illustrated as follows:

Suppose the individual control input has a form $u_j(k)=-k_j x(k)$ for discrete time. T-S fuzzy models which is the overall system can be made stable if

- There exists a common input matrix B for all subsystems
- The individual gain matrices Kj is such that $A_j'=A_j-B_j K_j$ f haven singular values less than unity

For continuous T-S fuzzy model, the overall system can be made stable if

- There exists a common input matrix B for all subsystems
- The individual gain matrices Kj are designed such that $\frac{1}{2}(A_j'^T+A_j')$ have action part's stability signal values

, where $A'_j = A_j - B_j K_j$ where , $u_j = -k_j x_j$ for all system controller $u(k) = \sum_{j=1}^{r} \delta_j u_j(k)$.

The system's stability is dependent on Hrmashan part

$\{\frac{1}{2}(A'^T_j + A'_j), A'_j\}$

For both continuous and discreet time systems the overall system can be made stable if

- There exists a common input matrix B for all subsystems.
- The individual gain matrices K_j 's are designed such that $A'_j = A_j - B_j K_j$'s and symmetric [17,18]

Many fuzzy clustering studies have been conducted based on dissimilar and similar relationships between plants. Subsequently rules were extracted utilizing fuzzy clustering method [35-37]. Permanent magnet synchronous motors have been used as servo motors under vector control techniques and various control methods have been applied to (permanent magnet synchronous motor)PMSM motors [38]-[39].There are two types of PMSM. The first one is Surface PMSM(SPMSM) and the other is interior PMSM(IPMSM(interior permanent magnet synchronous motor)).In the control of SPMSM, the system can be considered as linear with the d-axis current controlled to be zero. In this case, SPMSM can be modeled as DC motors [40][41]. In the T-S fuzzy identification of IPMSM, a set of local dynamic linear models will be provided with high accuracy. T-S fuzzy identification can provide an accurate system description with membership functions and a series of linear dynamic equations [42 -44].One of the best control method for nonlinear system is T-S fuzzy control. In the actual IPMSM, it is very difficult to get the parameters of IPMSM. An efficient method is used to derive T-S fuzzy model of IPMSM using the data from the actual IPMSM.

2. 6 Linear controller using robust control approach

TS fuzzy model is normally expressed in terms of a single linear plant while the rest of the linear models are expressed as a disturbances to this. The norm bound on the disturbance is computed based on the norm bound of the controller which is designed to make the overall system Lyapunov stable.

The T-S model is expressed in terms of r fuzzy rules:

Rule i: if xi (t) is F_i^n AND …………….AND xn(t)is F_i^n THEN $x(t) = A_i x(t) + B_i u(t)$ F_j^n ,j=1,2,…..n is the j^{th} fuzzy set of the i^{th} rule . Let $\mu_j = \prod_{j=1}^{r} \mu_j^i(x_i)$.Where $\mu_r^j(x_i)$ is the membership function of the fuzzy set F_i^n ,j=1,2,……………..r the overall system is $x(t) = \sum_{j=1}^{r} \delta_j (A_j r(t) + B_j u(t))$ where

$$\delta_j = \frac{\mu_j}{\sum_{j=1}^{r} \mu_j} \sum_{k=1}^{r} \delta_j = 1 \cdot$$

The T-S model linear plant with nonlinear disturbance

The T-S fuzzy model can be rewritten as

$$\dot{x}(t) = Ax(t) + Bu(t) + \sum_{j=1}^{r} \delta_j (A_j - A)x(t) + \sum_{j=1}^{r} \delta_j (B_j - B)u(t)$$

$Ax(t) + Bu(t) + F(x(t), u(t))$ where $Ax(t) + Bu(t)$ is the linear system and $F(x(t) + u(t))$ is the nonlinear disturbance given by $F(x(t), u(t)) = f(x(t) + Bh1(x(t)) + Bh2(u(t))$ Computing the norm bounds of f ,h1 and h2 controllers are designed to make the T-S fuzzy model Lyapunov stable. S;H.Zak(1999) and(Prem Kumar PI.Kar and I Behera(2006)) [45-46] have proposed several applications of T-S Fuzzy model when it is Lyapunov stable. For a control system, the fundamental requirement is stability. While numerous high efficient converters have been constructed for various applications, there have been continuing efforts devoted to the stability analysis of power electronic converters [47]. A nonlinear system approach was developed for analysis and design of power electronic converters [48], where the DC-DC converter was modeled as a differential equation with a bilinear term and input saturation (the hard limit on the duty cycle). Another non linear system approach uses boost, buck-boo stand converters which have been used to condition the power supplied by photovoltaic batteries [49]. Of late, different control approaches have been applied to space vector modulated direct torque controlled IPMSM (interior permanent magnet synchronous motor) drives in the search for more desirable drive performances in terms of both steady state and transient responses [50-55]. As far as intelligent based direct torque control schemes are concerned, some Fuzzy controlled DTCs [50] and Neuro-Fuzzy controlled DTCs [51] have been reported. Despite a more robust performance especially in the case of ill-defined and uncertain systems, the fuzzy controller still encounters the lack of a systematic method for tuning. Such a difficulty was resolved by adding the learning capability of neural networks, but the performance in the presence of disturbances, parameters variation and system uncertainties was not optimal. Some other researchers proposed the direct torque control schemes based on adaptive controllers such as input-output feedback linearization [56] and adaptive back-stepping [57].Although, a much smoother steady state performance were obtained, the transient drive response was not satisfactory which was mainly due to the sluggish estimation of motor parameters through the generated adaptation laws. In addition, all adaptive based DTCs demand a precise motor model, thus some modeled dynamics and disturbances could considerably deteriorate the drive performance.

2. 7 Fuzzy controller using LMI technique

In this control strategy the stability of the closed loop system is guaranteed by finding a common Lyapunov function for all the local linear models. This can be expressed in the form of a Linear Matrix Inequality (LIM). A stable fuzzy controller can be designed by solving the LMI's. Let us consider the following T-S Fuzzy model which is locally described by ith rule. According to ith rule, if x1(t) is F1 and x2 (t) is F2 and xn(t) is F_n^r THEN $\dot{x}(t) = A_i x(t) + B_i u(t)$

t=1,2,…r. $u(t) = -k_i x(t)$ t=1,2,..r

In addition , as described earlier, given a current state vector x(t) and an input u(t) the T-S model infers that the value of $\dot{x}(t)$ can change as follows: $\dot{x}(t) = \sum_j^r \delta_i (A_i x(t) + B_i u(t))$ .Where δ_i have been defined earlier.

The final output of the fuzzy controller is $u(t) = \sum_j^r \delta_i K_i x(t)$ where $u_i = -k_i x_i(t)$, for individual closed loop. The subsystem becomes $\dot{x}(t) = \sum_{j=1}^r \delta_j (A_i x(t) - B_i \sum_{j=1}^r \delta_i K_i x(t)$. After simplification $\dot{x}$ can be written as

$$\dot{x}(t) = \sum_{j=1}^r \delta_i^2 H_i x(t) + 2\sum_{j=1}^r \delta_j \delta_i \{\frac{H_{ij} + H_{ij}}{2}\} x(t)$$

where $H_{ij} = A_i - B_i K_i$.

Consider a Lyapunov function candidate, $V = x^T P_x$ and $\dot{V} = \dot{x}^T P_x + x^T P_x$, giving

$$\dot{x}(t) = \sum_{j=1}^r \delta_i^2 H_i x(t) + 2\sum_{j=1}^r \delta_j \delta_i \{\frac{H_{ij} + H_{ij}}{2}\} x(t)$$

where $H_{ij} = A_i - B_i K_i$ we can write

$$\dot{v} = \sum_{j=1}^r \delta_i^2 x^T H_i^T P_x + 2\sum_{j=1}^r \delta_j \delta_i x^T \{\frac{H_{ij} + H_{ij}}{2}\} P_x$$

$$+ x^T P \sum_{j=1}^r \delta_i^2 H_i x + 2x^T P \sum_{j=1}^r \delta_j \delta_i \{\frac{H_{ij} + H_{ij}}{2}\} x$$

$$\dot{v} = \sum_{j=1}^r \delta_i^2 x^T (H_i^T P_x + PH_i) X$$

$$+ 2\sum_{j=1}^r \delta_j \delta_i x^T \left(\frac{H_{ij} + H_{ij}}{2}\right)^T P_x + P\left(\frac{H_{ij} + H_{ij}}{2}\right) x$$

Since δ_i is a position quantity, $\dot{v}$ will be negative definite if $H_i^T P_x + PH_i < 0$ for r=1……r LMI eq. $\left(\frac{H_{ij}+H_{ij}}{2}\right)^T P + P\left(\frac{H_{ij}+H_{ij}}{2}\right) \le 0, i < j\delta_j\delta_i \ne 0$……LMI eq. The above expressions are basic stability conditions. The controller parameter K_i' is hidden in that expression. The above can be further re-expressed in different suitable forms and the controller parameter K_i' can then be obtained by solving those equations stated earlier.

Thus $u_j = k_j x_j, u = \sum_{j=1}^r \delta_j u_j$ For discrete time case the equilibrium point of the overall fuzzy system is generally asymptotically stable if there exists a common positive definite matrix P such that $H_i^T P_x H_{ij} - P < 0$ for r=1……r.

LMI eq. is normally expressed (for discrete as well as for continuous time) as $\left(\frac{H_{ij}+H_{ij}}{2}\right)^T P + P\left(\frac{H_{ij}+H_{ij}}{2}\right) \le 0, i < j\delta_j\delta_i \ne 0$

There are various algorithms available in literature{ H.O.Wang K.Tanaka and M.F.Griffen (1996),E.Kian and D.Kim (2001),H.K.Larn and F.H.F.Leungand Peter K.S.Tam.A.(2002),K.Tanaka , T.Ievade and H.O.Wang(May 1998.),E.Kain and H.Lee(Oct 2000),C.H Fang Y-S Liui.S-W Kau. I .Hong and C-H Lee(June 2006) and D. Giaouris, S. Banerjee, B. Zahawi, and V. Pickert, (May 2008) [57-63]}. on how to get the controller parameters by solving the above LMI's. Floquet theory has also been used to study the stability of system trajectories by deriving the absolute value of the eigenvalues of the monodromy matrix (i.e., the so-called Floquet multipliers of the system) [64]–[65]. The implementation of these strategies is still not widely adopted since they are vulnerable to noise and suffer from a high-computation- time requirement [66]. The TS fuzzy approach (model based or non model based) has already been applied to control power electronic converters [68], [67]. One of the main drawbacks of these previous attempts is the derivation of the fuzzy model from the average dynamical model of the converter, thus ignoring all converter fast-scale instabilities as outlined previously.

3 Conclusion

The research on the intelligent system fuzzy was reviewed with a focus on the historical development of new technical and strategies to improve the activity of the intelligent control systems .As described the above, in the search for intelligent control, significant effort has been devoted to the development of new control technique and active sites on intelligent, as well as elucidating the major methods. This has led to significant progress in the field of an intelligent control systems fuzzy, especially in least years. However, the development of an intelligent control with fuzzy is still needed. The drawback of both general and Lyapunov like Mamdani type (fuzzy logic controller)FLC is that the parameters associated with the FLC are heuristically updated .In general, Takugesugeno type fuzzy logic controller is an example of indirect adaptive control. The main steps are identifying the nonlinear system in terms of T-S fuzzy model and designing the controller based on the identified T-S fuzzy model. There are three different control approaches using a T-S fuzzy model the first controller design with common input matrix, the second linear controllers using robust control approach and the third controller design using LMI techniques.

Acknowledgment

The author gratefully acknowledges the Faculty of Electrical Engineering, Universiti Teknologi Malaysia for giving the support in this work.

REFERENCES

[1] J. Antsaklis Panos, A.Stiver James and M. Lemmon, "Hybrid system modeling autonomous control system ",Deportment of electrical engineering university of Notre Dame , Notre Dame in 46556 USA.vol 736,pp.366-392, 1993 .

[2] P.J. Antsaklis, "Intelligent Control," Encyclopedia of Electrical and Electronics Engineering, Vol. 10, pp. 493-503, John Wiley & Sons, Inc., 1999.

[3] J.R.Slagle, , M.W. Gaynor, and E.J. Halpern," An intelligent control strategy for computer consultation," IEEE Trans Pattern Anal Mach Intell, vol.6 no.2,pp. 129-36 ,1984.

[4] J.A. Blom, " Intelligent bed-side data management and control systems," Biomed Tech (Berl), vol.35 no. 3, pp. 268-9, 1990.

[5] A.Homater and E.McCormick ,"Simultaneous Design of Membership Functions and rule sets for fuzzy controllers using Genetic algorithms ,"IEEE Trans.Fuzzy systems ,vol.3,no2, pp 129-138,1996

[6] K.K.N.Sartry .L.Behera and I.J.Nagrath," Differential evaluation based fuzzy logic controller for nonlinear process control, "Fundaments information,1999 .

[7] K.Tanaka,"Stability and stabilizabilty of fuzzy –neural-linear control systems,"LMI IEEE Trans Fuzzy syst, 1995.

[8] E.H.Mandani ,"Application of Fuzzy algorithms for the control of a Dynamic Plant ,"Proc IEEE,vol.121,no.12,pp,1686-1688 ,1974.

[9] L.A.Zedeh ,"A fuzzy –algorithmic approach to the delft ration of complex or imp rose concept ,"Int. Jour Man-Machine students ,vol.8,pp.249-291,1976.

[10] W.J.M.Klchant and C.H ,"Mamdani Analysis of a fuzzy logic controller," Fuzzy sets and systems ,vol.1,pp 29-44, 1978.

[11] C.C.Lee Fuzzy logic in control systems ,"Fuzzy logic controller parts I and II,"IEEE TNN,Syst.Man Cybern.,vol,20,no,2,pp 404-435, 1990

[12] M.Mzumoto ,"Relazation of PID controller by fuzzy control methods," Fuzzy Sets and systems,vol.70,pp 171-182,1996.

[13] G.K.I Mann, H. Bao-Gang, R.G. Gosine ," Analysis of direct action fuzzy PID controller structures ,vol.29,no,3,pp.371-388,1999.

[14] A.-Lopez ,A.Aguilar-martin ,J.A simplified version of mamdani fuzzy controller :the natural logic controller ,"IEEE TNN ,Fuzzy Syst ,vol .14, no.1,pp.16-30,2006.

[15] M.Margaint and G.Lunghotz," Fuzzy lyapunov-based approach to design the fuzzy controllers,"Fuzzy sets and systems,vol.106,pp.49-59,1999.

[16] C .L. Karr and E.J.Gentry ,"Fuzzy control of PH using Genetic Algorithms ,"IEEE TNN Fuzzy syst, vol. 1, no .1,pp:46-53,1993.

[17] T.Takage and M .Sugeno ,"Fuzzy identify coition of system and Its application to modeling and control ,"IEEE Trana SMC 1985.

[18] I.Kar, P.Prem Kumar, and L. Behera ,"On identification and stabilization of nonlinear plants using Fuzzy neural network ,"IEEE conf.on SMC ,Harans USA ,2005.

[19] S.H.Zak ," stabilizing fuzzy system models using linear controller,"IEEE trans. Fuzzy syst.1999.

[20] P. Prem Kumar , I.Kar ,and L. Behera ,"Variable gain controllers for Nolinear systems using T-S Fuzzy model ,"IEEE Trans on SMC,2006

[21] H .K.Lam and F.H.F.Leung and peter K.S.Tam ,"A linear matrix inequity approach for the control of Uncertain Fuzzy systems ,"IEEE Control Systems Magazine 2002.

[22] S. Coupland, R. John,"Geometric Type-1 and Type-2 Fuzzy Logic Systems," in IEEE Trans. on Fuzzy Systems, vol.15,no.1,pp. 3-15,February 2007.

[23] M. Biglarbegian, W. Melek, J. M. Mendel, "On the robustness of Type-1 and Interval Type-2 fuzzy logic systems in modeling," in Information Sciences,vol. 181,no.7,pp. 1325-1347,April 2011.

[24] O. Linda, M. Manic, "Interval Type-2 Fuzzy Voter Design for Fault Tolerant Systems," in Information Sciences, in press, 2011.

[25] O. Linda, M. Manic, "Comparative Analysis of Type-1 and Type-2 Fuzzy Control in Context of Learning Behaviors for Mobile Robotics", Glendale, Arizona, USA in Proc. IEEE IECON'10, 36th Annual Conference of the IEEE Industrial Electronics Society,pp. 7-10,Nov 2010.

[26] Q. Ren, L. Baron, K. Jemielniak, M. Balazinski, "Modeling of Dynamic Micromilling Cutting Forces Using Type-2 Fuzzy Rule-Based System," Spain in Proc. IEEE World Congress on Computational Intelligence, Barcelona, 2311-2317, 18-23 , July 2010.

[27] Wu, J. M. Mendel ,"Uncertainty measures for interval type-2 fuzzy sets," in Information Sciences, no. 177, pp.5378-5393 , 2007.

[28] O. Linda, M. Manic, "Uncertainty Modeling for Interval Type-2 Fuzzy Logic System Based on Sensor Characteristics," in Proc. 2011 IEEE Symposium Series on Computational Intelligence, pp.31-37, April 2011..

[29] O. Castillo and P. Melin," Type-2 Fuzzy Logic Theory and Applications," Berlin: Springer-Verlag ,2008.

[30] ——,"Type-2 FLCs: A new generation of fuzzy controllers," IEEE Computational Intelligence Magazine, vol.2,no.1,pp. 30–43,2007.

[31] D. Wu and W. W. Tan, "A type-2 fuzzy logic controller for the liquid-levelprocess," in Proc. Budapest, Hungary ,IEEE Int'l Conf. on Fuzzy Systems,vol. 2,pp. 953–958, July 2004.

[32] ——, "Genetic learning and performance evaluation of type-2 fuzzy logic controllers," Engineering Applications of Artificial Intelligence,vol.19,no.8,pp. 829–841, 2006.

[33] ——, "A simplified type-2 fuzzy controller for real-time control," ISA Transactions,vol.15,no.4,pp. 503–516 , 2006.

[34] D. Wu," On the Fundamental Differences between Interval Type-2 and Type-1 Fuzzy Logic Controllers," IEEE Transactions on, vol.99,pp. 1 – 1, 2012.

[35] L. Jin-ze, Z. Q,i ,and W. We,l et al, "PoClustering: lossless clustering of dissimilarity data[C] / /Proc of the 7th SIAM International Conference on Data Mining,pp.55-81, 2007.

[36] K. Ngm,J. Lim, and J. Huang, et al. On the impact of dissimilarity measure in k-modes clustering algorithm [J].IEEE Trans on Pattern analysis and Machine Intelligence, vol.29, no.3, pp: 503-507, 2007.

[37] D. B .Hitchcock, and Z.-min Chen," Smoothing dissimilarities to cluster binary data[J],"Computational Statistics and Data Analysis, vol.52,no.10:pp.4699-4711, 2008.

[38] K.Rajesh, R. A. Gupta and S.Rajesh ," Surjuse.High-Performance SVPWM-VCIM Drive with Adaptive Neuro-Fuzzy Speed Controller,"International Journal of Computer and Electrical Engineering, vol.2,no.1,pp.1793-8163, Feb 2010.

[39] A.G. Aissaoui, M. Abid, A. Tahour and A. C. Megherbi, "A Fuzzy Logic and Variable Structure Control for Permanent Magnet Synchronous Motors," International Journal of Systems Control,vol.1,no.1,pp.13-21,2010.

[40] I.Boldea, , M.C. Paicu, G.D. Andreescu, and F. Blaabjerg ,"Active flux orientation vector sensorless control of IPMSM," Proc. Of IEEE Optimization of Electrical and Electronic Equipment, pp.161-168 , May 2008.

[41] C. Md. and M.N ,Uddin ,"Nonlinear Control of Interior Permanent Magnet Synchronous Motor Incorporating Flux Control" , Canadian Proc. Of IEEE Electrical and Computer Engineering,pp. 815-818,May

2006.

[42] P.-Tsun Lin, C.-Hsu Wang and T.-Tian Lee ,"Time-Optimal Control of T-S Fuzzy Models via Lie Algebra," IEEE Transactions on Fuzzy Systems, vol.17,no.4, pp.737 – 749 , 2009.

[43] C.-Feng Juang and C.-Da Hsieh,"A Locally Recurrent Fuzzy Neural Network With Support Vector Regression for Dynamic-System Modeling," IEEE Transactions on Fuzzy Systems, vol.18no. 2, pp.261 – 273, 2010.

[44] M., M.N., D. Costa, C.T. Barra, W. and B. J.A.L,"Identification, digital control and fuzzy logic techniques applied to a synchronous generator," IEEE Latin America Transactions,vol.7,no.2, pp.141 – 150 , 2009.

[45] S .H.Zak ,"Stabilizing fuzzy system models using linear controller,"Fuzzy Syst ,IEEE Trans ,1999.

[46] Prem Kumar P.I Kar and I Behera ,"Variable Gain controllers for Nonlinear Systems Using T-S Fuzzy Model ,"IEEE Trans on SMC , 2009 .

[47] Y. V. Hote, D. R. Choudhury, and J. R. P. Gupta,"Robust stability analysis of the PWM push-pull DC-DC converter,"IEEE Trans. Power Electron,vol.24,no.10,pp. 2353–2357, Oct. 2009.

[48] T. Hu,"A nonlinear system approach to analysis and design of power electronic converters with saturation and bilinear terms," IEEE Trans.Power Electron, vol.26,no. 2,pp. 339–410, Feb. 2011.

[49] D. D.-C. Lu and V. G," AgelidisPhotovoltaic-battery-powered DC bus system for common portable electronic devices," IEEE Trans. Power Electron,vol. 24,no. 3,pp. 849–855, Mar. 2009.

[50] M.M.I. Chy and M.N. Uddin,"A Novel Fuzzy-Logic-Controller-Based Torque and Flux Controls of IPM Synchronous Motor," IEEE Trans onIndustrial Application, vol.46,no.3 , 2010.

[51] R. Toufouti, S. Meziane and H. Benalla,"New Direct Torque Neuro-Fuzzy Control Based SVM For Dual Two Level Inverter-Fed Induction Motor," CEAI Journal, vol.11,no.2,pp. 3-13,2009.

[52] H.A.Zarchi, J.Soltani and G.A.Markadeh, "Adaptive Input-Output Feedback Linearization Based Torque Control of Synchronous Reluctance Motor without Mechanical Sensor," IEEE Transactions on Industrial Electronics, vol.57,January 2010.

[53] G. Foo and M.F. Rahman ,"Direct Torque and Flux Control of an IPM Synchronous Motor Drive using a Backstepping Approach", IET Journal on Electric Power Applications,vol.3,no.5, 2009.

[54] S. Sayeef, G. Foo, and M.F. Rahman, "Rotor Position and Speed Estimation of a Variable Structure Direct Torque Controlled IPM Synchronous Motor Drive at Very Low Speeds including Standstill," IEEE Transactions on Industrial Electronics, Early access,2010.

[55] S.M. Fazeli, H.W. Ping, M.A. Rahman, J.Soltani and H.A.Zarchi,"A Modified DTC of Speed Sensorless IPMSM Drives Using Variable Structure Approach,"Taichung, Taiwan, the 5th International Conference on Industrial Electronics and Application (ICIEA), June 2010.

[56] H.A.Zarchi, J.Soltani and G.A.Markadeh, "Adaptive Input-Output Feedback Linearization Based Torque Control of Synchronous Reluctance Motor without Mechanical Sensor," IEEE Transactions on Industrial Electronics, vol.57,January 2010.

[57] H.O.Wang K.Tanaka and M.F.Griffen ,"An Approach to fuzzy control of nonlinear systems.Stability and Design Issuas,"IEEE Trans.Fuzzy Syst.vol. 4,1996.

[58] E.Kian and D.Kim ,"Stability analysis and syntheses for an Affine Fuzzy system via LMI and ILMI Discreate case ," Syst.Man Cybern IEEE Trans, 2001 .

[59] H.K.Larn and F.H.F.Leung and Peter K.S.Tam.A,"Linear Matrix inqualty Approach for the control of uncerten Fuzzy Systems ,"IEEE Control Systems Magazine , 2002.

[60] K.Tanaka , T.Ievade and H.O.Wang,"Fuzzy regulators and fuzzy observers Relaxed stability conditions and LMI-Based Designs ,"IEEE Trans.Fuzzy Syst.6,May 1998.

[61] E.Kain and H.Lee,"New approaches to relaxed quadratic stability condition of fuzzy control systems,"IEEE Trans .Fuzzy syst. Vol.8,Oct 2000.

[62] C.H Fang Y-S Liui.S-W Kau. I .Hong and C-H Lee,"A new LMI Based approach to Relaxed Quadratic Stabilization of T-S Fuzzy control systems ,"IEEE Trans. Fuzzy Syst . vol.14, June 2006.

[63] D. Giaouris, S. Banerjee, B. Zahawi, and V. Pickert,,"Stability analysis of the continuous-conduction-mode buck converter via Filippov'smethod,"IEEE Trans. Circuits Syst. I, Reg. Papers,vol. 55,no.4, pp.1084–1096,May 2008.

[64] D. Giaouris, S. Banerjee, B. Zahawi, and V. Pickert,"Control of fast scale bifurcations in power-factor correction converters,"IEEE Trans.Circuits Syst. II, Exp. Briefs,vol. 54,no.9, pp.805–809 , Sep. 2007.

[65] S. C. Tan, Y. M. Lai, I. Nagy, and C. K. Tse,"General design issues of sliding-mode controllers in DC–DC converters ,"IEEE Trans. Ind.Electron.,vol. 55,no. 3, pp.1160–1174, Mar. 2008.

[66] K. Guesmi, A. Hamzaoui, and J. Zaytoon,"Control of nonlinear phenomena in DC–DC converters: Fuzzy logic approach," Int. J. Circuit Theory Appl., vol.36,no.7,pp. 857–874,Oct. 2008.

[67] K. Y. Lian, J. J. Liou, and C. Y. Huang,"LMI-based integral fuzzy control of DC–DC converters," IEEE Trans Fuzzy Syst.,vol. 14,no.1,pp. 71–80, Feb. 2006.