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Design of Speed Controller for Squirrel-cage Induction Motor using Fuzzy logic based Techniques

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ABSTRACT

This paper presents a performance based comparative study of various fuzzy logic controllers (FLCs) to control the speed of squirrel-cage induction motor (SCIM) by replacing the conventional proportional−integral (PI) controller. The fuzzy logic based controller does not require any identification of motor dynamic to control its speed and also assures the disturbance rejection with high robustness. Performances of the different fuzzy controllers (i.e. PD−, PI− and PID−like) are also compared with the conventional PI speed controller in terms of several performance measures such as peak overshoot ($M_p\%$), settling time (t_s), rise time (t_r), steady state error (ess), integral absolute error (IAE), integral squared error (ISE), integral of time-multiplied absolute error (ITAE) and integral of time-multiplied squared error (ITSE), at different values of load (torque). The simulation results show the effectiveness of the controllers based on fuzzy logic techniques and, for each performance index, the PI−like fuzzy speed controller outperformed its conventional counterpart. Moreover, the performance of proportional−integral−derivative (PID−like) fuzzy speed controller is found best among all the fuzzy controllers discussed in this paper.

Keywords:

Fuzzy logic controller, indirect field-oriented control, proportional-integral-derivative (PID) controller, squirrel-cage induction motor.ifx

NOMENCLATURE

$\mathbf{P}$ number of poles.
$\mathbf{J}_{eq}$ inertial constant.
$\mathbf{I}_d$, $\mathbf{I}_q$ direct- and quadrature-axis components of the induction motor armature current.
$\mathbf{V}_d$, $\mathbf{V}_q$ direct- and quadrature-axis components of the induction motor armature voltage.
$\mathbf{R}_s$ stator resistance.
$\mathbf{R}_r$ rotor resistance.
$\mathbf{L}_s$ stator inductance.
$\mathbf{L}_r$ rotor inductance.
$\mathbf{L}_m$ mutual inductance.
ω_{mech} rotor speed, in actual (mechanical) radians per second.
ω_s supply frequency.
$\mathbf{T}_{em}$ electromagnetic torque.
$\mathbf{T}_L$ load torque.

1. INTRODUCTION

AC motors, particularly the squirrel-cage induction motor (SCIM), have several inherent advantages like simplicity, reliability, low cost and virtually maintenance-free electrical drives. However, for high dynamic performance industrial application, their control remains a challenging problem because they exhibit significant non-linearities and many of the parameters, mainly rotor resistance, vary with the operating conditions. Over the years, the control of processes, systems and motors is customarily done by experts through the conventional proportional−integral (PI), proportional−derivative (PD) and proportional−integral−derivative (PID) control techniques [1], [2]. Though the PID controllers have gained wide spread usage across technological industries, it must also be pointed out that the unnecessary mathematical rigorosity, preciseness and accuracy involved with the design of the controllers have been a major drawback.

There are a number of speed control methods available for induction motors including scalar control, vector or field-oriented control, direct and flux control, sliding mode control and the adaptive control [3]. The scalar control of induction motor inherently suffers from coupling and high order effects which makes the system response sluggish and easily prone to instability. This problem can be solved by vector or field-oriented control. Moreover, it is often difficult to develop an accurate system mathematical model due to unknown load variation, unknown and unavoidable parameters variations due to saturation, temperature variation and system disturbances. In order to overcome these problems the Fuzzy Logic controller (FLC) is being used for motor control purpose.

The pioneer concepts on fuzzy sets proposed by L. A. Zadeh [4] became the motivation to Mamdani [5], Takagi, Sugeno [6] and many other researchers working in the area of fuzzy control modeling. The fuzzy logic controllers have been reported to be successfully used for number of complex and nonlinear processes i.e. water purification process [7], automatic train operating system [8], automatic container crane operation system [9], nuclear reactor control [10] and fuzzy hardware and memory devices [11].

The main advantage of fuzzy logic control when compared to conventional control is the fact that no mathematical modeling is required for the controller design. Fuzzy logic has been successfully used to control ill-known or complex systems where precise modeling is difficult or impossible. In motion control systems, fuzzy logic can be considered as an alternative approach to conventional feedback control. It has been demonstrated that dynamic performance of electric drives as well as robustness regard to parameter variations can be improved by adopting the non-linear speed control techniques like fuzzy control.

Fuzzy Logic Controller (FLC) [12], [13], [14] is based on single human reasoning models, therefore their design are guided by intuition, expert knowledge and engineering. Fuzzy Logic Controllers can be classified according to their input and output variables, when typical variables such as error, change of error and error sum are used alone or combined , FLCs become Fuzzy Proportional, Fuzzy Integral, and so on [15], [17]. A comprehensive review on the design and implementation of FLCs can be found in [18].

Recently, hybrid control techniques (based on combination of two or more softcomputing methods (e.g. neural networks, fuzzy logic, genetic algorithms and evolutionary computing etc.) are

also being proposed by various researchers [19], [20] for perfomance enhancement of the controller.
In this paper the speed controller for a squirrel-cage induction motor (SCIM) with field-oriented control method is modeled based on various fuzzy logic techniques in simulink environment. Though the scope of this paper is limited to fuzzy logic based techniques but the other hybrid techniques (e.g. neuro-fuzzy, fuzzy genetic and fuzzy-neuro-genetic etc.) can also combine with the proposed speed controller model to improve its performance in future.
This paper describes an approach for indirect field-oriented speed control method of an ac machine based on the fuzzy logic techniques, using speed control of an squirrel-cage induction motor as an example. Section 2 presents internal dynamics of the induction motor in state space form. In section 3, the different speed control techniques of an ac motor are discussed. Section 4 presents the design of fuzzy logic controllers (i.e. PD− , PI− and PID−like) and their equivalent simulink models. The simulation results are presented and discussed in section 5. Conclusion and future work is proposed in section 6.

2. DYNAMICS OF INDUCTION MOTOR

Here, the mathematical modeling of induction motor is established using a rotating (d,q) field reference (without saturation) concept [21]. The equivalent circuit used for obtaining the mathematical model of the induction motor is shown in the Fig. 1. Before the implementation of any control mode, it was necessary to define the function equations. The equation system for stator is expressed as:

$$V_{sd} = R_s i_{sd} + \frac{d}{dt}\lambda_{sd} - \omega_d \lambda_{sq}, \tag{1}$$

$$V_{sq} = R_s i_{sq} + \frac{d}{dt}\lambda_{sq} - \omega_d \lambda_{sd}, \tag{2}$$

For the rotor, the equation system is expressed as:

$$V_{rd} = R_r i_{rd} + \frac{d}{dt}\lambda_{rd} - \omega_{dA} \lambda_{rq}, \tag{3}$$

$$V_{rq} = R_r i_{rq} + \frac{d}{dt}\lambda_{rq} - \omega_{dA} \lambda_{rd}, \tag{4}$$

where V_{sd} and V_{sq}, V_{rd} and V_{rq} are the direct− and quadrature axes stator and rotor voltages. As we consider a squirrel cage induction motor for this simulation study, the $d-$ and $q-$axis components of the rotor voltage are zero. The relations of fluxes to currents can be given as:

$$\begin{bmatrix} \lambda_{sd} \\ \lambda_{sq} \\ \lambda_{rd} \\ \lambda_{rq} \end{bmatrix} = M \begin{bmatrix} i_{sd} \\ i_{sq} \\ i_{rd} \\ i_{rq} \end{bmatrix}; \; M = \begin{bmatrix} L_s & 0 & L_m & 0 \\ 0 & L_s & 0 & L_m \\ L_m & 0 & L_r & 0 \\ 0 & L_m & 0 & L_r \end{bmatrix} \tag{5}$$

The electrical part of an induction motor can thus be described by a fourth-order state space model as given in Eq. (6) , by combining equations (1) - (5) :

$$\begin{bmatrix} i_{sd} \\ i_{sq} \\ i_{rd} \\ i_{rq} \end{bmatrix} = \frac{1}{L_m^2 - L_r L_s} \times \left[A \begin{bmatrix} i_{sd} \\ i_{sq} \\ i_{rd} \\ i_{rq} \end{bmatrix} + M \begin{bmatrix} V_{sd} \\ V_{sq} \\ V_{rd} \\ V_{rq} \end{bmatrix} \right] \tag{6}$$

where the value of A is evaluated as shown in Eq. (7).

By superposition, i.e., adding the torques acting on the d-axis and the q-axis of the rotor windings, the instantaneous torque produced in the electromechanical interaction is given by

$$T_{em} = \frac{P}{2}(\lambda_{rq} i_{rd} - \lambda_{rd} i_{rq}) \tag{7}$$

The electromagnetic torque expressed in terms of inductances is given by

$$T_{em} = \frac{P}{2} L_m (i_{sq} i_{rd} - i_{sd} i_{rq}) \tag{8}$$

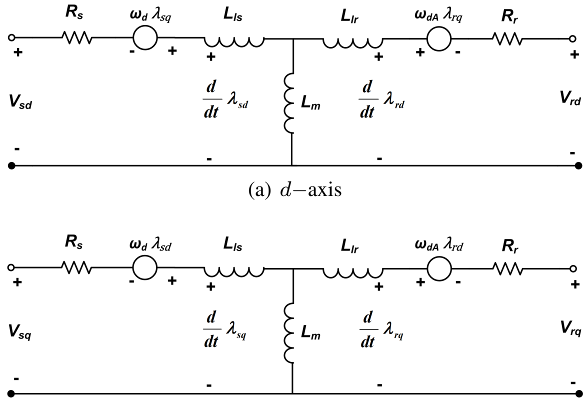
The mechanical part of the motor is modeled by the equation

$$\begin{aligned} \frac{d}{dt}\omega_{mech} &= \frac{T_{em} - T_L}{J_{eq}} \\ &= \frac{\frac{P}{2} L_m (i_{sq} i_{rd} - i_{sd} i_{rq}) - T_L}{J_{eq}} \end{aligned} \tag{9}$$

where,
J_{eq}= Equivelent Moment of Inertia,

$$\begin{aligned} \omega_{dA} &= \omega_{slip} = \omega_s - \omega_m, \\ \omega_m &= \frac{P}{2}\omega_{mech}, \; \omega_d = \omega_s, \\ L_s &= L_{sl} + L_m, \; L_r = L_{rl} + L_m \end{aligned}$$

These mathematical relationships are not only useful to understand the dynamics of motor but to implement the motor model in Simulink environment. In this paper an inbuilt simulink model of induction motor (50 HP/460 V) as shown in Fig. 9 is used to simulate the proposed speed controller design based on similar state space equations.



(a) $d-$axis

(b) $q-$axis

Fig. 1. Equivalent circuit of induction motor in $d - q$ frame

3. SPEED CONTROL TECHNIQUES

Though the various speed control schemes are proposed in literature [3], i.e. scalar control, vector field-oriented control, flux and direct torque control etc, but each one of them has its own advantages and drawbacks.
In scalar control scheme, only the magnitude (scalar quantity) of input variables (i.e. frequency and voltage) is controlled. In this method, the inductor motor is fed with variable frequency signal generated by the pulse-width modulation (PWM) control using inverters. In order to get constant torque over the entire range, the V/f ratio is kept constant. The major drawback of this scheme is that the torque is not controlled directly and shows load dependency. Moreover, due to predicted switching pattern of the inverter, the transient response of such a control is not fast enough. The scalar control scheme can be implemented using sinusoidal PWM, six-step PWM and space vector modulation PWM (SVM-PWM).
The direct torque control (DTC) or flux control method switches the inverter according to the load requirement and has no fixed switching patterns. Due to absence of fixed switching patterns, the response of DTC is extremely, fast during the instant load

$$A = \begin{bmatrix} L_r R_s & \omega_{dA} L_m^2 - \omega_s L_r L_s & -L_m R_r & -L_r L_m(\omega_s - \omega_{dA}) \\ -(\omega_{dA} L_m^2 - \omega_s L_r L_s) & L_r R_s & L_r L_m(\omega_s - \omega_{dA}) & -L_m R_r \\ -L_m R_s & L_s L_m(\omega_s - \omega_{dA}) & L_s R_r & \omega_s L_m^2 - \omega_{dA} L_r L_s \\ -L_s L_m(\omega_s - \omega_{dA}) & -L_m R_s & -(\omega_s L_m^2 - \omega_{dA} L_r L_s) & L_s R_r \end{bmatrix} \quad (7)$$

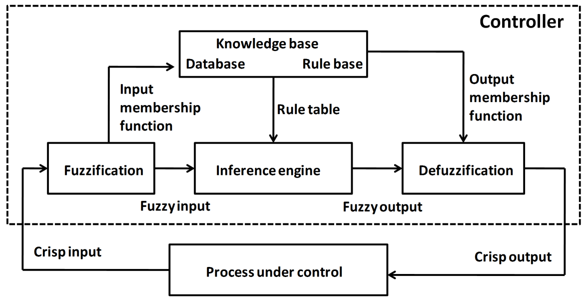


Fig. 2. Block diagram of fuzzy logic controller (a basic structure)

changes. The scheme has disadvantage to show high torque and flux ripples due to inherent hysteresis of the two-level comparator.

The vector control method is also known as the flux oriented control, field oriented control or indirect torque control. In this scheme, three−phase current vectors are converted to a two dimensional rotating reference frame $(d - q)$ from a three-dimensional stationary reference frame with the help of field orientation (Clarke−Park transformation). The d and q phase current vectors represent the flux producing component of the stator current and torque producing component respectively. The vector control is divided into two subcategories depending on the method of measurement: direct and indirect vector control.

The flux sensing coils or the Hall devices are used to measure the flux in direct vector control method. This not only provides less accurate flux measurement but also adds to additional hardware cost. Therefore, it is a seldom used method in control schemes.

The most popular method is indirect vector control. In this scheme, instead of measure the flux angle directly it is estimated from the equivalent circuit model and from measurements of the rotor speed, the stator current and the voltage.

In this paper the indirect vector control method is chosen as a speed control technique to simulate controller model in simulink environment as shown in Fig. 9 .

4. DESIGN OF SPEED CONTROLLERS

Fuzzy logic based techniques have been recognized in recent years as powerful tools for dealing with the modeling and control of complex systems for which no easy mathematical descriptions can be provided [14], [22] . In fact, expert controllers have been successfully applied in recent years to a wide range of control applications characterized by difficult modeling and ill-definedness of the operating environment.

The basic structure of fuzzy logic controller is shown in Fig. 2 which dipicted the essential blocks i.e. fuzzification, defuzzification, inference engine and knowledge base. Like the conventional one fuzzy logic based controllers are also classified in PD, PI and PID type. The Fig. 3, 4 and 5 show the block diagram of PD− and PI− and PID−like fuzzy controllers respectively.

The output equation for a PD−like fuzzy controller is given as follows:

$$u(t) = K_p \times e(t) + K_d \times \triangle e(t), \quad (10)$$

where K_p and K_d are the proportional and differential gain factors respectively.

For PI−like fuzzy controller, the control output equation is evaluated as:

$$\begin{aligned} u(t) &= \int (K_1 e(t) + K_2 \triangle e(t))\, K_3\, dt \\ &= K_2\, K_3\, e(t) + K_1\, K_3 \int e(t)\, dt \\ &= K_p \int e(t) dt + K_i\, e(t), \quad (11) \end{aligned}$$

where $K_p = K_2\ K_3$ and $K_i = K_1\ K_3$ are the proportional and integral gain factors respectively.

.

Similarly, the output equation of a PID controller is given as follows:

$$\begin{aligned} u(t) &= \left(K_2 K_3 e(t) + K_2 K_3 \int e(t) dt \right) \\ &\quad + (K_1 e(t) + K_2 \triangle e(t))\, K_4 \\ &= (K_2\, K_3 + K_1\, K_4)\, e(t) + K_2\, K_4 \triangle e(t) \\ &\quad + K_1\, K_3 \int e(t)\, dt \\ &= K_p\, e(t)\, dt + K_d \triangle e(t) + K_i \int e(t) dt, \quad (12) \end{aligned}$$

where $K_p = (K_2\, K_3 + K_1\, K_4)$, $K_d = K_2\, K_4$ and $K_i = K_1\, K_3$ are the proportional, differential and integral gain factors respectively [23].

In this paper fuzzy logic based controllers, or simply expert controllers, are conventional type of controllers whose parameters are tuned and fed to the compensator through a fuzzy logic based inference engine system. This is done in a hierarchical structure described subsequently.

4.1 Fuzzy Logic-Based Controller

A fuzzy logic controller (FLC) can be regarded as a mapping a set of antecedent fuzzy sets into consequent set. Formally, it is a mapping from $U = U_1 \times U_2 \times \ldots \times U_n$, where $U_i \subset \Re, i = 1, 2, \ldots, n$, into $V \subset \Re$ and consists of four main components:

a) fuzzification interface;
b) knowledge base;
c) inference engine;
d) defuzzification interface.

First, the FLC fuzzifies its crisp valued input vector $x = (x_1, \ldots, x_n)^T \in U$, by mapping it into a fuzzy set in U . This is achieved by the means of the membership functions stored in the knowledge base. The $if - then$ rules, also stored in the knowledge base, and the composition rule of inference are then used by the inference engine to map sets in U into sets in V. The $if - Then$ rules are in the form of

$R^{(l)}$:if x_1 is $A_1^{(l)}, \ldots$ and x_n is $A_n^{(l)}$ $then$ y is $B^{(l)}$

where $y \in V$ is the output of the FLC, A_i^l, $i = 1, 2, \ldots, n$, and $B^{(l)}$ are fuzzy sets in U_i and V, respectively, and $l = 1, 2, \ldots, L$, where L denotes the total number of rules. Finally, the defuzzification process maps a fuzzy set in V to a

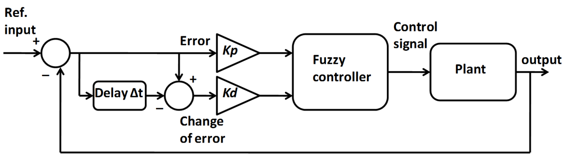


Fig. 3. Block diagram of PD−like fuzzy control system

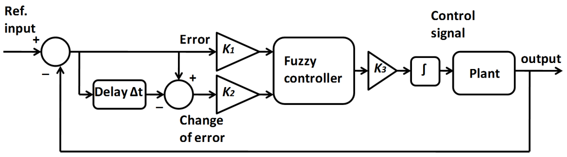


Fig. 4. Block diagram of PI−like fuzzy control system

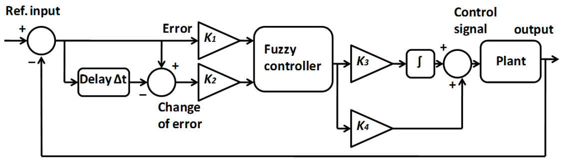


Fig. 5. Block diagram of PID−like fuzzy control system

crisp point value in V. The numerical crisp output of the fuzzy controller then has the following form:

$$y^* = f(x) = \frac{\sum_{l=1}^{L} \beta^{(l)} \left(\prod_{i=1}^{n} \mu_{A_i^{(l)}}(x_i) \right)}{\sum_{l=1}^{L} \left(\prod_{i=1}^{n} \mu_{A_i^{(l)}}(x_i) \right)} \tag{13}$$

where $\mu_{A_i^{(l)}}$ are the membership functions of the fuzzy sets A_i^l, $i = 1, 2, \ldots, n$, $l = 1, 2, \ldots, L$, $\prod$ and $\sum$ denote the fuzzy t-norm and t-conorm operations used, respectively, and $\beta^{(l)} \in \Re$. Although the above discussion describes single output systems, it can be easily generalized to multioutput systems as they can be formulated in terms of a group of single output FLCs. More details can be found in [14].

4.2 Selection of Membership Functions

All membership functions (MFs) for: 1) two controller inputs, i.e., error (e) and change of error $(\triangle e)$ and 2) single control output (u) are defined on the common interval [-2, 2]. A desired number of asymmetric triangles (except the two MFs at the extreme ends) with different base and overlap with neighboring MFs are used in the fuzzy inference as shown in Fig. 6. The two inputs and one output of the fuzzy controller is partitioned and represented linguistically in seven and nine membership functions respectively (i.e. for two inputs as NB = negative big, NM = negative medium, NS = negative small, Z = zero, PS = positive small, PM = positive medium, PB = positive big and for single output as NB = negative big, NM = negative medium, NS = negative small , NVS = negative very small, Z = zero, PVS = positive very small, PS = positive small, PM = positive medium, PB = positive big). As shown in Fig. 7, both inputs and output are normalized between -2 and 2.

4.3 Fuzzy Inference and Rule Base

A fuzzy system is characterized by a set of linguistic statements based on expert knowledge. The expert knowledge is usually in the form of $if - then$ rules, which are easily implemented by fuzzy conditional statements in fuzzy logic. The collection of fuzzy control rules that are expressed as fuzzy conditional statements forms the rule base or the rule set of an FLC.

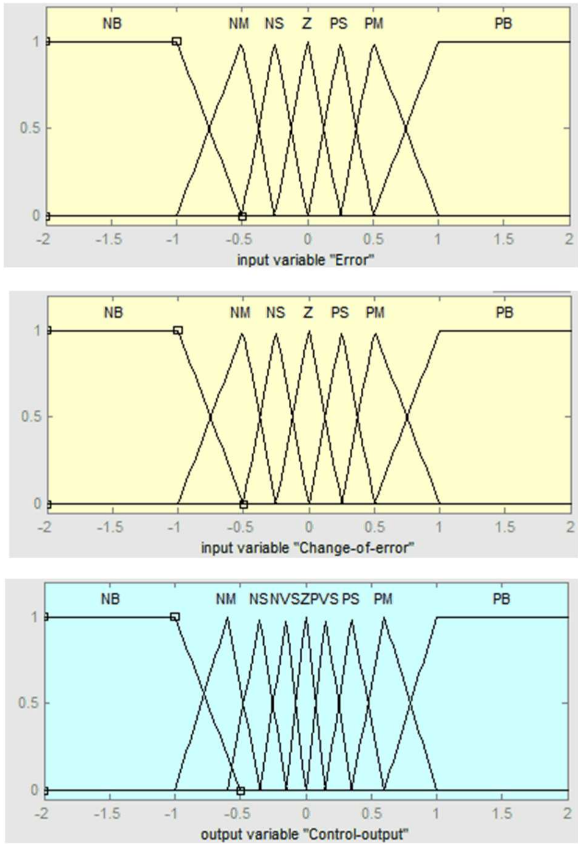


Fig. 6. Fuzzy membership functions for 2 input variables (Error (e) and Change of error $(\triangle e)$) and 1 output variable (Control-output (u))

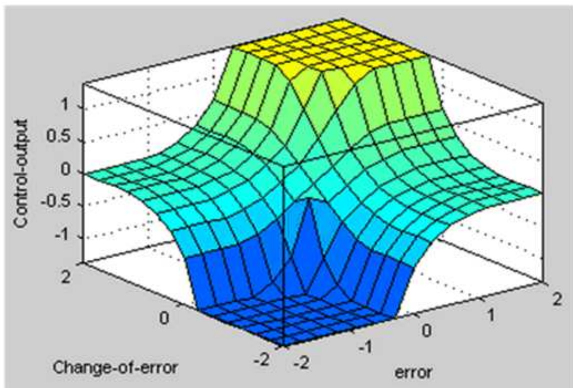


Fig. 7. Rule surface of fuzzy controller (based on Table 1)

In Takagi-Sugeno, method of fuzzy inference the first two parts of the fuzzy inference process (i.e. fuzzifying the inputs and applying the fuzzy operator) are exactly the same as Mamdani method. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the form

if Input 1 (e) is $zero$ and Input 2 $(\triangle e)$ is $zero$,
$then$ Output is $z = a * e + b * (\triangle e) + c$.

where a, b and c are all constants. For a zero-order Sugeno model, the output level z is a constant$(a = b = 0)$.

The output level z_i of each rule is weighted by the firing strength

Table 1. Fuzzy Associative Memory (FAM) Table for fuzzy controller

$e \rightarrow$ $\triangle e \downarrow$	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	NS	NVS	Z
NM	NB	NB	NM	NS	NVS	Z	PVS
NS	NB	NM	NS	NVS	Z	PVS	PS
Z	NM	NS	NVS	Z	PVS	PS	PM
PS	NS	NVS	Z	PVS	PS	PM	PB
PM	NVS	Z	PVS	PS	PM	PB	PB
PB	Z	PVS	PS	PM	PB	PB	PB

e- Error, $\triangle$ e- Change of error

w_i of the rule. For example, for an AND rule with Input 1 = e and Input 2 = $\triangle e$, the firing strength is w_i=$ANDMethod$ $(F_1(x), F_2(y))$, where $F_{1,2}(.)$ are the membership functions for Inputs 1 and 2.
The final output of the system is the weighted average of all rule outputs, computed as
Final output=$\frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$, where N is the number of rules.
The rule base for computing u is shown in Table 1. This is a very often used rule base designed with a two-dimensional phase plane in mind where the FLC drives the system into the so-called sliding mode. The rule base contains 49 rules and the control surfaces (control output versus e and $\triangle e$) are depicted in Fig. 7. The performance parameters are evaluated on the basis of same rule base used in all the fuzzy speed controller (i.e. PD$-$, PI$-$ and PID$-$like) during simulation.

4.4 Selection of Performance Parameters

In literature [22]various techniques are used to evaluate the stability of a system such as Rouths stability criterion, Nyquist stability criterion, describing-function and phase-plane method etc. Unfortunately, due to some reason or other none of the technique found suitable for fuzzy control system stability analysis.
Routh-Hurwitzs and Nyquist criteria require z transform or Laplace transform of a mathematical control model. Due to characteristics of z and Laplace transform the model usually has a linear kind of relationship. Moreover, if the control system is time-variant, these two criterions often fail to find stability of the system.
The describing function approach is only used to determine stability in approximate sense and does not provide accurate value. The phase-plane method is applied usually to find the stability of first and second order systems only.
Therefore the stability of fuzzy control system often judges on the basis of its dynamic response. The performance parameters used in this paper are rise time (t_r), settling time (t_s), peak overshoot $(M_p\%)$ and steady state error (e_{ss}) of the dynamic response curve of control system.
Moreover, the essential function of a feedback control system is to reduce the error, $e(t)$, between any variable and its demanded value to zero as quickly as possible. Therefore, any criterion used to measure the quality of system response must take into account the variation of e over the whole range of time. The four basic criteria are in commonly used i.e. Integral of absolute error (IAE), Integral of squared error (ISE), Integral of time multiplied by absolute error (ITAE) and Integral of time multiplied by squared error (ITSE) [16]. These parameters are evaluated as follows:

$$IAE = \int_0^\infty |e(t)|.dt \tag{14}$$

$$ISE = \int_0^\infty \{e(t)\}^2 .dt \tag{15}$$

$$ITAE = \int_0^\infty t|e(t)|.dt \tag{16}$$

$$ITSE = \int_0^\infty t\{e(t)\}^2 .dt \tag{17}$$

Though, the IAE is mainly used, where the system is being simulated digitally but it is incapable in analytical work environment, because the absolute value of error function does not possess an analytic form [17].
This problem is overcome by the ISE criterion. The ITAE and ITSE have an additional time multiplier of the error function, which emphasizes long-duration errors, and therefore these criteria are most often applied in systems requiring a fast settling time. Large errors contribute heavily to IAE; on the other hand ITAE penalizes heavily errors that occur late in time. Thus, IAE and ITAE reject the transient and steady-state characteristics of a control system, respectively.
For performance comparison all the parameters discussed in this section are evaluated.

5. SIMULATION RESULTS

In this section, the simulation results of some typical FLCs (i.e. PD$-$ and PI$-$ and PID$-$like) applied to speed control of SQIM are discussed. The performances of the simulated FLCs (PD$-$, PI$-$like and PID$-$like) are compared with the conventional PI controller. The values of different performance indexes are shown in Table 2 for each FLC separately. Since peak overshoot and rise time usually conflict each other they may not be reduced simultaneously. If one of them is made smaller, the other tends to become larger.
The FLCs are simulated in the environment software MATLAB/SIMULINK, and tested with various operating condition. A complete simulink model of speed controller for SCIM is shown in Fig. 9. The numerical ode-45 (Dormand-Prince) method with variable-step mode is used to simulate this model. The computational time interval is fixed at 3 second with sampling time period of 2e-006 second. The squirrel-cage induction motor (SQIM) (50 HP/460 V) is chosen as equivalent to the motor used in general industrial applications. The specifications of SQIM are given in appendix A.
The speed response curve of various controller schemes are shown in Fig. 10 . Though the response of PI (conventional) model looks resonable at load of 0 Nm but it deteriorates at 200 Nm (as load increases). On the contrary the speed response of all fuzzy models (i.e. PD$-$, PI$-$ and PID$-$ like) shows robustness against variation of load in the range from 0 Nm to 200 Nm.

5.1 Conventional PI controller

The simulink model of conventional PI controller is shown in Fig. 8(a). To get the optimum performance the values of K_p and K_i are tuned to 13 and 26 respectively. The performance parameters of controller model are shown in Table 2 at different values of load.
The simulated parameters of PI (conventional) controller are used as a reference during its comparison with different fuzzy logic controllers.

5.2 PD$-$like fuzzy controller

The simulink model of PD$-$like fuzzy controller is shown in Fig. 8(c). The model is designed with gain coefficients K_p, K_d

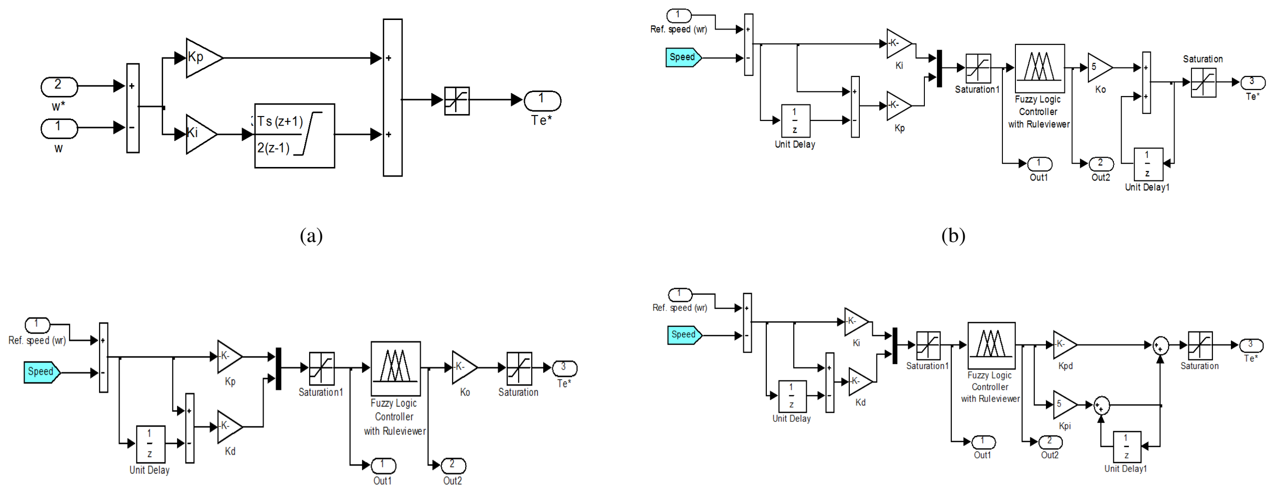


Fig. 8. Simulink models of different speed controller block. (a) conventional PI controller, (b) fuzzy PI−like controller, (c) fuzzy PD−like controller and (d) fuzzy PID−like controller

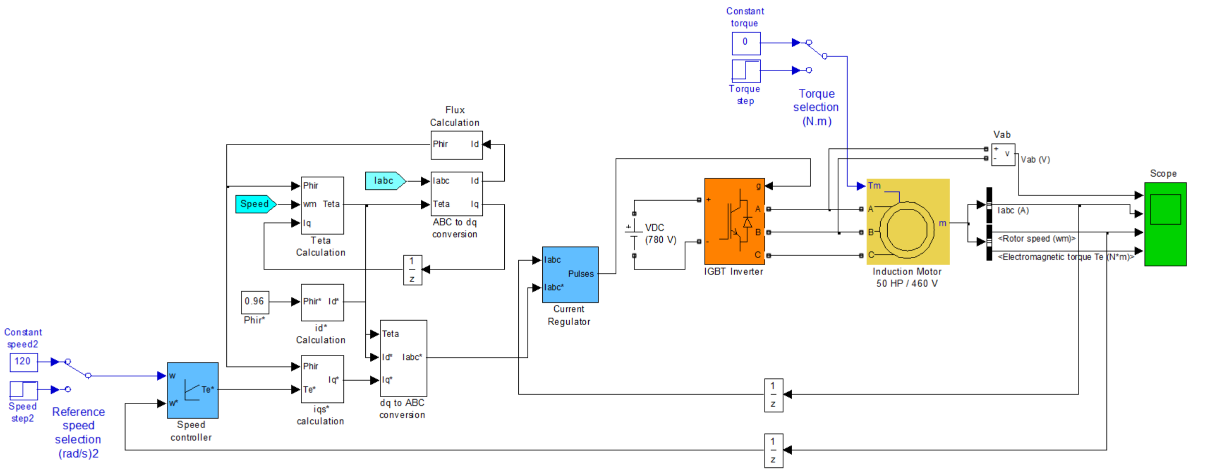


Fig. 9. Simulink model of speed controller system for Squirrel cage Induction Motor (SCIM)

and K_o tuned at 0.01, 1000 and 10000 respectively. The Sugeno-type fuzzy inference system (FIS) is used for the simulation of this controller model with two inputs (e, $\triangle e$) and one output (u) as shown in Fig. 6. The 49 (7x7) rules are generated based on the fuzzy associative memory table shown in Table 1.

The PD-like controller is found to provide a reasonably good performance as compared with PI (conventional) model as shown in Table 2. It shows that the PD-like controller (IAE=31.35, ISE=1913, ITAE= 10.0 and ITSE= 235.5) depicts better results than PI-conventional (IAE=51.75, ISE=3381, ITAE=22.21 and ITSE=679.8) at load of 0 Nm. Similarly, as shown in Fig. 11, at load 0 Nm, the parameters like rise time and settling time of PD-like fuzzy are at par with PI (conventional) model but as the load increases, it improve (numerical value reduces) gradually.

Though the PD-like fuzzy model shows significant reduction in peak overshoot ($M_p(\%)$=0.0013) as compared with PI (conventional) (peak overshoot=13.336) but steady state error is quite high in case of PD−like fuzzy (ess=1.1510) as in PI (conventional) model (ess=0.0216) which is undesirable and should be minimum.

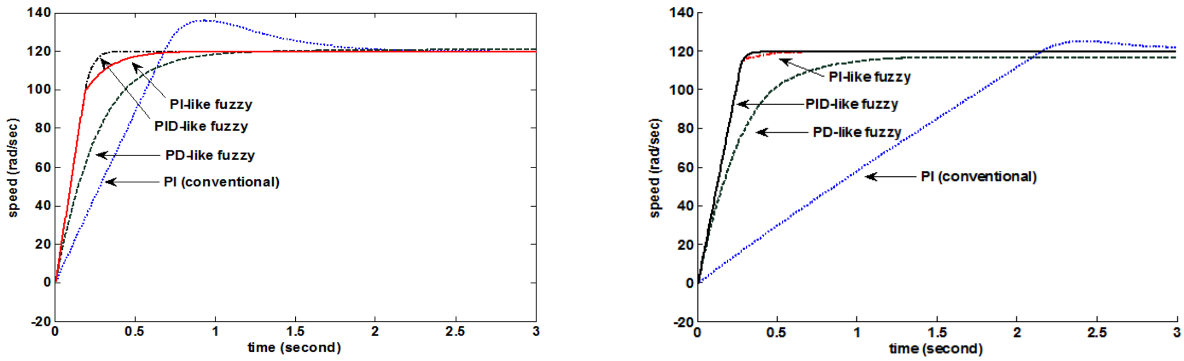
5.3 PI−like fuzzy controller

The simulink model of PI−like fuzzy controller is designed as shown in Fig. 8(b). The speed controller block of main system model is replaced by PD−like fuzzy controller model with gain coefficients K_p, K_i and K_o tuned at 0.01, 1000 and 5 respectively. The values of these gain may vary to get the optimum performance. The same Sugeno−type fuzzy inference system (FIS) is designed using FIS editor to simulate the controller model. The membership functions used for two inputs (e, $\triangle e$) and one output (u) are shown in Fig. 6.

The PI−like fuzzy controller shows a better performance (IAE=17.85, ISE=1297, ITAE= 2.172 and ITSE= 87.09) at load of 100 Nm (and on other loads also) as compared with its conventional counterpart i.e. PI (conventional) model (IAE=68.79, ISE=4996, ITAE=32.11 and ITSE=1333) at the same load. The rise time (0.2388), settling time (0.5182), ess (0.0005) and peak overshoot (0.0025) of PI−like fuzzy is also much better than PI (conventional) model (t_r=0.8286, t_s=1.9852, ess=0.0810, peak overshoot=8.6160) at the same load.

Table 2. Performance analysis of different speed controllers for squirrel-cage induction motor at load (a) 0 Nm. (b) 50 Nm, (c) 100 Nm. and (d) 150 Nm, (e) 200 Nm.

Load (Nm)	Controller	$t_r(sec.)$	$t_s(sec.)$	M_p (%)	ess	IAE	ISE	ITAE	ITSE
0	PI (conventional)	0.5448	1.7776	13.336	0.0216	51.75	3381	22.21	679.8
	PD (fuzzy)	0.5450	1.0343	0.0013	1.1510	31.35	1913	10.03	235.5
	PI (fuzzy)	0.2516	0.5286	0.0010	0.0022	16.76	1167	2.059	72.80
	PID (fuzzy)	0.1883	0.2847	0.0023	0.0020	14.49	1143	1.209	65.68
50	PI (conventional)	0.6574	1.8501	10.981	0.0413	58.13	4003	25.34	898.2
	PD (fuzzy)	0.5248	0.9217	0.0005	0.9726	32.98	1958	11.45	249.1
	PI (fuzzy)	0.2584	0.5356	0.0026	0.0035	17.50	1233	2.193	80.54
	PID (fuzzy)	0.1985	0.2979	0.0025	0.0003	15.30	1209	1.336	73.50
100	PI (conventional)	0.8286	1.9852	8.6160	0.0810	68.79	4996	32.11	1333
	PD (fuzzy)	0.5284	0.9406	0.0002	1.7500	35.43	2007	15.07	271.2
	PI (fuzzy)	0.2388	0.5182	0.0025	0.0005	17.85	1297	2.172	87.09
	PID (fuzzy)	0.2073	0.3096	0.0065	0.0001	16.17	1283	1.482	82.63
150	PI (conventional)	1.1220	2.2188	6.1512	0.2369	88.13	6621	48.26	2325
	PD (fuzzy)	0.5312	0.9585	0.0003	2.5320	37.88	2060	18.91	298.9
	PI (fuzzy)	0.2130	0.4732	0.0037	0.0028	18.10	1372	2.085	95.22
	PID (fuzzy)	0.2130	0.3154	0.0045	0.0003	17.07	1366	1.633	93.38
200	PI (conventional)	0.6574	1.8501	10.985	0.0413	58.13	4003	25.34	898.2
	PD (fuzzy)	0.5332	0.9760	0.0010	3.3090	40.30	2116	22.32	332.1
	PI (fuzzy)	0.2283	0.4009	0.0029	0.0028	18.63	1464	2.059	107.3
	PID (fuzzy)	0.2283	0.3126	0.0091	0.0002	18.10	1462	1.813	106.7



(a) (b)

Fig. 10. Speed response curve of SQIM model using various speed controllers scheme at load (a) 0 Nm, and (b) 200 Nm.

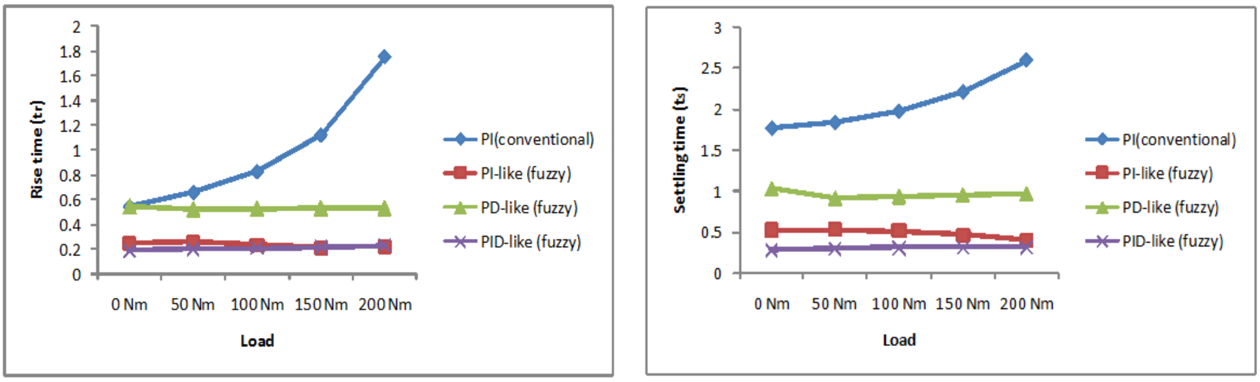
5.4 PID−like fuzzy controller

The PID−like fuzzy controller is also designed in simulink as shown in Fig. 8(d) with gain coefficients K_i, K_d, K_{pi} and K_{pd} tuned at 0.01, 1000, 5 and 10000 respectively. Simulated data in Table 2 shows that the PID−like fuzzy controller depicts best performance among all the fuzzy controller and gives smoother speed response as shown in Fig. 10. On the basis of performance the PID−like fuzzy controller (t_r=0.2130 , t_s=03154 , ess=0.0003 , M_p%=0.0045 , IAE=17.07, ISE=1366, ITAE= 1.633 and ITSE= 93.38 at 150 Nm) clearly shows very good regulation against load variations compared to PI (conventional) as well as all the other fuzzy controllers.

On the basis of simulated data shown in Table 2 the numerical values of IAE, ISE, ITAE and ITSE of the various speed controllers are compared in the form of bar charts as shown in Fig. 12. From these bar charts it is clearly visible that the fuzzy speed controllers absolutely outperformed the PI (conventional) controller in this application.

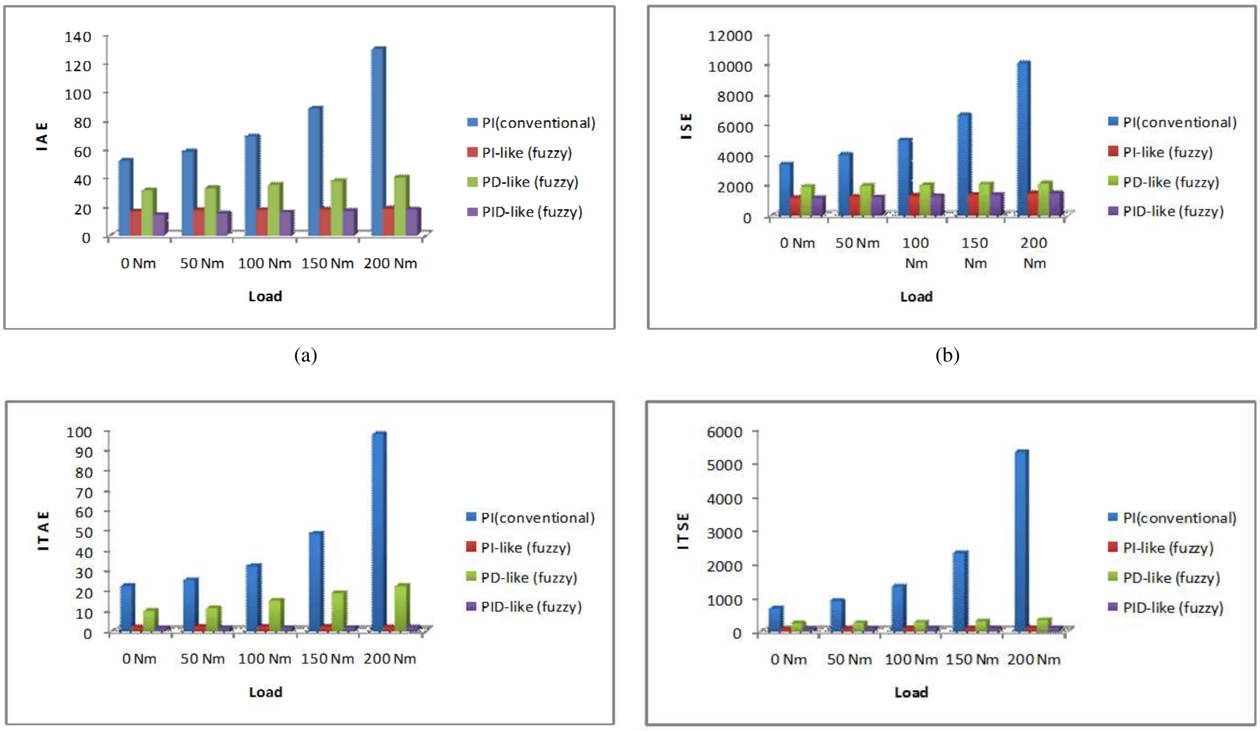
6. CONCLUSION

In this paper, a simulation based study on fuzzy logic controllers to control the speed of SQIM is presented. PI−, PD− and PID−like fuzzy speed controllers are designed for a wide range of load (0 to 200 Nm). The performance and robustness of all FLC's have been evaluated under a vriety of operating conditions of the SQIM system. A comparative study of different fuzzy control strategies in terms of performance and robustness has been conducted with respect to several indexes such as rise time (t_r), settling time (t_s), peak overshoot (M_p%), steady state error ess, IAE, ISE, ITAE, and ITSE. These results prove fuzzy controller to be an excellent approach for different operating conditions, with good behaviors in speed tracking and regulation, and confirm a good robustness beside uncertainties of load and the variations of the motor parameters. Moreover, the proposed speed controller design can also be used with combination of other softcomputing techniques (i.e. artificial neural network, genetic algorithm and hybrid method) to further enhance the performance parameters of the model.



(a) (b)

Fig. 11. Dynamic response parameters of SQIM model with different speed controller schemes (a) Rise time (t_r) , and (b) Settling time (t_s)



(a) (b)

(c) (d)

Fig. 12. Bar chart of SQIM model with different speed controller schemes for the performance parameter. (a) IAE, (b) ISE, (c) ITAE and (d) ITSE

Appendix

(A) Specification of squirrel-cage induction motor (SCIM)

3-phase, 2-pair poles, 50 HP, 1800 rpm, 460 V, 60 Hz
Stator: R_s = 0.087 Ω, L_s = 0.8 mH
Rotor: R_r = 0.228 Ω, L_r = 0.8 mH
L_m = 34.7 mH , J = 1.662 $kg.m^2$

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