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Self Computational Emotional Learning Based Intelligent Controller for Induction Motor Drive using Variable Structure Control

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Abstract:

In this paper novel self computational emotional learning based intelligent controller (SCELIC) is proposed for induction motor control. Variable structure control is a method proposed for an induction motor to offer reliable performance even with the robust and fast changes in the parameters of the motor. To improve the performance of the system, this article proposes a SCELIC controller as a speed controller in VSC. The design is simple and easy to be implemented. Matlab / Simulink based simulation model is developed to examine the effectiveness of the proposed drive. Performance of a drive using SCELIC VSC is analysed and compared with artificial intelligent adaptive neuro fuzzy in VSC. Reliability of the drive is examined under various conditions such as various speeds and various loads.

Keywords: Induction Motor, variable structure controller, SCELIC, ANFIS

1. Introduction:

Induction motors are widely used in domestic and industrial applications. Though induction motor establishes a theoretically challenging control problem, meanwhile the dynamical system is extremely coupled, nonlinear and multivariable. Variable structure controller (VSC) is a method to control the system with nonlinearities[1]. In the previous decade, many researchers focused on the variable structure control strategy for the control of the ac servo drive systems[2, 3]. Application of conventional PI controllers in motor control deliversdecentconcert only in case of linear progressions whose precise model is identified.

Fuzzy logic controller-based induction motor control is analyzed in various control schemes like field-oriented control[4, 5], variable voltage/ frequency control[6], variable frequency control[7], direct torque and flux control[8]and variable structure control[9]. Similarly, the artificial neural network controller is also studied for the above methods of control of an induction motor[10-13]. Adaptive neuro fuzzy is an advanced control algorithm which offers better performance than fuzzy and ANN since it has advantages of both controllers[14].

An emotional learning algorithm is an artificial intelligence control method imitates human brain introduced by Lucas in 2004[15]. An emotional controller is examined in control of numerous motors like an induction motor, BLDC motor and permanent magnet synchronous motor. In this paper novel Self Computational Emotional Learning based Intelligent Controller (SCELIC) is proposed for VSC control of induction motor, which is an improved form of conventional emotional controller. Performance SCELIC is compared with the ANFIS based VSC control of induction motor.

2. Variable structure control algorithm description:

The vector controlled induction motor drives can smoothly adapt VSC algorithm. In a sliding mode (SM) control, the represented model is stored in the form of a predefined phase plane path, and the system response is enforced to track or slide along the path by a switching control algorithm[16]. Sliding surface or sliding line is stated as the initial point of a sliding mode control design[17].

In this study, for obtaining a constant motor speed, the speed of the motor is in controlled manner. So, the vector control has the work to impose the junction of the motor speed magnitude to a reference one. This can be achieved by applying the VSC synthesis procedure to the error speed system equation. Fig. 1 shows the block diagram of the variable structure control of an induction motor drive.

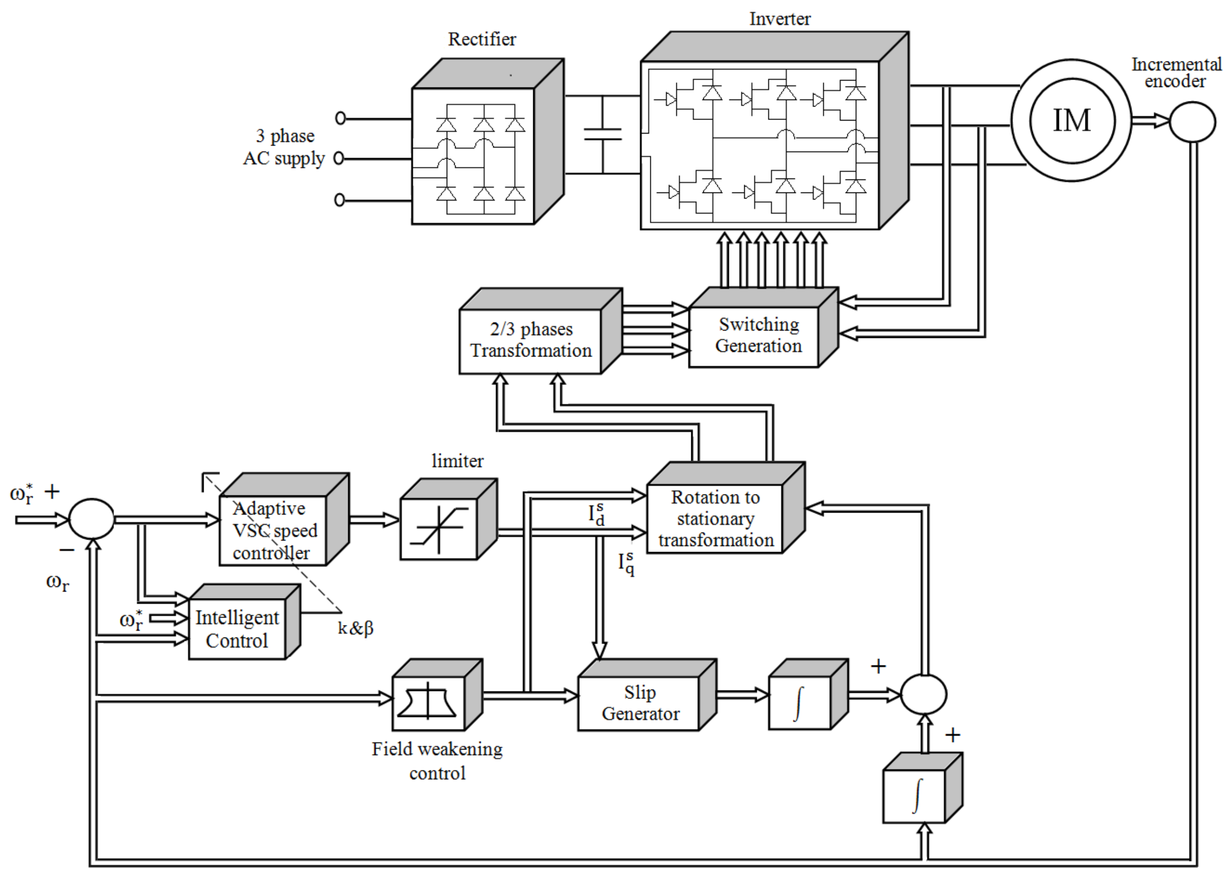

Figure 1. Block diagram of the variable structure control of an induction motor drive

The speed error is the difference between the motor speed and its reference and its derivative can be acquired as[1];

$$\omega_{\mathrm{err}}^{0}(t) = \left(-\frac{B}{J} + \frac{3P}{2}\frac{L_m}{L_r}k\right)\omega_{\mathrm{err}}(t) \qquad (1)$$

Where k is a linear feedback-gain, B is the viscous friction, J is the moment of inertia, p is the pair poles, Lm is the mutual inductance, and Lr is the self-inductance of the rotor per phase of the induction motor. So, the equivalent dynamic response of a control system can be stated as[18];

$$\omega_{\mathrm{err}}^{0}(t) = (a + bk)\omega_{\mathrm{err}}(t) \qquad (2)$$

Where, a= −B/J ,b= 3p/2. Lm/Lr , k is a feedback gain, and (a + bk) is made as negative. The switching surface of the speed controller is given as[18];

$$\mathrm{S(t)} = \omega_{\mathrm{err}}(t) - \int_0^t (\mathrm{a + bk})\, \omega_{\mathrm{err}}(\Gamma)\, d\Gamma \qquad (3)$$

It is clear that from the equation (3) that when the pole is located on the left-hand plane makes the speed error to zero. Hence, the speed controller in VSC is planned as the succeeding,

$$I_q^s(t) = k\omega_{\mathrm{err}}(t) - \beta \mathrm{sgn}\big(\mathrm{S(t)}\big) \qquad (4)$$

Where, β is referred as switching gain, with consideration of $\beta \geq 0$, I_q is the reference torque parameter current and sgn(·) is a signum operation represented by,

$$\mathrm{Sgn(S)} = \begin{cases} 1 & \text{for } S > 0, \\ 0 & \text{for } S = 0, \\ -1 & \text{for } S < 0, \end{cases} \qquad (5)$$

Hereafter, the dynamic actions on the sliding surface can be stated by Equation (3), and the tracking error err (t) reaches to zero exponentially. The torque current command can be obtained as per the Equation (5). The values of k and β play a crucial role in the speed controller of variable structure control. In this study, ANFIS and SCELIC based determination of these parameters and throughput of drive are analysed.

3. VSC using ANFIS controller:

The fuzzy rules are human knowledge oriented and hence, rules will diverge from person to person irrespective of the same performance of the system. Still, the main problem of FLC is short of the design method. The choosing of suitable membership functions and choosing by the correct rule base reliant on the condition can understand by using an ANFIS control system and it is intended to adjust the values of k and β in the speed controller of VSC. The capability to learn fuzzy logic is based on an expert's thinking is the solution given by neural networks. Speed error is fed as an input. Figure 2 shows the basic diagram of the ANFIS controller.

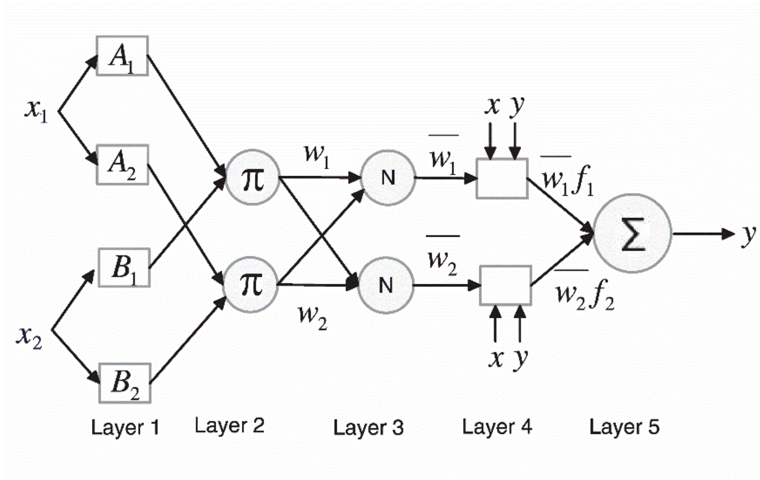

Figure 2. Basic diagram of ANFIS controller

ANFIS model uses a particular input and output (I/O) data set to develop a fuzzy system. At first, for ANFIS learning, a training data that holds the required I/Odata pairs of selective systems to be modelled is necessary. The design components are essential for ANFIS training are data pairs, training data sets, checking data sets, fuzzy inference system. For initializing the ANFIS training, few epochs are selected. The outcome of learning's is checked after executing all 25 steps, based on several rules. The intended ANFIS has two inputs which is the speed error and change in speed error while the output is the k for one ANFIS and β is separately controlled by another ANFIS control system. In this study, the triangularly shaped membership function is implemented.

It contains a Takagi-Sugeno modelfive-layer fuzzy neural network using feed forward technique. For initializing the ANFIS learning first training information that covers the anticipated I/O data pairs of objective systems to be modeled is needed. The number of data pairs, training data sets, checking data sets, fuzzy inference systems for training, numerous epochs have to be selected to initialize the training, the outcome of the learning are checked after defining the step size is made through the design components for all ANFIS control system[19].

It is a feed forward fuzzy neural network and it has five-layer. Each layer has a different significance.

Layer 1 (Input Layer): Input layer represents input, which is a variable of a control system, which is a speed error and its variance ratio represented as x_1, x_2. This layer gives the input values x_i to the next layer, where i = 1 to n

Layer 2 (Fuzzification Layer): This layer is a membership layer that observes the weights of each membership functions (MFs). It receives the input values from the 1st layer and acts as MFs to express the fuzzy sets of the input variables. Furthermore, it works for the membership values that indicates the level in which the input value Xi be on the right place to the fuzzy set, which are inputs to the next layer.

Layer 3 (Rule layer): each node (each neuron) in this layer produces the pre-condition corresponding of the fuzzy rules, i.e., it computes all rule activation, the number of layers present and the number of fuzzy rules should be equal. Every node of these layers computes the weights, which are regularized.

Layer 4 (Defuzzification Layer): Layer 4 gives the output values "*y*" which is acquired from the inference of rules. Connections between the Layer 3 &Layer four are weighted by the fuzzy singletons that stand for another set of parameters for the fuzzy neuro network.

Layer 5 (Output Layer): It augments all the inputs from previous layer and converts the fuzzy classification results into a crisp value.

3.1 Simulation of the VSC with developed ANFIS controller

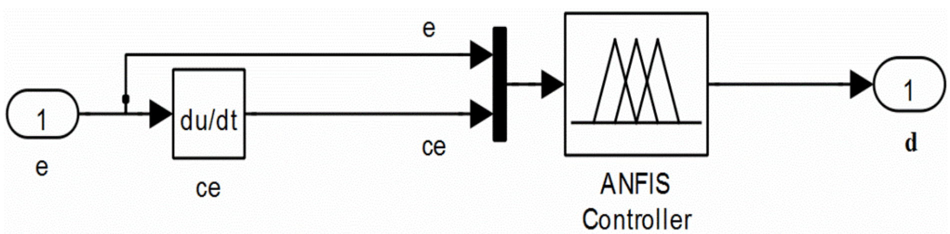

Figure 3. Simulink model of ANFIS controller

Figure 3 and Figure 4 shows the Simulink model of ANFIS controller and training outcome of ANFIS control system. The induction motor can be control with the help of using ANFIS control system. An ANFIS is a fuzzy system whose membership function components are adjusted by using the neuro-adaptive learning techniques. Speed error *e* and change in error *ec* are processed by ANFIS control system to adjust k and β. The choosing of proper rule base depends upon the condition is achieved using an ANFIS control system.

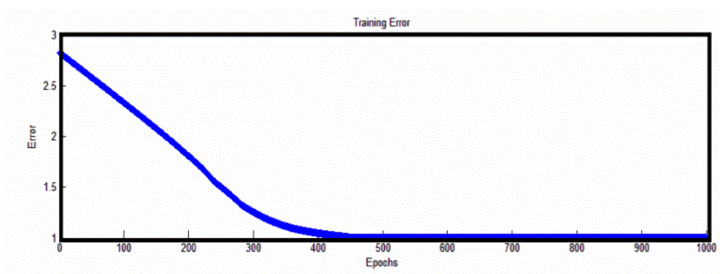

Figure4.Training result of ANFIS controller

This training technique is one of the general techniques for the implementation of neural networks in electrical drives. The required outcome will be trained by using the ANFIS Matlab toolbox function. The components of ANFIS control system is found out by a training process that requires three data, namely two input data (actual speed and reference speed) and the output data that is the k/β for controlling the speed of induction motor using VSC. After the network is trained, an ANN can be processed with new data and estimations can be created. A back-propagation algorithm is used to tune the weights by this the speed error is reduced. By the reputation of this process at numerous times the network is trained. The objective of the training is to attain an optimum solution based on through put computations. The optimum response is acquired after the training show that the speed error is minimized and which indicates that the through put of the ANFIS control system is improved and can implemented easily.

4. VSC using SCELIC controller:

For determining the k/β of the VSC, self computational emotional learning based intelligent control system is intended in this study. It imitates the limbic system of a human brain. In the limbic system, a part of the mammalian brain is mostly responsible for the emotional processes[20]. The limbic system is located in the cerebral cortex containing following main parts, namely, amygdala, orbito frontal cortex, thalamus, sensorycortex, hypothalamus, and the hippocampus.

The initial step of sufficient training of the system happens in amygdale, it is a smallalmond-shaped present in the sub-cortical zone. It is placed in manner of communicating with every sensory cortical area within the limbic system.

Commonly, sensory inputs (S_i) utter the current condition in which the system is associate with. In SCELIC sensory input is ANFIS control system which decides the k/β initially which is furthermore processed by the below steps. In a conventional emotional control system sensory input is a non intelligent controller.

Every sensory input has a node A in this model. A_{th} is a node in the amygdala which directly gets the maximum stimuli signals by the trail from the thalamus. This trail is known as the thalamic connection. It is notable that the thalamic input is not passed into the orbito frontal part and cannot be inhibited through itself.

$$A_{th} = max(S_i) \qquad (6)$$

The outcome of every node A is estimated on the basis on the multiplication of pre-defined plastic connection weight V into the corresponding input. In the orbitofrontal cortex, each node O is alike$A$ nodes, and the output is produced by put on connection weight (V_i) into the input signal.

$$A_i = S_i V_i \qquad (7)$$

The connection weight is adjusted proportionally to the variations among the activation of A nodes and the reinforcement signal (emotional signal) *Rew*. The term *Rew* is a constant that helps to tune the learning speed. The variations among the reinforcement signal and activation of the A nodes decides the apprising of the connection weight which lastly proceeds to the learning progression in the amygdala. The rate of learning is expressed by the symbol α.

$$\Delta V_i = \alpha\left(S_i\, max\left(0, Rew - \textstyle\sum_j A_j\right)\right) \quad (8)$$

The connection weights does not reduce. This is the major thing for the design because once it learns an emotional response; it must be permanent and cannot be unlearned. The O nodes act proportionally, with a connection weight W employed to the input signal to produce an output.

$$O_i = S_i W_i \qquad (9)$$

Where O_i is referred as the i^{th} value of orbitofrontal cortex, S_i is referred as the i^{th} value of the sensory input, and W_i is referred as the i^{th} value connection weight. $\Delta W_i$is given as,

$$\Delta W_i = \beta\left(S_i(E' - Rew)\right)(10)$$

β is another learning rate constant. The node E just adding up the outputs of the nodes $A$and then subtracts the inhibitory outputs from the nodes O. The outcome of these will be the output of the model. The nodes A give outputs proportional to their contribution in the prediction of the *Rew*reward, while the nodes O inhibit the output of E as essential. The node E' is the sum of outputs of A except for $A_{th}$and then subtracted from the inhibitory outputs of the nodes O.

In equation (8), the term *max* represents the weight (V_i) that cannot be decreased. The striking proof for this model is that once the amygdala learns a reaction, it will be permanent. Simply, the amygdala never forgets the emotional evaluation. Generally, orbitofrontal cortex have the rejection of unfitting reaction. The learning rule in the orbitofrontal cortex is calculated on the basis of assessment between the anticipated and established reinforcement signal and inhibits the output of the design if there is any disparity.

$$E=\sum_{i=0}^{n} A_i - \sum_{i=0}^{n} O_i \text{ (including } A_{th}) \quad (11)$$

$$E'=\sum_{i=0}^{n} A_i - \sum_{i=0}^{n} O_i \text{ (excluding } A_{th})(12)$$

Apprising the adaptive weights in the orbitofrontal cortex is more or less same as to the amygdala rule. The individual point is that for following the unsuitable outcome from the amygdala, the orbitofrontal weights must be changed. The A nodes gives their outputs proportionally to their contribution in predicting the reward or stress, while the O nodes prevents the output of E if it is essential. The difference of the response of amygdala and orbitofrontal nodes gives the model output k/β.

5. Simulation results and analysis:

Matlab based simulation models are developed for ANFIS and SCELIC based VSC for 5HP 3 phase squirrel cage induction motor. Drive is analysed under various speeds and loads. Specification of a motor is presented in table 1:

Condition 1:

In this condition, three phase induction motor is analysed with the reference speed of 1800RPM under no load. The speed performance of motor by ANFIS and SCELIC in VSC are shown in figures 5 and 6.

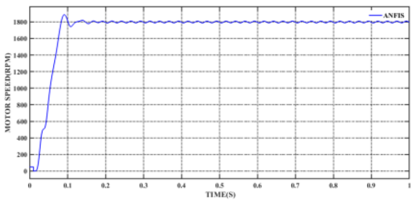

Figure 5. Speed performance of ANFIS based VSC control under condition 1

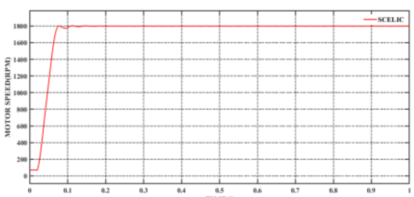

Figure 6. Speed performance of SCELIC based VSC control under condition 1

From figure 5 and 6, it is noted that peak overshoot produced by ANFIS is 4.25% while SCELIC produces 0.11%.

Comparative performance of both controllers under condition 1 is shown in figure 7.

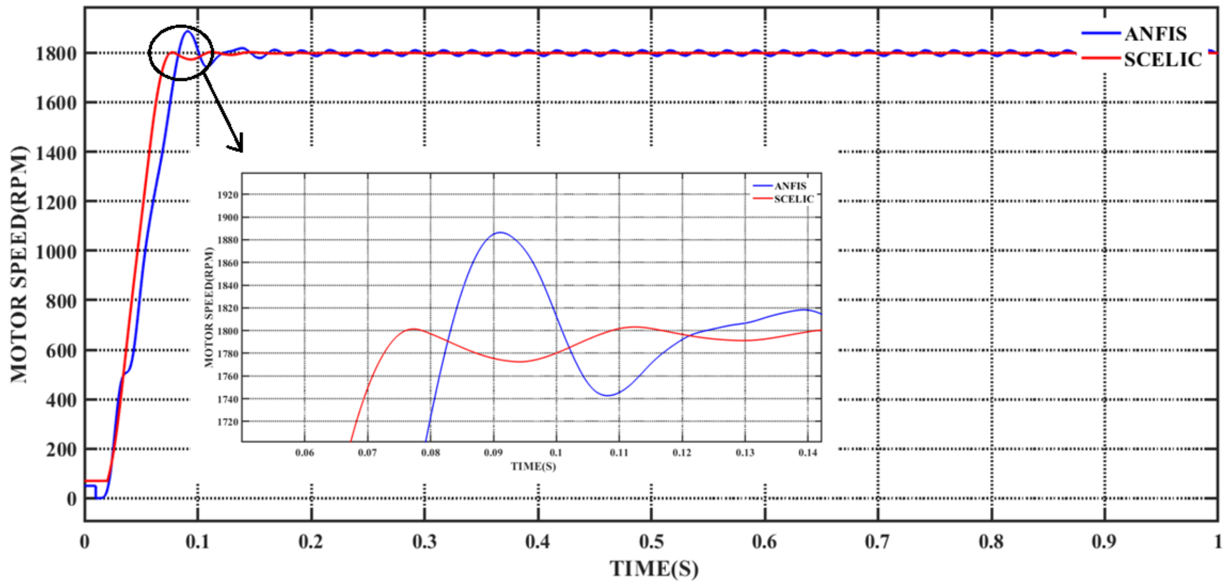

Fig. 7. Comparative performance of ANFIS and SCELIC based VSCunder condition 1

From figure 7, it is observed that peak overshoot produced bySCELIC is 97% reduced compared to ANFIS based VSC.

Condition 2:
The dynamic performance of the drive is analysed in this condition by increasing the load at the time of 0.7sec while motor starts with the no-load of reference speed 1800RPM. The speed performance of motor by ANFIS and SCELIC in VSC are shown in figures 8 and 9.

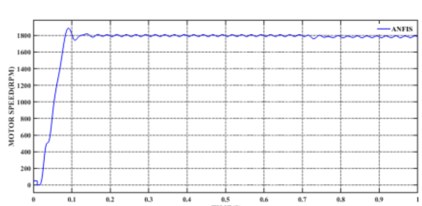

Figure 8. Speed performance of ANFIS based VSC control under condition 2

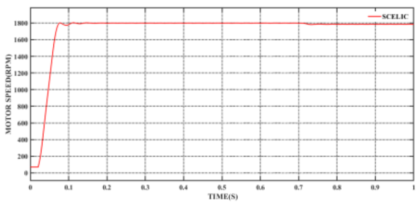

Figure9. Speed performance of SCELIC based VSC control under condition 2

From figure 8 and 9, it is noted that speed drop during a change in load produced by ANFIS is 2.67% while SCELIC produces 1.0%.

Comparative performance of both controllers under condition 2 is shown in figure 10.

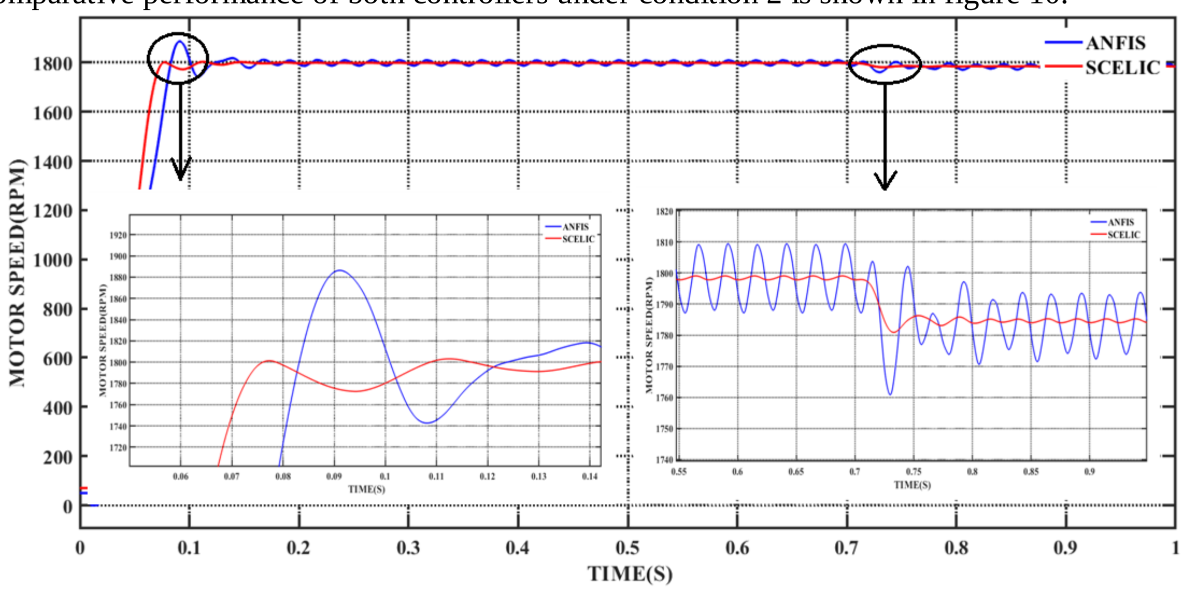

Figure 10. Comparative performance of ANFIS and SCELIC based VSC under condition 2

From figure 10, it is noted that the speed drop produced bySCELIC is 62.5% reduced compared to ANFIS based VSC.

Condition 3:

Condition 3 is the same as to condition 2 with the reference speed of 1600RPM. The speed performance of motor by ANFIS and SCELIC in VSC are shown in figures 11 and 12.

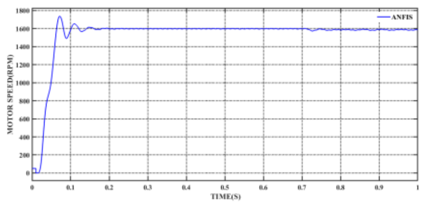

Figure 11. Speed performance of ANFIS based VSC control under condition 3

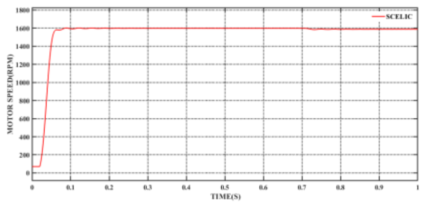

Figure12. Speed performance of SCELIC based VSC control under condition 3

From figure 11 and 12, it is noted that steady state error in speed produced by ANFIS is 0.08% while SCELIC produces 0.056%.

Comparative performance of both controllers under condition 3 is shown in figure 13.

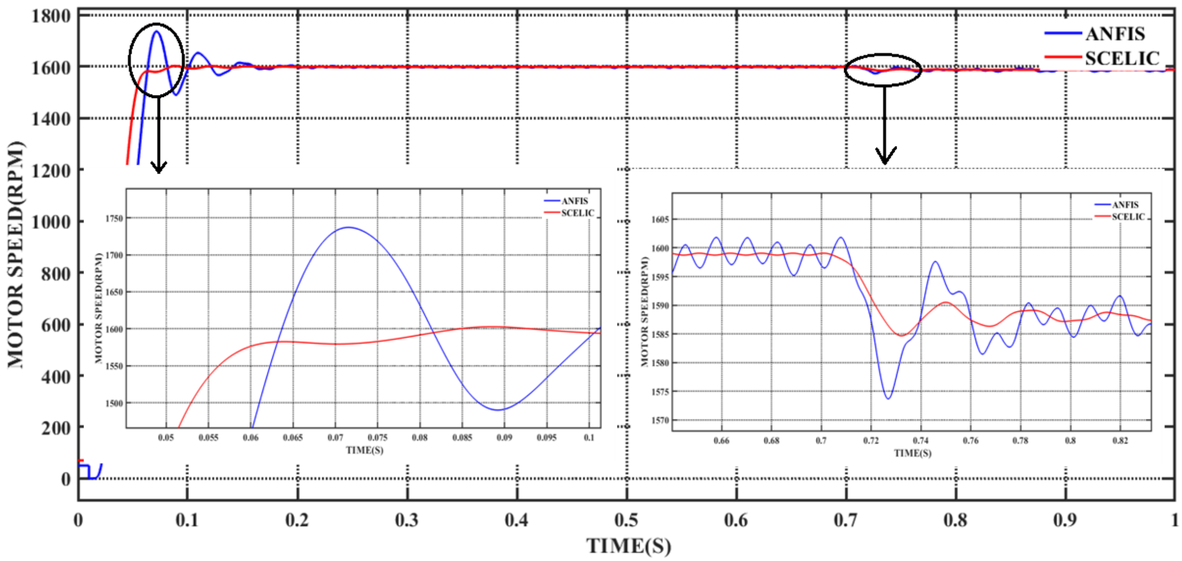

Figure 13. Comparative performance of ANFIS and SCELIC based VSC under condition 3

From figure 13 it is noted that steady state error produced bySCELIC is 30% reduced compared to ANFIS based VSC.

Comparative performance of ANFIS and SCELIC based VSC under various conditions are presented in table 2.

6. CONCLUSIONS:

Analysis of self-computational emotional learning based intelligent controller (SCELIC)as speed controller in variable structure control of an induction motor is discussed in this paper. Hence the induction motors are massively utilized for various commercial and domestic applications, researches to improve performance of an induction motor is still going on which starts before a few decades. Artificial intelligent ANFIS based VSC control of induction motor is also analysed and compared with the proposed SCELIC based VSC, to validate the enhancement of the proposed system in a drive. Performance of ANFIS and SCELIC based VSC of an induction motor has been analysed under various speeds and loads to show the effectiveness of the proposed system.

List of symbols and Abbreviations

SCELIC	Self Computational Emotional Learning based Intelligent Controller
VSC	Variable Structure Controller
PI	Proportional Integral

ANN	Artificial Neural Network
BLDC	Brushless Direct Current Motor
ANFIS	Adaptive Neuro Fuzzy Inference System
SM	Sliding mode
FLC	Fuzzy Logic Controller
k	Linear feedback-gain
B	Viscous friction
J	Moment of inertia
Lr	Self-inductance of the rotor
β	Switching gain
e	Speed error
ec	Change in error
S_i	Sensory inputs
Rew	Reinforcement signal
W	Connection weight
α	The rate of learning

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Table 1 Motor Parameters

Line Voltage	415
Frequency	50 Hz
Stator Resistance (R_s)	1.15Ω
Rotor Resistance (R_r)	1.083Ω
Statorinductance (L_s)	5.974mH
Rotor inductance(L_r)	5.974mH
Mutual inductance(L_m)	0.2037H
Moment of Inertia (J)	0.02 Kg.m^2
Number of poles (P)	4

Table 2 Performance comparison of ANFIS and SCELIC Controller

CASES	**Peak overshoot in %**		**Rise time in Sec**		**Settling time in Sec**		**Steady state error in %**		**Change in speed during load change in %**	
	ANFIS	SCELIC	ANFIS	SCELIC	ANFIS	SCELIC	ANFIS	SCELIC	ANFIS	SCELIC
CASE 1	4.25	0.11	0.091	0.077	0.2	0.2	0.52	0.05	-	-
CASE 2	4.25	0.11	0.091	0.077	0.2	0.2	0.52	0.05	2.67	1.0
CASE 3	8.47	1.03	0.072	0.062	0.24	0.24	0.08	0.056	1.72	0.9