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Inimizing Peak Overshoot with Reduced Rule Base on Pid Controller of Switched Reluctance Motor Drive

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Abstract: Switched Reluctance Motor (SRM) is a machine where electromagnetic torque is designed and developed with variable changes in the reluctance process. Both stator and rotor has salient poles but only stator carries windings, hence a steady state error occurs in higher ratio on the Proportional-Integral-Derivative (PID) Controller. PID controller with variable gains on SRM consumes more peak overshoot time on the limited DC voltage supply saturation on specific devices. PID Fuzzy Controller for SRM shows the response time with very little bit variation over different load disturbances. But, the rise time on high speed electronics SRM drive fails to respond the circuit to fast input signals. All these limitations, planned to set up a SRM system design with PID Neuro Fuzzy Controller. To overcome high peak overshoot time on varying load disturbances, a framework called Neural Learning of PID Neuro Fuzzy based on Condensed Multi layer Perceptrons (NLPID Controller-NFCMP) is proposed in this paper. Initially, PID Neuro Fuzzy Controller uses the neural network learning techniques to tune the fuzzy membership function. The integration of neural network and fuzzy logic with the PID controller helps in handling multiple speed SRM drive machines. Here, multiple input points are taken and dynamic output system is generated with if-then rule fuzzification. Second, the Neuro fuzzy membership function with 49 rules in NLPID Controller-NFCMP framework is tuned to 12 rules using the Condensed Multi layer Perceptrons method. This proposed method is a feed forward artificial neural network which takes the previous if-then rule result to map the set using the activation function. Activation function in NLPID Controller-NFCMP framework condenses the rule based on the weighted input. As a result, the distributed load factor reduces the peak overshoot time and rise time. Experiment is carried out on the 8/6-pole SRM drive with varied load and speed and analyzed rising time, settling time and overshoot on load disturbances.

Key words: Multi layer Perceptrons · PID Controller · Switched Reluctance Motor Drive · Neuro Fuzzy Design Circuit · If-Then Rule and Peak Overshoot Time

INTRODUCTION

Due to several advantages in the design of switched reluctance machine (SRM), it had received greater and significant attention from numerous researchers over the last decade. PI controller with Variable Gains (PI-VG) [1] was constructed with the motive of increasing gain adaptation through magnetic saturation and on the basis of rotor position and current. The source of disturbance was also compensation in PI-VG using back electro-magnetic field. But, PID controller with increasing gains on SRM consumes more peak overshoot time increasing the complexity.

Modified PI-like Fuzzy Logic Controller (MPI-FLC) [2] on SRM drive was designed to reduce the complexity by minimizing the membership functions using fuzzy logic reasoning. However, the rise time on high speed electronics SRM drive failed to respond the circuit including fast input signals. Modified R Dump Converter [3] was designed with the objective of by reducing the average speed for numerous fast input signals through unidirectional current flow, but compromising the voltage.

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To reduce the force and voltage ripples the author in [4] constructed Fuzzy Logic Control (FLC) and Proportional Integral (PI) techniques. The application of FLC with PI techniques also reduced the velocity of the translator with respect to position. In the current scenario, the rotating motor is used for shunting systems of railway channels with an efficient mechanism for movement transformation. Switched Reluctance Motor comprising of double stator linear device was used in [5] using flux and force to improve the reliability and maintainability of the shunting system. However, high propulsion force with respect to various channels remained unaddressed.

A Multi Objective Differential Evolution (MODE) technique [6] was designed to provide optimality that proved to be attractive for industrial applications with maximum average torque and minimum copper losses. Another method called, PC-based data acquisition for Linear Switched Reluctance Motor was designed in [7] for controlling motors travelling distance, but at the cost of maximum torque ripple. In [8], a framework was designed to regulate the speed for SRM using Fuzzy-PID and Neural and Neuro Fuzzy controllers. Though robustness was ensured, optimization with respect to current was not provided.

The Ant Colony Optimization with Genetic Algorithm was proposed in [9] to reduce the time domain objective function. In addition, high speed SRM was also controlled by Photo Voltaic (PV) system improving the overall performance of the system. But with the increasing individuals, program complexity also gets increased. To reduce the program complexity, in [10], the author designed Fuzzy Logic Controller (FLC) with the aid of output Scaling Factor (SF) improving the feasibility of the system. The method also reduced the fuzzy set membership functions without compromising the performance of the system and stability through adjustable controller gain. However, torque ripple with respect to stability of the model remained unaddressed. To address the above said issue, torque ripple minimization was achieved through torque sharing functions in [11].

Despite robustness and reliability, fault tolerance is one of the inherent problems faced in switched reluctance motor (SRM). A reconfigurable fault tolerant system was designed in [12] with the motive of detecting the fault at an early stage through flux differential detector. Another method for fault tolerance in SRM was designed in [13] using PWM controller with two different speeds and three different load torques. The acoustic radiation properties of SRM was analyzed in [14] with the objective of reducing the noise with respect to the acoustic behavior of motor. However, the above mentioned methods lack automatized method of referring to lookup tables deteriorating the performance of the system. A fully digital embedded SRM based on the Field Programmable Gate Array (FPGA) was designed in [15] to solve the issues related to nonlinearity and automatization and was also proved to be flexible using parallel processing algorithms.

The switched reluctance motor (SRM) consists of a double featured motor that include simple concentric windings with no permanent magnets on the rotor. In [16], Artificial Neural Network was used to control the SRM with the increase in the flux density. A Finite Element method was introduced in [17] in addition to core loss model to improve the efficiency and power ratio in ANSYS. However, noise with respect to numerous flux density waveforms remained unsolved. To reduce the noise, classification of SRM configurations was introduced in [18] with the objective of minimizing the voltage drops. However, the ripple of torque with reference to voltage drops remained unaddressed.

To improve the ripple of torque, Adaptive Neural Fuzzy Inference and Fuzzy Logic Controller was introduced in [19]. The method was proved to be efficient than the classic controller in terms of torque ripple. Another method called, the Direct Torque Control (DTC) [20] was introduced with the objective of reducing the torque ripple using switching table that included flux linkages.

In this study, to overcome high peak overshoot time and varying load disturbances, first, a 8/6-pole, 500 W, 350 V and 2.2 A Switched Reluctance Motor (SRM) drive having a rated torque of 5 N?m is used. The Neural Learning of PID Neuro Fuzzy based on Condensed Multi layer Perceptrons integration of neural network and fuzzy logic with the PID controller handles multiple speed SRM drive machines and switching sections as Neuro fuzzy membership function with 49 rules is tuned to 12 rules using the Condensed Multi layer Perceptrons method were simulated.

In the simulation and experimental study, four-phase 8/6-pole SRM and the equivalent circuit of one phase winding is used. The rising time, settling time and overshoot on PID controller versus the position by the fuzzy logic control (FLC) and NFLC techniques was examined. The motor was controlled with a PIC18F452 microcontroller and the results of the rise time on multiple speed of the SRM drive were compared with the simulation results of the PI-VG (existing PI Controller) and

MPI-FLC (existing Fuzzy Controller) techniques. It was seen that the PIC18F452 microcontroller is sufficient to reduce the peak overshoot time on load disturbances of the SRM and in the NLPID Controller-NFCMP framework, the rise time on multiple sp and peak overshoot time are lower than in the PI-VG and MPI-FLC techniques.

The organization of the paper is as follows: In Section 1, related works by numerous researchers for SRM drive machines is presented. In section 2, an elaborate design of neural learning of PIC neural fuzzy based on condensed multi layer perceptrons is presented. Section 3 includes the experimental setup and analysis of discussion made by comparing the state-of-the-art methods. Finally, the paper concludes with concluding remarks in Section 4.

Neural Learning of Pid Neuro Fuzzy Based on Condensed

Multi Layer Perceptrons: The Neuro fuzzy control model is build in our proposed work to deal with multiple speed and load disturbance SRM drive machines. The transformation of the fuzzy membership rule from the larger rule set to the compress rule set is performed using the neural machine learning procedure. The quality of Neuro fuzzy controller in our proposed framework works effectively between different choices of membership functions. In order to work with different choices of membership functions, a Condensed Multi layer Perceptrons method is introduced for tuning the Neuro fuzzy logic controllers.

In NLPID Controller-NFCMP framework, neural networks are used in a novel way to solve the steady state errors and peak overshoot time. Let us consider multiple input on PID controller and produce a single output system whose states at any instant is defined by "m" variables such as I1, I2,...,Im. The controller action of the PID derives the system to the continuous state of 12 rules using the if-then rule fuzzification procedure. The integration of the rules in NLPID Controller-NFCMP (i.e., proposed Neuro Fuzzy) framework helps to reduce the time taken for the peak shoot measurement.

The objective of the research work is to design a simple converter for SRM drive to be operated with the direct current with the minimal steady state errors. The switching device of the SRM operates with bidirectional currents with direct excitation. The bidirectional currents reduce the rise time on getting the input signal for varying speed of the motor. In SRM drive the stator and rotor generates the torque with push and pull between the reluctance forces. The torque produced in NLPID Controller is related to co-energy measurement with flux linkage, excitation current and rotor location. Four-phase 8/6-pole SRM and the equivalent circuit of one phase winding respectively are designed in our research work for improving the current flow speed in the circuit. The block circuit of Neuro Fuzzy PID Controller is shown in Figure 1.

Figure 1 shows the circuit design of SRM drive with PID Controller and Neuro Fuzzy Controller. The PID controller in our proposed framework performs neural learning for analyzing the control loop feedback mechanism. The control loop feedback mechanism calculates the error value on the steady state between the process variable and desired set point. On the other hand, the Neuro Fuzzy controller controls the speed error signal and converts it into phase current with 12 fuzzy relationship rules in SRM drive.

The mean value of the developed torque is used to displace from the associated to the unassociated position in SRM drive. The input points 'θ' are selected and the co-energy 'w'' is formularized as,

$$Co-energy = w' = \int \psi(\theta, i)dt \tag{1}$$

where 'Ψ' denotes the flux linkage with the angular rotor location 'θ' on current excitation is measured. The co-energy for different speeding of the motor is measured based on the above three factors. The flux linkage function is then described as,

$$Flux\ linkage, \psi = \frac{dw'}{d\theta} \tag{2}$$

The flux linkage in (2) is then obtained from the ratio of the estimated current 'dw' to the given row index dè. The indexing uses the look up table to store the information. The second order interpolation based speed of the SRM drive is measured as,

$$\frac{dw}{dt} = T(\theta, i) \tag{3}$$

where 'T' denotes the time taken on rotating the motor based on the angular rotor location 'θ' on current excitation 'i'. The error speed is also measured from the difference between the rotor speed and its desired set point.

Neuro Fuzzy Logic Controller: Neuro Fuzzy is a high level model designed with logical structure. The structure contains Fuzzy membership function rule set with optimized result. The integration of neural network and the fuzzy logic are used in the design of PID controller to

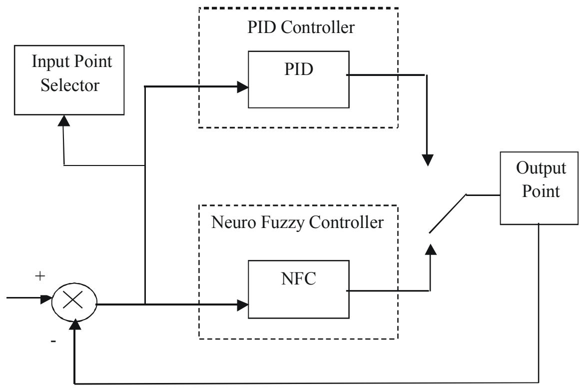

Fig. 1: Block diagram of Neuro fuzzy PID controller

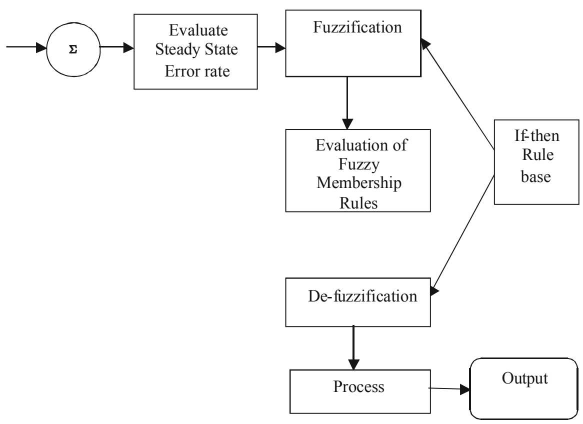

Fig. 2: Fuzzification steps with if-then rules

handle multiple speed SRM drive machines in NLPID Controller-NFCMP framework. In the proposed framework, multiple input points are considered and a dynamic output system is generated with if-then rule fuzzification. A fuzzy system is trained with a set of neural learning procedure in PID controller. The neural learning procedure in PID controller is used to estimate the function when control speed of the motor and load factor varies.

If-Then Rule Fuzzification: The estimated functional value through the fuzzified output takes multiple input functions in NLPID Controller-NFCMP framework. The neural learning helps to evaluate the steady state error rate. The fuzzification procedure converts the membership functional rule of 49 set into a crisp value using if then rule base. De-fuzzification is also carried out to process the value of the steady state on varying moving speed of the rotor and distribution load.

Figure 2 shows the steps involved in the design of fuzzification with if-then rules. Initially, if-then rule base is evaluated. Based on the results obtained through if-then rule, fuzzification and defuzzification is performed. In case of fuzzification, evaluation of fuzzy membership rules and steady state error rate is obtained or else in case of defuzzification, if-then rule set evaluated provide the least structured to derive the Neuro fuzzy rule in NLPID Controller-NFCMP framework. The Neuro fuzzy rule base from the knowledge of system operates according to the behavior of control of SRM drive is given as below:

If 'e' *is rule with condition* (1&2), *then* 'e' *is integrater* (4)

The proposed framework obtains the input as error 'e' that measures the difference between the desired position and actual set output position. The rule uses the fuzzy equivalent torque to appropriate the fuzzy membership function. The Neuro-fuzzy rule evaluation focuses on operation in the antecedent of the fuzzy rules and Neuro learning in Neuro-fuzzy mode controller. The de-fuzzification step transform fuzzy set to crisp set with the aggregated output current factor. The lookup table values are then updated after the steady state error measurement.

Condensed Multi Layer Perceptrons: The Neuro fuzzy membership rules generated from input output pairs using if-then rule in NLPID Controller-NFCMP framework now develops a condensed multi-layer perceptrons method. This method combines the rules of the Neuro fuzzy membership functions to reduce the rule set. The Neuro fuzzy membership functions use a feed forward artificial neural network to work with the if-then rule result.

Figure 3 shows the design of multi-layer perceptrons on multi-load distribution. As shown in the figure, the multi-load distribution distributes the current load to different devices with minimal delay factor. The delay factor is reduced as Neuro Fuzzy a membership rule is reduced to the 12 rules using condensed multi-layer rule. The factors are attained by feed forward loop where if rule is helped to reduce the rules and attain minimal time peak overshoot rate. The step by step procedure for condensed multi-layer perceptrons is formularized as,

Begin
Input: Set of 49 Neuro Fuzzy Membership Functions
Output: A condensed set of 12 rules attained on the PID controller

Step 1: Initially a set of rules are obtained and processed with the help of if-then procedure.
Step 2: Feed forward artificial neural network is then applied to the set of rules.
Step 3: Condenses the rule set on multi-load distributions.

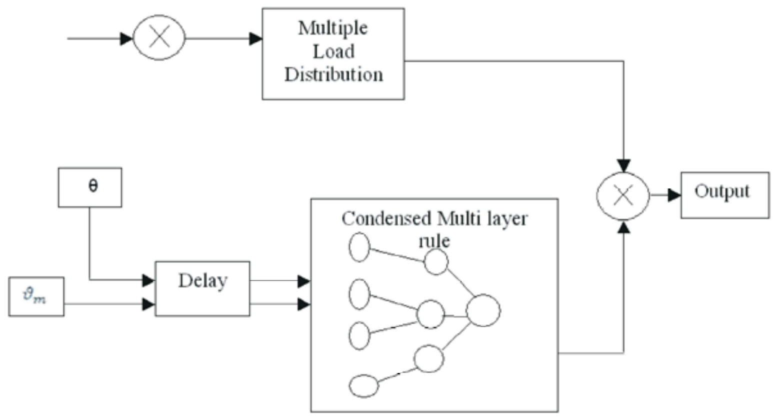

Fig. 3: Multi layer perceptrons on multi-load distribution

Step 4: Application of activation function on the Neuro Fuzzy SRM drive

End

The rule set is reduced and attains higher range of rise time with minimal steady state error rate. The overshoot rate is achieved with minimal time taken on multiple speed of the SRM drive. The achievement of the SRM drive machines is then applied through the activation function.

Activation Function: Activation function in NLPID Controller-NFCMP framework condense the rule based on the weighted input, so that the distributed load factor reduces the peak overshoot time and rise time. The activation function is formularized as,

$$A(\vartheta i) = \tanh(\vartheta i) \quad (4)$$

The activation function 'A' in (4) is a hyperbolic tangent 'tanh' used to work with the condensed rules with a flux linkage 'Ψ' for input points 'i'. The specialized activation functions include radial basis functions which are used in the neural network and fuzzy controller. As a result, the fuzzy controller and Neuro PID controller helps to improve the load disturbance based high performance rate for varying speed motors.

Experimental Evaluation: Simulation experiments are conducted with 8/6-pole Switched Reluctance Motor (SRM) drive for experiment the proposed Neural Learning of PID Neuro Fuzzy based on Condensed Multi layer Perceptrons (NLPID Controller-NFCMP) framework with existing PI Controller [1] and Fuzzy Controller (FC) [2] on SRM drive. A encoder mounted on the shaft of the SRM drive, where machine loads the power supply for feeding the dc bus of the inverter. The source of the PID microcontroller system contains the 500 W, 350 V and 2.2 A which is capable to develop a rated torque of 5 N•m.

The NLPID Controller-NFCMP is constructed by a PC through a friendly user interface of Matlab coding. The following are the high system integration which used to balance the multiple speeds and load distribution on the SRM drive. The feasible study of the system is done by experimenting through the factors such as steady state error rate on load distributed PID controller, rise time on the multiple speed of the SRM drive, peak overshoot time on load disturbances and rise time on the varying load disturbance factor. Details of switched reluctance motor and its configuration are given in Table 1 are obtained as input. The maximum iteration for the condensed multilayer perceptrons is set to 50.

The performance indices when load applied to 0 Nm with speed varying from 1000 rpm to 1500 rpm using the three methods namely, Proposed Neuro fuzzy, Existing PI Controller and Existing Fuzzy controller are tabulated in Table 2. These statistical performance indices with varying speed gives a clear picture of performance improvement for proposed Neuro Fuzzy when compared to the existing methods PI Controller and Fuzzy Controller respectively. From the table it is illustrative that the proposed Neuro fuzzy has improved performance results in a steady manner with respect to differing speeds. The quantitative results for these performance indices are given in Table 2.

In a similar manner, the performance indices when load applied to 5 Nm with speed varying from 1000 rpm to 1500 rpm using the three methods namely, Proposed Neuro fuzzy, Existing PI Controller and Existing Fuzzy controller are tabulated in Table 3. These statistical performance indices with varying speed for proposed

Table 1: Switched reluctance motor and its configuration

Motor specifications	Values
Current	2.2A
Power	500 W
Stator poles	6
Rotor poles	8
Voltage	350 V
Acquisition speed	100

Table 2: Tabulation with Load 0Nm and Speed varying at 1000 rpm to 2000 rpm using Proposed Neuro fuzzy, Existing PI Controller and Existing Fuzzy controller

	Proposed Neuro Fuzzy			Existing PI Controller			Existing Fuzzy Controller		
Speed	Rise time t_r(s)	Settling Time t_s(s)	Overshoot in %	Rise time t_r(s)	Settling Time t_s(s)	Overshoot in %	Rise Time t_r(s)	Settling Time t_s(s)	Overshoot in %
1000	1.33	3.8	2%	1.54	5	2.5%	1.67	6.00	2.67
1500	2.0	4.33	3%	2.31	4.85	3.31%	2.50	6.73	4
2000	2.6	5.6	4%	3.08	6.39	4.28%	3.33	7.24	4.73

Table 3: Tabulation with Load 5Nm and Speed varying at 1000 rpm to 2000 rpm using Proposed Neuro fuzzy, Existing PI Controller and Existing Fuzzy controller

	Proposed Neuro Fuzzy			Existing PI Controller			Existing Fuzzy Controller		
Speed	Rise time t_r(s)	Settling Time t_s(s)	Overshoot in %	Rise time t_r(s)	Settling Time t_s(s)	Overshoot in %	Rise Time t_r(s)	Settling Time t_s(s)	Overshoot in %
1000	1.54	4	3%	1.67	6	3.17%	1.82	6.05	3.3
1500	2.3	5.3	3.8%	2.50	7	4%	2.7	6.96	4.2
2000	3	6.8	4.58%	3.33	7.34	4.8%	3.6	7.8	5

Neuro Fuzzy is observed to be better when compared to the existing methods PI Controller and Fuzzy Controller respectively. The quantitative results with respect to varying speed are given in Table 3.

In order to check the robustness of the proposed Neuro Fuzzy framework, series of speed is applied to the system. Figure 4 shows the measure of rise time and settling time when load applied to 0 Nm and speed at 1000 rpm.

From the figure it is illustrative that the rise time observed using proposed Neuro Fuzzy framework was 1.33 second, whereas in the existing PI Controller and Fuzzy controller it was observed to be 1.54 second and 1.67 second respectively. In a similar manner, the setting time was observed to be 3.8 second, 5 second and 6 second when the proposed Neuro Fuzzy, existing PI Controller and Fuzzy controller was applied at 1000 rpm. This clearly shows that the rise time and settling time is comparatively lower in the proposed framework by 19.1 % compared to PI Controller and 36.62 % compared to Fuzzy Controller. The duration of 7 cycles is applied at varied speed with 1000 RPM to 2000 RPM. This performance improvement is because of the application of if-then rule fuzzification that measures the difference between the desired position and actual set output position as compared to rotor position and stator current, therefore, more suitable for the commercial systems with higher input points.

Figure 5 and 6 shows the measure of rise time and settling time when load applied to 0 Nm and speed varied at 1500 and 2000 rpm. Experiments are carried out with the speed rate 1000 RPM and 2000 RPM and the response of the system is investigated in Figure 5 and Figure 6 respectively. When speed applied to 1500 rpm, the rising time using the proposed Neuro Fuzzy framework was 2.0 whereas the rising was observed to be 2.31 second and 2.50 second when the existing PI Controller and Fuzzy Controller was applied.

Correspondingly the setting time for the proposed framework 4.33 second and 4.85 second and 6.73 second when existing PI Controller and Fuzzy Controller was used. Subsequently, the overshoot was observed to be 3 %, 3.31 % and 4 % using Neuro Fuzzy, PI Controller and Fuzzy Controller respectively. The rise time and settling time is comparatively minimum than the state-of-the-art methods which varies according to the delay factor and Neuro Fuzzy membership rules being applied.

The maximum rise time on multiple speed of SRM drive reaches to 2.50 second which declines to 2.31 second and 2.0 second respectively compared with the existing PI Controller [1] and Fuzzy Controller [2] respectively. This is because of the application of condensed multi-layer perceptrons, Neuro Fuzzy membership rule making an inference of 7.81 % and 38.24 % better comparatively to the two other existing methods [1, 2] with a load of 0 Nm and 1500 rpm. It is therefore significant that the proposed Neuro Fuzzy framework overcome high peak overshoot time that manages voltage supply and current flows is an appropriate and flexible manner.

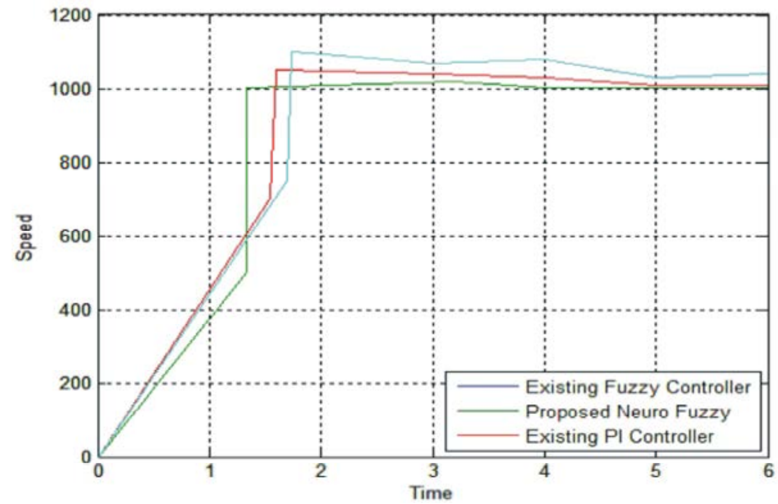

Fig. 4: Speed response of different controllers when T_L= 0 and speed at 1000 rpm

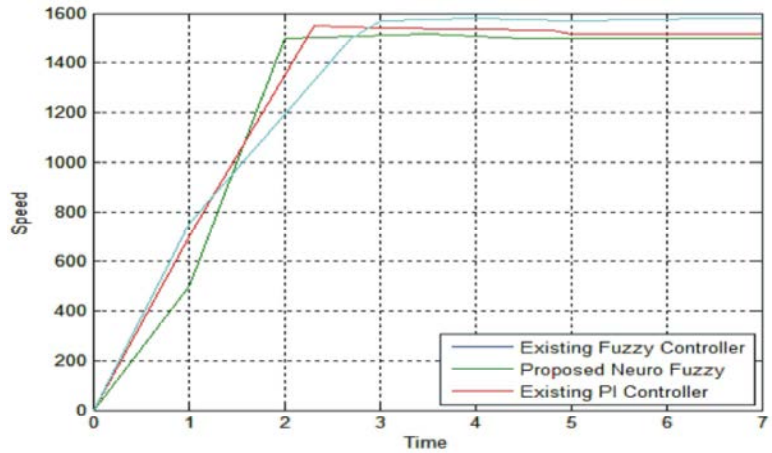

Fig. 5: Speed response of different controllers when T_L= 0 and speed at 1500 rpm

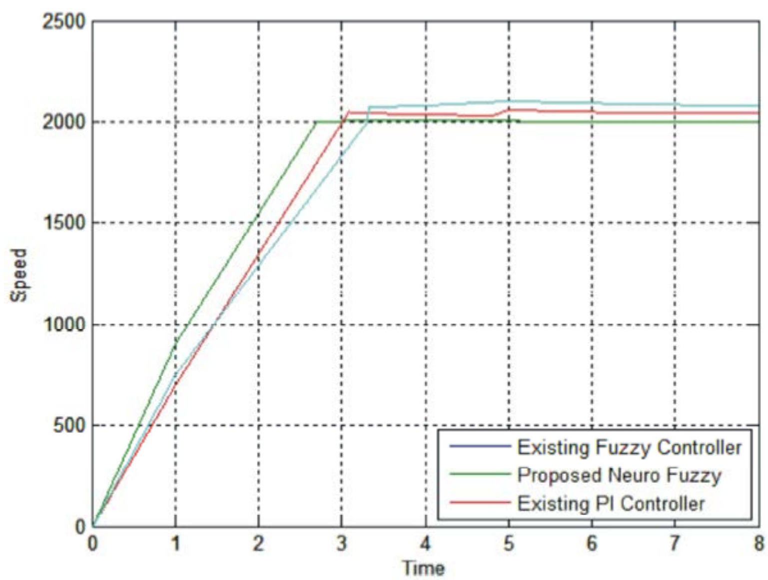

Fig. 6: Speed response of different controllers when T_L= 0 and speed at 2000 rpm

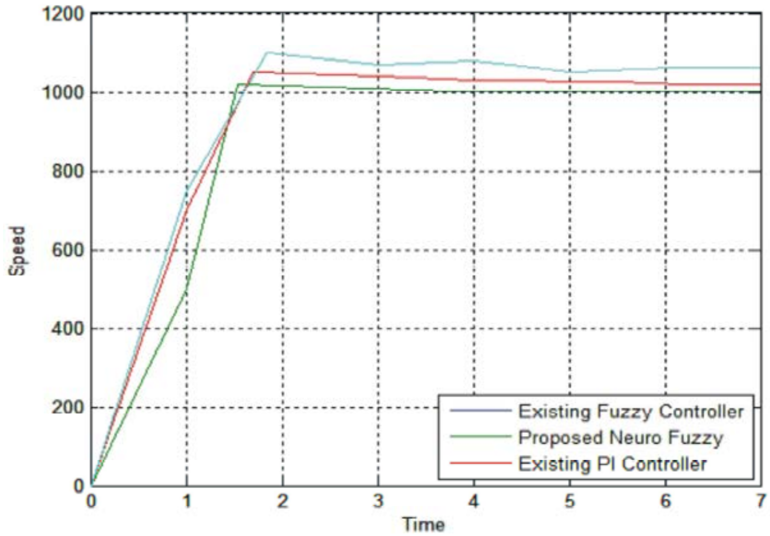

Fig. 7: Speed response of different controllers when T_L= 5 and speed at 1000 rpm

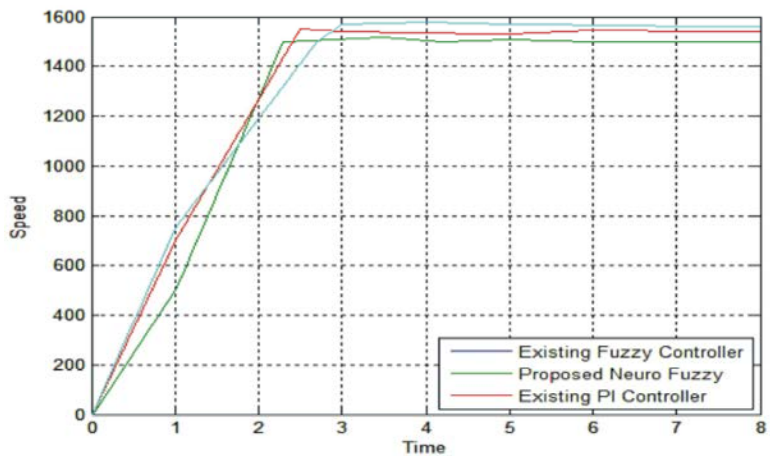

Fig. 8: Speed response of different controllers when T_L= 5 and speed at 1500 rpm

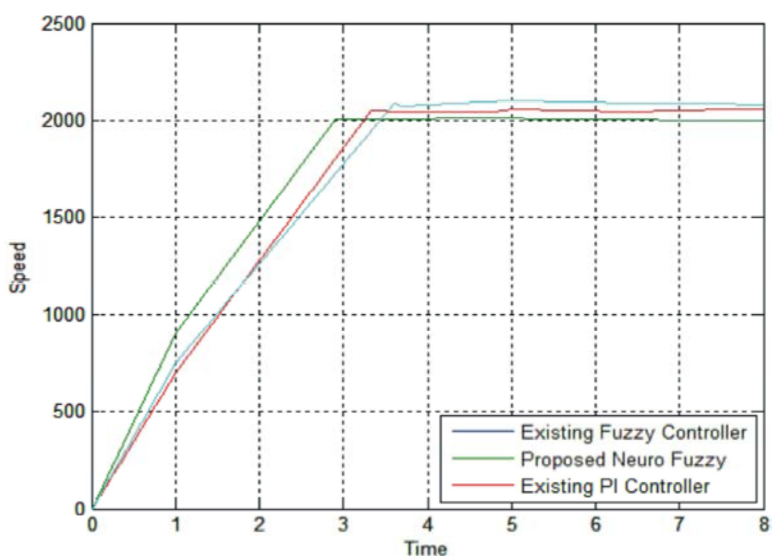

Fig. 9: Speed response of different controllers when T_L= 5 and speed at 2000 rpm

Figure 7 shows the measure of rise time and settling time when load was applied to 5 NM at a speed of 1000 rpm. The rising time was observed to be 1.54 second using the proposed Neuro Fuzzy framework and 1.67 second and 1.82 second when applied with existing PI and Fuzzy Controller. In a similar manner, the settling time for the proposed Neuro Fuzzy was noticed at 4 second, 6 second and 6.05 second when applied with existing PI and Fuzzy Controller respectively.

The overshoot time also increased from 3 % (proposed framework) to 3.3 %. The reduced overshoot time is due to the application of condensed multi-layer perceptrons method that is integrated with Neuro fuzzy membership functions to reduce the rule set from 49 rules to 12 rules using feed forward loop. The overall power shoot time is determined by the activation function, a product of hyperbolic tangent with a flux linkage to the various input points applying step by step procedure of condensed multi-layer perceptrons.

Figure 8 and figure 9 shows the measure of rise time and settling time when load was applied to 5 Nm and speed at 1500 and 2000 rpm respectively. From the figure it is evident that both the rising time settling time was observed to be less comparative to the existing PI and Fuzzy Controller. Also, the overshoot was reduced to 4.58 % using Neuro Fuzzy whereas 4.8 % and 5 % by applying existing PI and Fuzzy Controller respectively. The minimum time taken for rising and settling using the proposed framework is due to the application of neural learning procedure in PID controller. It efficiently estimates the activation function using the condensed rule based on the weighted input that manages the flux linkage for various samples that reduces the rise time on varying load torque by 27.04 % and 30.54 % compared to PI and Fuzzy Controller with a speed of 2000 rpm.

CONCLUSION

This research provides an insight into the study of PID controller of Switched Reluctance Motor drive used for overcoming high peak overshoot time on varying load disturbances using a framework called Neural Learning of PID Neuro Fuzzy based on Condensed Multi layer Perceptrons (NLPID Controller-NFCMP). The integrated framework neural network and fuzzy logic with the PID controller is combined with an activation function that efficiently helps in handling multiple speed SRM drive machines to minimize the steady state error rate on PID controller without any loss of peak overshoot time. A prototype of the multiple load distribution with different delay factors using stator and rotor poles was simulated and tested. A MATLAB environment with Simulink was used to calculate the effective rise time, settling time and overshoot on varying load disturbance factor and speed. Simulation results of the transient response test shows that the rise time on multiple speed of SRM drive at maximum is 1 A and at minimum it is 0.6 A. The experimental measurements show that the peak overshoot time on load torque varies from 2 Nm to 14 Nm. Experiments results indicated that the proposed NLPID Controller-NFCMP is an efficient framework that minimizes the peak overshoot time among various input points in order to provide a safer means and improving output power rate on peak load.

REFERENCES

1. Hannoun, Hala, Mickael Hilairet and Claude Marchand, 2011. High performance current control of aswitched reluctance machine based on a gain-scheduling PI controller, CONTROL ENG PRACT, Elsevier Journal.
2. Wang Shun-Chung and Yi-Hwa Liu, 2011. A Modified PI-Like Fuzzy Logic Controller for Switched Reluctance Motor Drives, IEEE T Ind Electron, 58(5).
3. Kavitha Pasumalaithevan and Bhaskaran Umamaheswari, 2015. R Dump Converter Without DC Link Capacitor for an 8/6 SRM: Experimental Investigation, Hindawi Publishing Corporation The Scientific World Journal.
4. Mahir DURSUN and Fatmagul KOC¸ 2013.Linear switched reluctance motor control with PIC18F452 microcontroller, TURK J ELECTR ENG CO.
5. El Manaa Barhoumi, Mansour Hajji and Boujemaa Ben Salah, 2014. Design of a double- stator linear switched reluctance motor for shunting railway Channels, Turk J. Electr. Eng. Co.
6. Yahia Hedi, Noureddine Liouane and Rachid Dhifaou, 2013. Multiobjective differential evolution-based performance optimization for switched reluctance motor drives, Turk J. Electr. Eng. Co.
7. Dursun Mahir and Semih Ozden, 2012. PC-based data acquisition system for PLC-Controlled linear switched reluctance Motor, Turk J. Electr. Eng. Co.
8. Pandiarajan K., R. Goutham Govind Raju, K. Naveen Kumar and D. Balaji, 2014. Speed Regulation of Switched Reluctance Motor, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 3(5).

9. Oshaba, A.S., E.S. Ali and S.M. Abd Elazim, 2014. Speed Control of Switched Reluctance Motor Fed by PV System Using Ant Colony Optimization Algorithm, Wseas Transactions on Power Systems, pp: 9.
10. Hari Prabhu M., 2013. An Improved Performance of the SRM Drives Using Z-Source Inverter with the Simplified Fuzzy Logic Rule Base, World Academy of Science, Engineering and Technology International Journal of Electrical, Computer, Electronics and Communication Engineering, 7(10).
11. Milad, Dowlatshahi Seyed Morteza Saghaian nejad, Jin-Woo Ahn and Mehdi Moallem, 2013. Minimization of Torque-Ripple in Switched Reluctance Motors Over Wide Speed Range, J. Electr Eng. Technol., pp: 8.
12. SSzabó Loránd, Rareş Terec, Mircea Ruba, Pavol Rafajdus, 2013. Detecting and Tolerating Faults in Switched Reluctance Motors, Universal Journal of Electrical and Electronic Engineering, 1(2): 16-25.
13. Srinivas, P.and P.V.N. Prasad, 2013. PWM Control of Asymmetrical Converter Fed Switched Reluctance Motor Drive, Proceedings of the World Congress on Engineering and Computer Science Wcecs 2013, 1: 23-25.
14. Dos Santos, Fábio L.M., Jan Anthonis, Francesco Naclerio, Johan J.C. Gyselinck, Herman Van Der Auweraer and Luiz C.S. Góes, 2014. Multiphysics NVH Modeling: Simulation of a Switched Reluctance Motor for an Electric Vehicle, IEEE T Ind Electron, 61(1).
15. Gorbounov, Yassen, 2014. FPGA Based Generalized Switched Reluctance Motor Controller, Journal of Engineering Research and Technology, 1(2).
16. Eyhab El, Kharashi and Hany M. Hassanien, 2012. Reconstruction of the Switched Reluctance Motor Stator, Journal of Electrical Engineering, 63(1): 3-12.
17. Ganji B., M. Heidarian and J. Faiz, 2014. Modeling and analysis of switched reluctance generator using finite element method, Ain Shams Engineering Journal, Elsevier.
18. Murthy, V.V.N., S.S. Tulasiram and J. Amarnath, 2014. A New Converter Topology for Switched Reluctance Drive with Reduced Active Switching Devices, International Journal Of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, 3(3).
19. Jian Liu Zhi, Nguyen Le Minh Tri, Nguyen Le Thai and Phan Xuan Le, 2015. Switching-off angle control for switched reluctance motor using adaptive neural fuzzy inference system, International Journal of Energy and Power Engineering.
20. Pratapgiri Srinivas, Prasad Polaki Venkata Narsimha, 2012. Direct torque control of 4 phase 8/6 switched reluctance motor drive for constant torque load, World Journal of Modeling and Simulation, 8(3).