Recent Developments of Artificial Intelligent Controllers for IPM Motor Drive Applications

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Abstract- **This paper investigates the state of the art work on intelligent controllers for interior permanent magnet motor (IPM) motor drive applications. Particular attention is paid for fuzzy logic, neural network, and neuro-fuzzy controllers. In many applications, especially in controlling nonlinear, time varying, and ill defined systems artificial intelligent controllers (AICs) have been proved to be superior in design and performance when compared to the conventional controllers. A survey on the design, development and implementation of AICs for interior permanent magnet synchronous motor (IPMSM) is provided in this paper. Thus, this paper provides useful information for researcher and practicing engineers about the application of artificial intelligent controller for IPMSM drives.**

***Keywords*: Fuzzy logic, Artificial neural network, Neuro-fuzzy controller, Vector control, Speed control, and Interior permanent magnet motor.**

I. INTRODUCTION

The interior permanent magnet synchronous motor (IPMSM) becomes popular day by day because of its some important advantages such as its high torque to current ratio, large power to weight ratio, high efficiency, high power factor, low noise and robustness etc. [1,3]. These features are due to the incorporation of high energy rare-earth alloys such as neodymium-iron-boron in its construction. The IPMSM has magnet buried in the rotor core, exhibits certain good properties, such as robust rotor construction, non-salient rotor and small effective air gap [4]. The design of high performance drives (HPD) for precise, fast and accurate speed response over a wide range of speed and quick recovery of speed from any disturbance becomes an engineering challenge. The precise speed control of an IPMSM drive becomes a complex issue because of the non-linearity couple among its winding currents and the rotor speed as well as the nonlinearity presents in the electromagnetic developed torque due to magnetic saturation of the rotor core. In order to achieve high performance in ac drives, field oriented control is the most popular choice in industry. In HPD systems used in robotics, rolling mills, traction and spindle drives, the motor speed should closely follow a specified reference trajectory regardless of any load disturbances, parameter variations and any model uncertainties. Traditionally, these control issues are handled by the conventional proportional-integral (PI) controller and other controllers such as model reference adaptive controller, sliding mode controller, variable structure controllers [5,6]. However, the difficulties of obtaining the exact d-q axis reactance parameters of the IPMSM lead to cumbersome design approach for these controllers. The conventional controllers like proportional integral (PI)) and proportional integral derivative (PID) controller have been widely used in IPMSM drives as speed controller. But conventional controllers have some limitations as their designs depend on exact machine model and accurate model parameters. Furthermore, the conventional fixed gain PI and PID controller are very sensitive to disturbances [7]. On the other hand, the designs of intelligent controllers do not need exact mathematical model of the system. Simplicity and less intensive mathematical design requirements are the main features of intelligent controllers, which are suitable to deal with nonlinearities and uncertainties of electric motors [7]. Therefore, the intelligent controllers demand particular attention for high performance IPMSM drive systems.

Recently, author and other researchers [9-41] have done extensive research for application of fuzzy logic controller (FLC), artificial neural network (ANN) and neuro-fuzzy (NF) controllers for HPD systems. However, each intelligent control algorithm has its own merits and drawbacks [2,8,46]. Among the AIC FLC is the simplest for speed control of high performance IPMSM drive. During the past decade, FLC has emerged as one of the most active and fruitful areas for research in the application of fuzzy set theory, fuzzy logic and fuzzy reasoning [2]. In contrast to conventional control techniques, FLC is the best in complex, ill-defined process that can be controlled by a skilled human operator without much knowledge of the underlying system dynamics. For application of FLC in IPMSM drive some works have been reported [13, 15-17] in this paper. However there is no theoretical guarantee that a general fuzzy logic controller will not become chaotic, although such a possibility appears to be extremely slim based on practical experience. As a result researchers did some work on the application of ANN controller and NFC for IPMSM drives [18-41]. ANN controllers are deliberately constructed to make use of some organizational principles resembling those of human brain. The connective behaviour of an ANN, like a human brain, demonstrates the ability to learn, recall and generalize from training patters or data. In [13] a radial basis function network (RBFN) is utilized as an ANN. The RBFN is based on the concept of the locally tuned and overlapping receptive field structure. The more advanced intelligent controller is the NFC, which is the combination of FLC and ANN controllers, has been applied by the researchers because of limitations of either fuzzy logic or neural network [ ]. A simple FLC has a narrow speed operation and needs much more manual adjusting by trial and error if high performance is wanted [ ]. On the other hand, it is extremely tough to create a serial of training data for ANN that can handle all the operating modes [ ]. NFC will ensure the low level learning and computational power of neural networks to fuzzy control systems and also provide the high level humanlike IF-THEN rule thinking and reasoning of fuzzy control system to neural networks. In [31,33] researchers developed a NFC based on a fuzzy basis function network (FBFN) in which the FLC concepts are embedded. In the FBFN, the controller is implemented as a series expansion of fuzzy basis functions which are algebraic superposition of membership functions. In order to test the performance of AIC based closed loop vector control scheme of IPMSM the complete drive system is successfully implemented in real-time using digital signal processor (DSP) board DS1102. The performances of various intelligent controllers for IPMSM drives are investigated experimentally at different operating conditions.

II. AIC BASED IPMSM DRIVES

For high performance ac motor drives the vector control scheme is utilized as it decouples the torque and flux controls and hence the control of ac motor becomes similar to a dc motor while maintaining the general advantages of ac over dc motors. The block diagram of a typical closed loop vector control scheme of IPMSM drive is shown in Fig. 1. Artificial intelligent controllers (AICs) can be utilized for either speed or current control purpose. However, in most of the reported works AICs are mainly used for speed control purpose. The design, development and sample application of AICs particularly, fuzzy logic, neural network, and neuro-fuzzy controllers for IPMSM drives are provided in the following subsections.

A. FLC Scheme

The basic idea behind FLC is to incorporate the "expert experience" of a human operator in the design of the controller in controlling a process whose input output relationship is described by a collection of fuzzy logic rules (e.g. rules) involving linguistic variables rather than a complicated dynamic model. Researchers [13-16] have already developed and applied different types of FLC for IPMSM drive. In [13], a conventional FLC is developed for IPMSM drive. In this FLC the speed error, $\Delta\omega_r$ and the rate of change of speed error, Δe, are considered as the input linguistic variables and the torque producing current component, i_q, is considered as the output linguistic variable. Thus, the functional relation of the FLC can be expressed as:

$$i_q(n) = f(\Delta e(n), \Delta\omega_r(n)) \qquad (1)$$

where, $\Delta e(n) = \Delta\omega_r(n) - \Delta\omega_r(n-1)$, $\Delta\omega_r(n) = \omega_r^*(n) - \omega_r(n)$, $\omega_r(n)$ is the present sample of actual speed, $\omega_r^*(n)$ is the present sample of command speed and f denotes the nonlinear function.

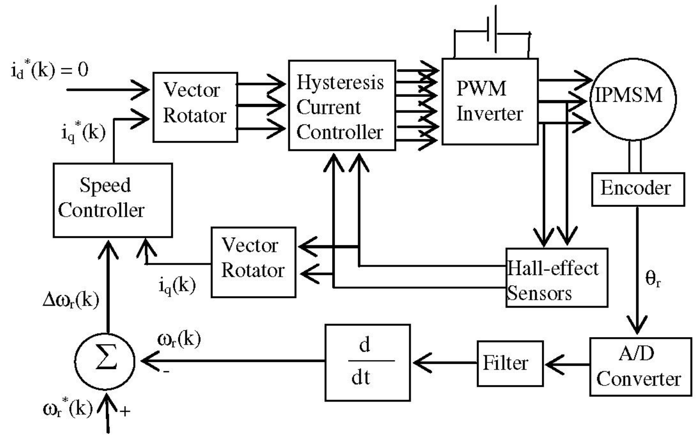

Fig. 1 Block diagram of a typical closed loop vector control of IPMSM drive.

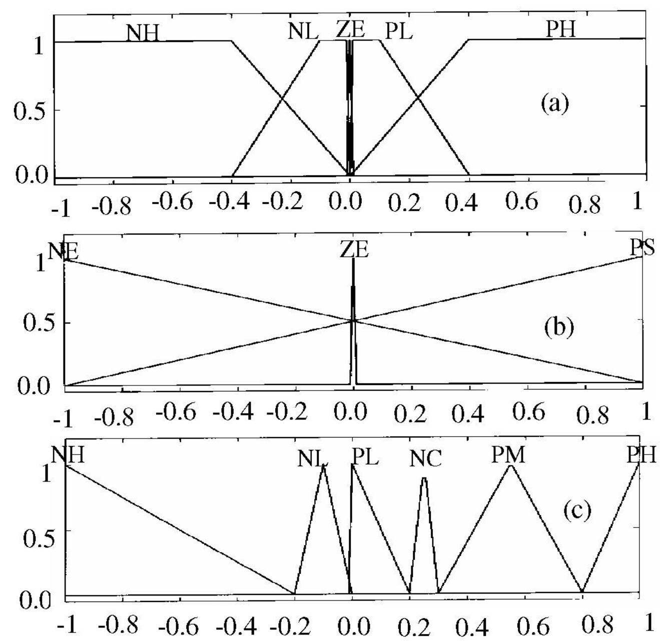

Fig. 2 Membership functions for: (a) speed error $\Delta\omega_{rn}$, (b) change of speed error Δe_n, and (c) q-axis command current i_{qn}^*.

The membership functions used for the input and output fuzzy sets are shown in Fig.2. The trapezoidal and the triangular functions are used to reduce the computation for on-line implementation. The values of the constants, membership functions, fuzzy sets for the input/output variables and the rules used in this work are selected by trial and error to obtain the optimum drive performance. The fuzzy rules used in this work can be found in [13]. Efforts [15,16] have been continuing to reduce the computational burden and minimize the torque ripple so that it will be suitable for industrial applications. In [16] Uddin et. al. developed another genetic based simplified FLC (GFLC) where the parameters of this new FLC were tuned offline by genetic algorithm. The computational burden of GFLC was very low as compared to the conventional FLC [13].

B. ANN Scheme

In order to meet the growing demand for high performance requirements of IPMSM drive researchers showed their interest to use the ANN in control systems because of their ability to learn, to approximate functions and to classify patterns and their potentiality for massively parallel hardware implementation [14,18-22]. The inputs and outputs of the ANN can be arbitrarily chosen from the system variables. However, it is preferred to model the dynamics of the drive system roughly so that inputs and outputs of the ANN can be selected in a more defined way. This guarantees that the ANN will capture the system dynamics.

The simplified discrete time model of IPMSM drive can be found by replacing all continuous quantities by their finite difference [21], giving

$$\omega_r(n+1)=\alpha\omega_r(n) + \beta\omega_r(n-1) + \gamma\, \omega_r^{\,2}(n) +\delta\, \omega_r^{\,2}(n-1) +\varepsilon v_q(n) + v$$

where, α , β , γ, δ , ε and v are functions of the motor parameters as well as sampling interval. This equation is modified in order to obtain the inverse model of the drive system as:

$$v_q(n)=[\omega_r(n+1)-\alpha\, \omega_r(n)-\beta\omega_r(n-1)-\gamma\omega_r^{\,2}(n)-\delta\omega_r^{\,2}(n-1)+v]/\,€ \quad (6)$$

Now in discrete form, the q-axis current can be expressed in terms of $v_q(n)$ and w_r , by replacing the continuous terms of motor equation by their finite differences as [21],

$$i_q(n)=Ai_q(n-1)+B_2v_q(n)+Cw_r(n) \quad (7)$$

where, $A=1-R\Delta T/L_q$, $B_2=\Delta T/L_q$, $C=\Delta TK_b/L_q$ and ΔT is the sampling interval. Thus the expressions for the q-axis currentcan further be modified as:

$$i_q(n) = Ai_q(n-1)+ B_2[\omega_r(n)-(\alpha+\varepsilon C/B)\omega_r(n-1)-\beta\omega_r(n-2)-\gamma\omega_r^{\,2}(n) -\delta\omega_r^{\,2}(n-2)+v]/\,€] \quad (8)$$

The right hand side of the equation is a non-linear function of the speed ω_r. The purpose of using the ANN is to map the nonlinear relationship between the q-axis current $i_q(n)$ and the speed $\omega_r(n)$. This reveals the structure of the ANN for the speed control of the IPMSM which is shown in Fig.3. In [14], another ANN is developed for online tuning of the gains of PI controller. In this work a radial basis function network (RBFN) network is utilized for the ANN. The schematic diagram is shown in Fig.4. Like the counter propagation network, the RBFN is designed to perform input output mapping based on the concept of locally tuned. The input variables are each assigned to a node in the input layer and pass directly to the hidden layer without weight. The hidden layer nodes are the RBF units. Each node in this layer contains a parameter vector called a center. The node calculates the Euclidean distance between the center and the network input vector and passes the result through a nonlinear function $\varphi(.)$. The output layer is essentially a set of linear combiners. For a general n-input and m-output RBFN structure, the i-th output y_i due to input vectors x, $x=[x_1,\ldots.x_n]'$ can be expressed as

$$y_i=\Theta_{0i}+\sum_{j=1}^{Mi} \theta_{ji}\, \varphi(\|x-c_j\|,\sigma_j) \quad (9)$$

where, M_i is the number of hidden units, c_j and σ_j are the center and the width of the jth hidden unit respectively, θ_{ji} represents the weight between the jth hidden unit and the ith output unit, and Θ_{0i} represents the bias term of the ith output unit. In this study, $\varphi(.)$. is chosen to be Gaussian activation function. That is, for learning purpose the orthogonal least square (OLS) method is used in this work [2,46]. This procedure chooses the centres of radial basis functions one by one in radial way until an adequate network has been constructed.

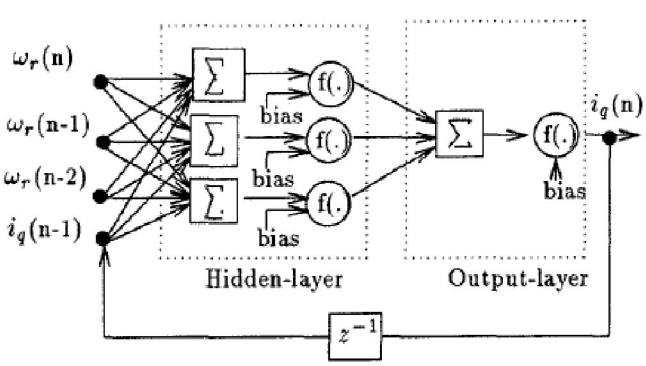

Fig.3: Structure of ANN controller for IPMSM drive.

C. NFC Scheme

Neuro-fuzzy logic controller possesses the advantages of both neural networks (e.g., learning abilities, optimization abilities and connectionist structures) and fuzzy logic control systems (e.g., humanlike IF-THEN rule thinking and ease of incorporating expert knowledge). The main purpose of a neural fuzzy control system is to apply neural learning techniques to find and tune the parameter of the neuro-fuzzy logic control system. The use of ANN alone to design a controller for IPMSM drive will be insufficient. If the test inputs used to generate training input/output pairs are not rich

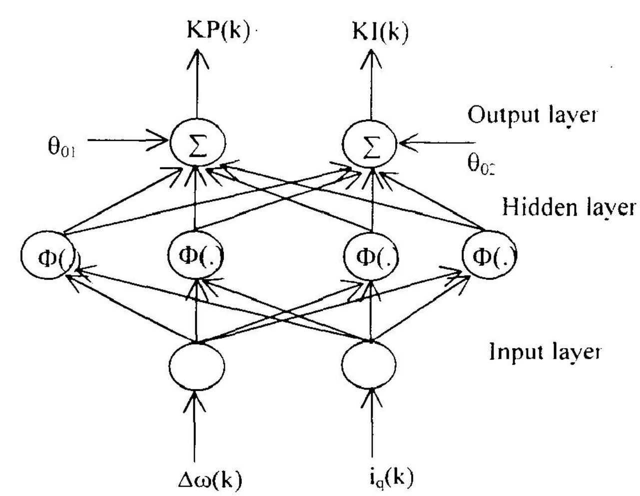

Fig.4: Schematic diagram of RBFN as ANN controller.

enough to excite all modes of the system. On the other hand, fuzzy logic controllers (FLCs) are subjective and somewhat heuristic. In most cases, the determination of fuzzy rules, input and output scaling factors and the choice of membership functions depend on trial-and-error that makes the design of FLC a time-consuming task. In [33] a fuzzy basis function network (FBFN) is utilized for online tuning of the PI controller parameters to ensure optimum drive performance under different disturbances. In this NF controller, initially different operating conditions are obtained based on motor dynamics incorporating uncertainties. At each operating condition a genetic algorithm is used to optimize the PI controller parameters in a closed-loop vector control scheme. In the optimization procedure a performance index is developed to reflect the minimum speed deviation, minimum settling time and zero steady-state error. The following performance index J is considered:

$$J = \sum_{k=1}^{L} [kT_s \Delta\omega(k)]^2 \qquad (10)$$

In the above index, the speed deviation $\Delta\omega(k)$ is weighted by the respective time kT_s. The FBFN-based PI controller provides a natural framework for combining numerical and linguistic information in a uniform fashion. The proposed scheme brings the learning capabilities of ANN to the robustness of fuzzy logic systems in the sense that the fuzzy logic concepts are embedded in the network structure and its operation. It also provides a natural framework for combining both numerical information in the form of input/output pairs and linguistic information in the form of IF-THEN rules in a uniform fashion and overcomes the drawbacks of ANN and FLC. A specific fuzzy basis function network (FBFN) as shown in Fig.4 is developed as a NF controller. The NF controller is used for online tuning of a PI controller. The output of the ith node in the kth layer is denoted by 0_i^k. The operation network with n inputs and m outputs can be described as follows:

Layer 1: For the ith input, every node in this layer computes the degree of membership of the input. Every node j has a function of

$$0_i^1 = \mu_{ij}(x_i),\ j=1,2,\ldots,M \qquad (11)$$

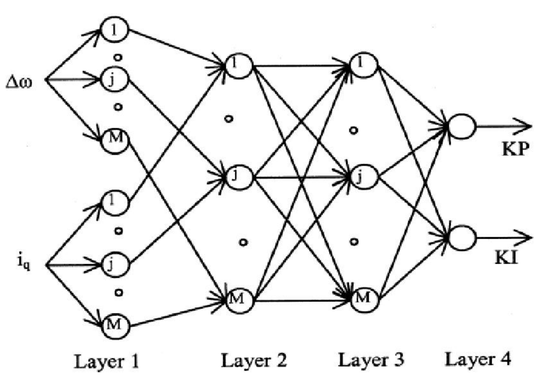

Fig.5: Schematic diagram of FBFN as a NF controller.

where $\mu_{ij}(x_i)$ is a gaussian membership function associated with ith input and jth rule. It can be expressed as,

$$\mu_{ij}(x_i)=exp(-\frac{1}{2}(\frac{x_i - c_{ij}1}{\sigma_{ij}})^2) \qquad (12)$$

where c_{ij} and σ_{ij} are the mean and the variance of the jth function.

Layer 2: Every node in this layer multiplies the incoming signals and sends the product out. i.e..

$$0_j^2 = \Pi_{i=1}^{n} \mu_{ij}(x_i),\ j=1,2,\ldots,M \qquad (13)$$

Each node output yields the firing strength of a fuzzy rule.

Layer 3: Every node in this layer calculates the ratio of jth rule's firing strength to the sum of all rules' firing strengths.

$$0_j^3 = \frac{\prod_{i=1}^{n} \mu_{ij}(x_i)}{\sum_{j=1}^{M} \prod_{i=1}^{n} \mu_{ij}(x_i)},\ j=1,2,\ldots,M \qquad (14)$$

The nodes in this layer compute the normalized firing strength of each rule. The output of each node in this layer represents a fuzzy basis function, $p_j(x)$ as

$p_j(x) = 0_j^3$, j=1,2, ... ,M

where, x = $x=[x_1,\ldots\ldots x_n]'$ is the input vector.

Layer 4: In this layer each node represents an output and linearly combines the fuzzy basis functions as

$$0_k^4 = \sum \sum_{j=1}^{M} p_i(x)\theta_{jk},\ k=1,2,\ldots,m) \qquad (15)$$

where, Θ_{ik} is the weight between the jth node in layer 3 and the X-th node in layer 4.

For learning purpose the orthogonal least square (OLS) method is used in this work [2, 46].

III. REAL-TIME IMPLEMENTATION AND RESULTS

The closed loop vector control scheme of IPMSM incorporating intelligent controller is experimentally implemented using digital signal processor (DSP) board DS1102 through both hardware and software. The DSP board is installed in a PC with uninterrupted communication capabilities through dual-port memory. The hardware schematic for real-time implementation of the proposed FLC based IPMSM drive is shown in Fig. 6. The DS1102 board is based on a Texas Instrument (TI) TMS320C31, 32-bit floating point digital signal processor. The DS I102 is also equipped with a (TI) TMS320P14, 16-bit micro controller DSP that acts as a slave processor and is sued for digital I/O configuration. The actual motor currents are measured by the Hall-effect sensors and fed to the DSP board through A/D converter. The rotor position is measured by an optical incremental encoder which is mounted at the rotor shaft end. Then it fed to the DSP board through encoder interface. The starting speed responses of FLC, GFLC, ANN and NFC are shown in Figs. 7, 8, 9, and 10, respectively. From these experimental results of these controllers it is observed that actual speed can follow the command speed without overshoot/undershot for all the AICs.

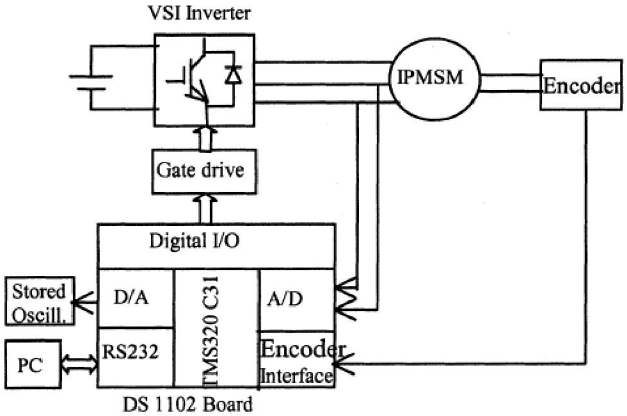

Fig. 6: Hardware schematic for real-time implementation.

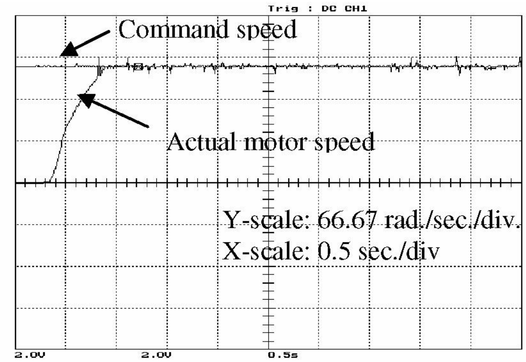

Fig.7: Speed response of FLC for IPMSM drive

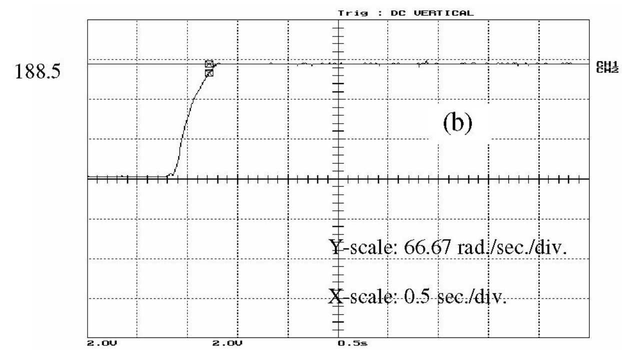

Fig. 8: Speed response of GFLC for IPMSM drive.

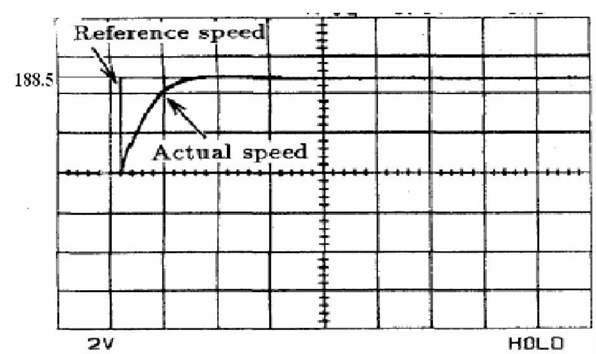

Fig. 9: Speed response of ANN controller for IPMSM drive

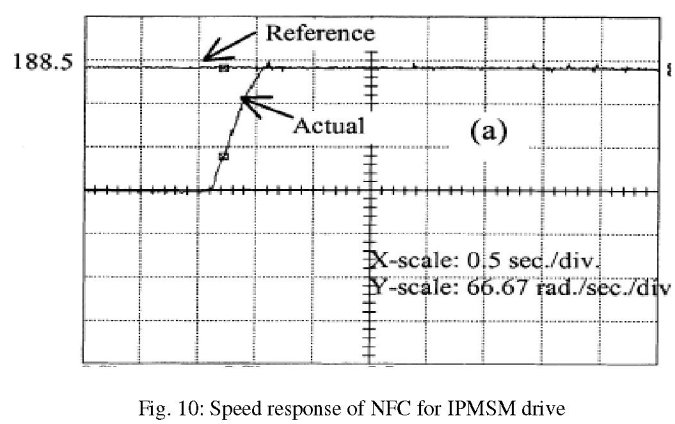

Fig. 10: Speed response of NFC for IPMSM drive

The GFLC provides smooth speed response as compared to the conventional FLC. The NFC provides the best performance by taking the advantages of both ANN and FLC.

IV. CONCLUSION

A review on the state of the art works on intelligent controllers for IPMSM drives has been provided in this paper. Particular attention has been paid for FLC, ANN and NF controllers. Design, implementation technique, sample results for all the above mentioned AIC have also been presented.

APPENDIX: The parameters of the motor used in this simulation are L_d=0.04244H, L_q=0.07957H, r_s=1.93Ω, B_m =0.0008Nm/rad/sec, ψ_m =0.314 volts/rad/s, J=0.003 kg.m^2, P=2 and rated output 1 hp.

REFERENCES

[1] G R Slemon. "Electric Machines and drives", *Addison-Wesley Publication Company,* 1992: pp. 503-51

[2] Chin-Teng Lin and C. S. George Lee "Neural Fuzzy Systems, A Neuro-Fuzzy Synergism to Intelligent Systems", *Prentice Hall P T R publication company.* pp.533-607.

[3] M A. Rahman and Ping Zhou, "Field circuit analysis of brushless permanent magnet synchronous motors". *IEEE Trans. on Ind. Elec.*vol 43. No.2, April 1996, pp 256-267

[4] B. Sneyers, D.W. Novotny, and T. A. Lipo, "Field-weakening in buried permanent magnet AC motor drives," *IEEE Trans. Ind. Applicat.*, vol.IA-21, Mar./Apr. 1985., pp. 398–407

[5] P. Pillay and R. Krishnan, "Control characteristics and speed controller design for a high performance permanent magnet synchronous motor drive," *in Proc. IEEE PESC'87*, 1987, pp. 598–606.

[6] T. M. Jahns, G. B. Kliman, and T. W. Neumann, "Interior permanent magnet synchronous motors for adjustable speed drives," *Conf. Rec. IEEE-IAS Annu. Meeting,* 1985, pp. 814–823.

[7] Z. Ibrahim and E. Levi. "A Comparative Analysis of Fuzzy Logic and PI Speed Control in High Perfbrmance AC Drives Using Experimental Approach". *IEEE Trans. Ind. Appl.,* Vol. 38, No. *5,* Sept./Oct 2002, pp1210-1218

[8] Butt, C.; Rahman, M.A, "Limitations of simplified fuzzy logic controller for IPM motor drive." *IEEE/IAS Annual Meeting Conf. Record*, 3-7 Oct.2004 vol: 3, pp:1891 – 1898.

[9] Y. Tang and L. Xu, "Fuzzy logic application for intelligent control of a variable speed drive," *IEEE Trans. Power Electron.*, vol.12, pp. 1028-1039, Nov. 1997.

[10] C. C. Lee, " Fuzzy logic in control system: Fuzzy logic controller – part I, II." *IEEE Trans. On system, man and cybernetics* Vol.20, No-2. pp. 404-435, 1990.

[11] M. R. Emami, I. B. Turksen, and A. A. Goldenburg, "Development of a systematic methodology of fuzzy logic modeling," *IEEE Trans. Fuzzy Syst.*, vol. 6, pp. 346–361, Aug. 1998

[12] S. Y. Yi and M. J. Chung, "Robustness of fuzzy logic control for an uncertain dynamic system," *IEEE Trans. Fuzzy Syst.,* vol. 6, pp. 216–224,May 1998

[13] M N Uddin and M A Rahman. "Fuzzy Logic Based Speed Control of an IPM Synchronous Motor Drive". *Journal of Advanced Computational Intelligence*, vol. 4, No. 3,2000, pp 212-219

[14] M A Rahman. M Nasir Uddin. and M. A. Abido. "An Anificial Neural Network for Online tuning of a Genetic Based PI Controller for Interior Permanent Magnet Synchronous Motor Drive", *Power Conversion Conference (PCC). Osaka. Japan,* April 2002, pp 154-160

[15] C. Butt, M. A. Hoque, M. A. Rahman, "Simplified fuzzy logic based MTPA speed control of IPMSM drive." *IAS Annual Meeting. Conference Record,* Oct. 2003. vol. 1, pp. 499 – 506.

[16] M. N. Uddin, M. A. Abido and M. A. Rahman, "Real-Time Performance Evaluation of a Genetic Algorithm Based Fuzzy Logic Controller for IPM Motor Drives", *IEEE/IAS Annual Meeting Conf. Record, Sault Lake City, Utah, USA,* October 2003.

[17] K. Zawirski, "Fuzzy robust speed control for permanent magnet synchronous motor servo drive" *Proc. Of 8th Int. Power Electronics & Motion control Conference – PEMC'98, Prague*, 8-10 Sept, 1998.

[18] Yang Yi; Vilathgamuwa, D.M.; Rahman, M.A. "Implementation of an artificial-neural-network-based real-time adaptive controller for an interior permanent-magnet motor drive." *IEEE Trans. on Industry App.* Vol: 39, Issue 1, Jan.-Feb. 2003 pp:96 – 104

[19] Urasaki, N.; Senjyu, T.; Uezato, K.;"Neural network based high efficiency drive for interior permanent magnet synchronous motors compensating EMF constant variation." *Power Conversion Conference,* 2002. PCC Osaka 2002. vol.:3, 2-5 April 2002 pp:1273 - 1278 .

[20] Yang Yi; Vilathgamuwa, D.M.; Rahman, M.A.; "A new artificial neural network controller for an interior permanent magnet motor drive." *IEEE/IAS Annual Meeting Conf. Record*, 30 Sept.-4 Oct. 2001 vol: 2, pp:945 - 952 .

[21] M.A Rahman and M.A. Hoque, "On-Line Adaptive Artificial Neural Network Based Vector Control of Permanent Magnet Synchronous Motors".*IEEE Trans. on En.Conv.* vol. 13. no 4. 1998: pp. 311-318.

[22] M.E Elbuluk. L long and I Husain: "Neural Network Based Model Reference Adaptive Systems for High-Performance Motor Drives and Motion Controls". IEEE Trans on industry applications. Vol. 38. May/June 2002, pp. 1063-1068.

[23] B Singh, V. k.Shanna and S. S Murthy, "Perlormance Analysis of Adaptive Fuzzy Logic Controller for Switched Reluctance Motor Drive System". *IEEE IAS Ann. Meet,* 1998, pp. 571-579

[24] S Bolognani and M. Zigliono. "Fuzzy Logic Control of a Switched Reluctance Motor Drive''. *IEEE Trans on Industry Applications.* Vol32. No 5: Sept./Oct. 1996, pp. 1063-1068

[25] M.A El-Sarkawi. A.A El-Samahy and M L El-Sved. "High Performance Drive of dc Brushless Motors Using Neural Network." *IEEE Trans. On En.Com,.* vol. 9. no. 2. June 1994, pp. 317-322

[26] M. R. Emami,I. B. Turksen and A. A. Goldenburg, "Development of A Systematic Methodology of Funy Logic Modeling", *IEEE Trans. On Fuzzy Systems. Vol.6, no.3, August,1998 .pp:346-361.*

[27] S.Y.Yi and M. J. Chung, "Robustness of Fuzzy Logic Control for an Uncertain Dynamic System", *IEEE Trans. on Fuzzy Sysrems,* vol.6, no. 2, May 1998, pp. 216-224.

[28] T. Fukuda and T. Shibata, "Theory and applications of neural networks for industrial control systems", *IEEE Trans. On Industrial Electronics,* Vol. 39, No. 6, 1992, pp. 472-489.

[29] K.S. Narendra and K. Parthasarathy ,"Identification and control of dynamical systems using neural networks", *IEEE Trans. on Neural Networks,* Vol. 1, No. 1, 1990, pp. 1-27.

[30] G. S. Buja and F. Todesco, "Neural network implementation of fuzzy logic controller," *IEEE Trans. Ind. Electron.*, vol. 41, pp. 663–667, Dec.1994.

[31] A.K. Nandi and D. K. Pratihar. "An expert system based on FBFN using a GA to predict surface finish in ultra-precision turning." *Journal of Materials Processing Tech.*, vol:155-156, 30 Nov., 2004, pp:1150-1156

[32] A.Rubaai, D.Ricketts, and M.D.Kankam, "Development and implementation of an adaptive fuzzy-neural-network controller for brushless drives," *IEEE Trans. Ind. Applicat.*, vol. 38, pp. 441–447, Mar./Apr.2002.

[33] M. N Uddin. M A Abido and M. A. Rahman. "Development and Implementation of a Hybrid Intelligent Controller for Interior Permanent Magnet Synchronous Motor Drive" *IEEE Transactions on Industry Applications*, vol. 40, no. 1, Jan./Feb. 2004, pp. 68-76

[34] Chiaberge, M.; Di Bene, G.; Di Pascoli, S.; Lazzerini, B.; Maggiore, A.; Reyneri, L.M. "An integrated hybrid approach to the design of high-performance intelligent controllers." *International IEEE/IAS Conference on Industrial Automation and Control: Emerging Technologies,* 22-27 May 1995 pp:436 – 443

[35] Kadjoudj, M.; Benbouzid, M.E.H.; Ghennai, C; Diallo, D. "A robust hybrid current control for permanent-magnet synchronous motor drive" *IEEE Trans. on Energy conv.* vol.:19, Issue:1, March,2004 pp:109 – 115

[36] Mobarakeh, B.N.; Meibody-Tabar, F.; Sargos, F.M "A self organizing intelligent controller for speed and torque control of a PMSM." *IEEE Conference on Industry App. 8-12 Oct.,2000.* vol: 2, pp:1283 - 1290

[37] M. Tursini, F. Parasiliti, and D. Zhang, "Real-time gain tuning of PI controllers for high-performance PMSM drives," *IEEE Trans. Ind. Applicat.*,vol. 38, pp. 1018–1026, July/Aug. 2002

[38] Faa-Jeng Lin and Rong-Jong Wai "Robust recurrent fuzzy neural network control for linear synchronous motor drive system" *Neurocomputing*, vol: 50, January 2003, pp: 365-390

[39] Mohammdi-Milasi, R.; Lucas, C.; Nadjar-Arrabi, B.; "Speed control of an interior permanent magnet synchronous motor using belbic (brain emotional learning based intelligent controller*)." World Automation Congress,2004. Proceedings,* vol:16, 28 June - 1 July 2004 pp:280 – 286

[40] Der-Fa Chen; Tain-Hua Liu "Implementation of a novel matrix converter PMSM drive.", IEEE Transactions on Aerospace and Electronic Systems. Vol: 37, Issue 3, July 2001 pp:863 – 875

[41] Yen-Shin Lai; Juo-Chiun Lin;"New hybrid fuzzy controller for direct torque control induction motor drives." IEEE Transactions on Power Electronics, Vol:18, Issue 5, Sept. 2003 pp:1211 – 1219

[42] Brock, S.; Deskur, J.; Zawirski, K.; "Robust speed and position control of PMSM." Proceedings of the IEEE International Symposium on Industrial Electronics, 1999. ISIE '99. vol:2, 12-16 July 1999 pp:667 - 672

[43] M. N. Uddin, "Comparative Analysis of Intelligent Controllers for High Performance Interior Permanent Magnet Synchronous Motor Drive" *Large Engineering Systems Conference on Power Engineering (LESCOPE), Montreal, Canada,* May 2003, pp. 50-54.

[44] Mathur, H.D.; Ghosh, S. "A comprehensive analysis of intelligent controllers for load frequency control" *Power India Conference, 2006 IEEE* 10-12 April 2006 Page(s):5 pp.

[45] P. Stewart, D. A. Stone and P. J. Fleming. "Design of robust fuzzy-logic control systems by multi-objective evolutionary methods with hardware in the loop." *Engineering App. of Artificial Intelligence*, vol: 17, Issue 3, April 2004, pp: 275-284

[46] A. Zilouchian and M Jamshidi, Intelligent Control Systems Using Soft. Computing Methodologies. CRC. 2001

[47] *dSPACE.* "Digital Signal Processing and Control Engineering. Manual Guide. GmbH. Paderborn. Germany. 1996

[48] Matlab. Simulink User Guide. The Math Works Inc.. 1995.