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A Novel Approach of PI Controller for Speed Regulation of PMSM by Back Propagated Spiking Neural Network Method Basedon Slime Mould Algorthim

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Abstract:- The efficient control of Permanent Magnet Synchronous Motors (PMSMs) is a critical challenge in modern electrical engineering, particularly for applications in renewable energy, automotive systems, and industrial automation. This study explores advanced control strategies for PMSM speed regulation, focusing on sliding mode control, fuzzy logic, neural networks, and optimization-based techniques. The integration of artificial intelligence methods, such as adaptive fuzzy controllers and neural networks, is emphasized for achieving robust and adaptive performance in dynamic environments. Additionally, novel optimization algorithms, including Particle Swarm *Optimization* (PSO) and Ant Lion Optimizer, are applied to enhance the design of controllers and improve efficiency, reliability, and system stability.

The research further investigates predictive speed control methods and hybrid approaches, highlighting their capacity to address challenges like parameter variations, nonlinearity, and disturbances in PMSM systems. Advanced simulation tools, including MATLAB/Simulink, are employed for the modeling, analysis, and validation of proposed methodologies. Practical implementations in renewable energy systems and electric vehicles demonstrate the feasibility and effectiveness of the studied techniques. The findings reveal that combining artificial intelligence with traditional control methods significantly improves speed regulation and energy efficiency. This work contributes to the advancement of intelligent motor control systems, providing insights into future research directions and real-world applications. The results promise to enhance the performance of PMSMs in high-demand scenarios.

Keywords: *PMSM Speed Control, Sliding Mode Control, Neural Network Optimization, Fuzzy PI Logic Controllers, Particle Swarm Optimization (PSO), BPSNN, Stochastic Slime Mould Algorithm.*

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1. Introduction

The presence of PMSM has replaced all other kinds of motors more particular towards servo applications. Permanent magnet synchronous motors are not easy to control, and they come across non-linear time-varying dynamic behavior. In recent years, PID and PI Controllers with advanced algorithms have been developed. The importance of magnetic components and semiconductor devices with power electronic circuits has built the role of PMSM massively significant and hence employed in numerous control applications. The growth and applicability of PMSM in real time industrial applications is simple structure, minimal size, friendly and ease of maintenance, less noise and high-power density.

The advancement of control strategies and optimization methods for Permanent Magnet Synchronous Motors (PMSMs) has gained significant attention due to their critical role in high-performance applications, such as renewable energy systems, electric vehicles, and industrial automation. This review synthesizes recent research in the domain, organized thematically around control strategies, optimization techniques, and applications.

a) Sliding Mode and Predictive Control Techniques

Sliding mode control (SMC) has emerged as a robust method for PMSM speed control, resisting disturbances and parameter variations. Zhao and Liu [1] integrated SMC with a nonlinear disturbance observer, achieving improved transient and steady-state performance. Similarly, Guo and Pan [8] proposed a predictive speed control method based on SMC, further enhancing robustness under dynamic conditions. Predictive control methods have also seen extensive applications. Carlet et al. [3] developed a continuous control set model predictive control (CCS-MPC) for synchronous motor drives, demonstrating improved precision under varying loads. Zhang and He [4] eliminated weighting factors in predictive direct speed control (MPDSC), simplifying control design and increasing computational efficiency.

b) Artificial Intelligence and Fuzzy Logic-Based Methods

Artificial intelligence techniques, including neural networks and fuzzy logic, have been widely used to improve adaptability and control precision. Anh et al. [13] employed a neural-based field-oriented control (FOC) method, optimizing speed control for PMSMs. Tian et al. [15] introduced a self-tuning speed controller based on neural networks, leveraging real-time adaptability. Fuzzy logic controllers have shown promise in handling nonlinearities. Zhang et al. [12] combined fuzzy logic with sliding mode control for robust, adaptive speed control. Hu and Zhang [11] demonstrated the effectiveness of fuzzy PI controllers in vector control systems, enhancing dynamic response.

c) Optimization Algorithms

Optimization algorithms have played a vital role in enhancing control performance. Rui et al. [10] applied chaos particle swarm optimization (PSO) for tuning PI controllers, achieving

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robust parameter optimization. Soundirarrajan and Srinivasan [14] evaluated Ant Lion Optimizer (ALO)-based PID controllers, reporting superior performance in speed control. Moreover, Dal et al. [17] utilized PSO to optimize PMSM design, improving efficiency and performance. Szczepanski et al. [21] leveraged the Artificial Bee Colony (ABC) algorithm for adaptive state feedback control, achieving efficient and reliable speed regulation.

d) Adaptive and Self-Tuning Methods

Adaptive control strategies have gained traction for their ability to respond to changing operating conditions. Cao et al. [7] proposed a low-cost adaptive speed estimator for PMSMs, integrating a self-tuning speed control system. Similarly, Wang et al. [24] introduced an adaptive integral backstepping controller with fuzzy self-tuning, ensuring stability under varying loads. Aguilar-Mejía et al. [16] demonstrated the effectiveness of artificial intelligence in designing adaptive speed controllers for PMSMs, enhancing system performance under diverse conditions.

e) Renewable Energy Applications

The integration of PMSMs in renewable energy systems has driven innovation in motor design and control. Shen et al. [5] explored the application of dual three-phase PMSMs in renewable energy systems, highlighting their reliability and energy efficiency. Zhao et al. [19] provided a comprehensive review of axial flux PMSM designs for renewable energy, emphasizing their potential in wind and solar applications. Meng et al. [25] investigated multi-winding PMSMs for solar-powered UAVs, showcasing lightweight and efficient designs tailored for renewable energy.

f) Hybrid and Multi-Objective Control Strategies

Hybrid control approaches, which combine multiple control methods, have demonstrated significant potential. Yadav and Verma [23] integrated adaptive neuro-fuzzy inference systems (ANFIS) with PID controllers, achieving improved dynamic performance. Kozubik and Friml [26] utilized differential evolution-based nonlinear model predictive control, implemented on GPUs for enhanced computational speed.

g) Advanced Control Architectures

Innovative control architectures have been proposed to address the demands of modern applications. Xie et al. [20] introduced a modified strategy for neutral-point clamped converter-fed PMSM drives integrated with energy storage, achieving better energy efficiency. Carlet et al. [3] proposed a CCS-MPC architecture, emphasizing precise speed and current control under dynamic conditions.

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h) Design Optimization for PMSMs

Optimization in motor design is essential for improving efficiency and performance. You [18] utilized finite element analysis and metamodeling for automated PMSM design, achieving precise and efficient results. Zhao et al. [19] explored axial flux PMSM designs tailored for renewable energy, focusing on sustainability and performance.

i) Soft Computing in PMSM Control

Soft computing methods have been extensively applied to PMSM control systems. Singh et al. [27] reviewed soft computing-based controllers for frequency regulation in hybrid and traditional power systems, highlighting their adaptability and efficiency. Öztürk and Çelik [22] combined fuzzy logic with genetic algorithms to optimize speed control, ensuring robust performance.

This review highlights the diverse strategies and innovations in PMSM speed control, ranging from robust sliding mode control and predictive methods to artificial intelligence and optimization algorithms. The integration of renewable energy systems and the development of adaptive, hybrid, and soft computing-based controllers underscore the growing complexity and demands of modern PMSM applications. Future research should focus on further integrating machine learning techniques and exploring lightweight, energy-efficient designs tailored for renewable energy and high-performance industrial systems.

The paper consists of 7 sections. Section 1 highlights the diverse strategies and innovations in PMSM speed control. Section 2 introduces the mathematical model of the Permanent Magnet Synchronous Motor (PMSM). Section 3 discusses the development of the New Optimized Back Propagation Spiking Neural Network (BPSNN). Section 4 delves into the design of a Slime Module Algorithm-based back propagated Spiking Neural Network (SNN) – PI controller enhanced with Fuzzy Logic for PMSM drive systems. Section 5 analyzes and discusses the simulation results. A comparative analysis between conventional and proposed methods is presented in Section 6. The paper concludes with Section 7, summarizing the findings and contributions of the study.

2. Mathematical model of PMSM

The voltage equation of the PMSM is given by,

$$v = Ri + \frac{d\lambda}{dt} \tag{1}$$

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \times \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} F_a \\ F_b \\ F_c \end{bmatrix} \tag{2}$$

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$$L_{sm} = L - M = L_{lk} + L_s - \left(-\frac{1}{2}L_s\right) = L_{lk} + \frac{3}{2}L_s \tag{3}$$

$$\frac{d}{dt}\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \frac{1}{L_{sm}}\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} - \begin{bmatrix} R/L_{sm} & 0 & 0 \\ 0 & R/L_{sm} & 0 \\ 0 & 0 & R/L_{sm} \end{bmatrix}\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} - \frac{1}{L_{sm}}\begin{bmatrix} F_a \\ F_b \\ F_c \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} F_a \\ F_b \\ F_c \end{bmatrix} = -\rho\omega_N \begin{bmatrix} \sin\theta_{rt} \\ \sin(\theta_{rt} - 2\pi/3) \\ \sin(\theta_{rt} + 2\pi/3) \end{bmatrix} \tag{5}$$

$$T_{ec} = -\rho\frac{p}{2}\{i_a \sin\theta_{rt} + i_b \sin(\theta_{rt} - 2\pi/3) + i_c \sin(\theta_{rt} + 2\pi/3)\} \tag{6}$$

$$J_e \frac{d}{dt}\omega_N = \frac{p}{2}\left(T_{ec} - T_{load} - B\left(\frac{2}{p}\right)\omega_N\right)$$

$$\frac{d}{dt}\omega_N = \frac{\frac{p}{2}\left(T_{ec} - T_{load} - B\left(\frac{2}{p}\right)\omega_N\right)}{J_e} \tag{7}$$

$$\frac{d}{dt}\theta_{rt} = \omega_N \tag{8}$$

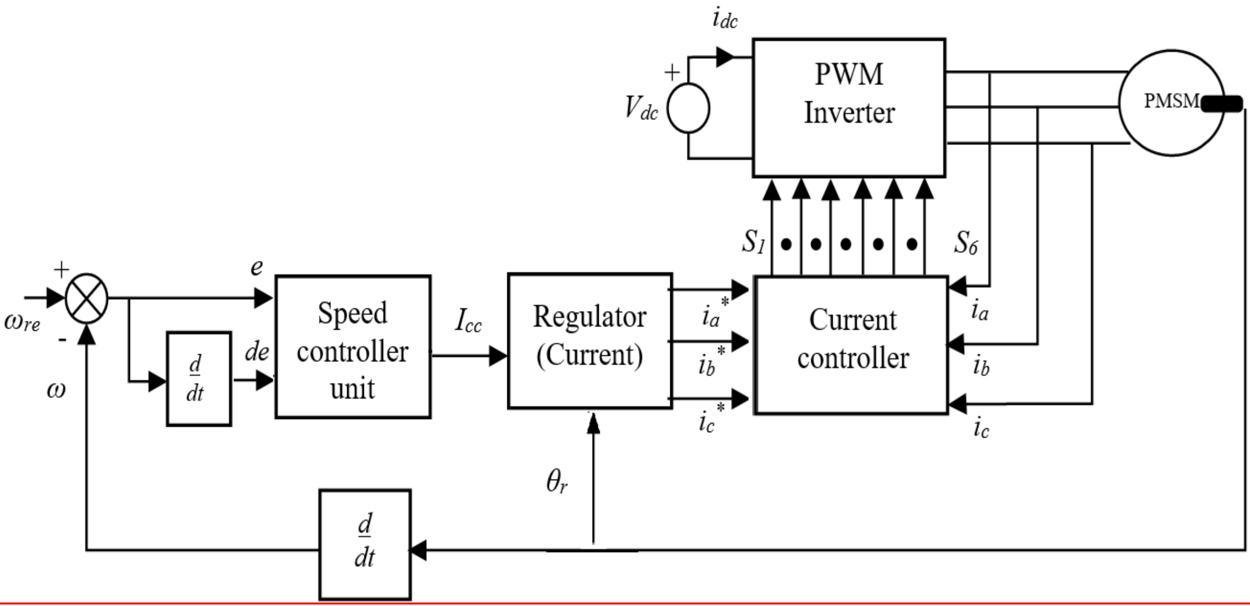

Fig.1. Block diagram of the PMSM Module

Developing precise mathematical models is essential for designing effective control systems for PMSMs, enabling the prediction of dynamic responses and enhancing operational stability.

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3. New Optimized back propagated spiking neural network

Originally, in a classical spiking neural network model, the spiking neuron fires and based on the number of spikes and duration of the spikes, the error is evaluated and carried out. This spiking neural network model elapses more time for convergence and gets saturated attaining global minima occurrences. To overcome the global minimal problem and to avoid reaching saturation during network training develops a new BPSNN model is designed to overcome the identified limitations. The new technique developed in this section hybridizes that classic slime mould algorithm and the new BPSNN technique. Henceforth, this SMA technique with its merits is employed to compute optimal weight parameters for the BPSNN model.

3.1 New BPSNN Model

The developed novel BPSNN model is a multi-layer feed forward architecture, but the errors simulated during network training are backpropagated to the previous layers like the one done is Conventional BPSNN model and based on the error gradient calculated, the weight update is done. Hence, in this new BPSNN both the features of spiking NN model and back-propagation neural network model are combined and versatile and stable neural network architecture is designed. The error evaluation in the proposed BPSNN is based on the timing sequence of generated spikes and the gradient descent training mechanism is employed to evaluate the weights to attain faster and accurate network convergence. The biological plausibility of spiking neurons along with the error gradient rule tends to make the developed BPSNN a better network architectural model and thereby designed to be a controller model for speed regulation of PMSM in this paper. Fig. 2 shows the designed new BPSNN architectural model.

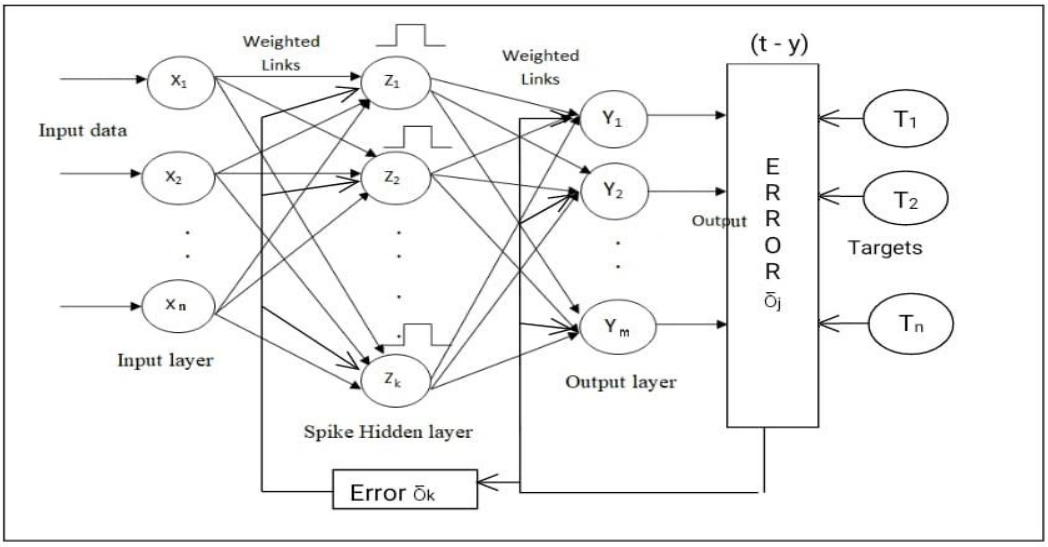

Fig. 2. Architecture design of new BPSNN model

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The algorithm of the developed back-propagated spiking neural network is as given below:

Step 1: Initiate the learning process.

Step 2: Perform weight initialization randomly (During the hybrid process, weights will be updated based on slime mould algorithm). The Threshold value is to be set.

Step 3: The input signals are fed through the input layer and then they are processed at the spiking hidden layer and the processing takes place and passed on to the output units.

Step 4: These two times, the values are compared to evaluate the error value.

Step 5: Gradient error back-propagation is carried out to compute the error values and thereby the evaluated errors are backpropagated to the previous layers and weight update is done. The error computation is done using,

$$Er_{mean} = \frac{1}{2}\sum_{j \subseteq v}(S_{time} - D_{time})^2 \tag{9}$$

Computation of error 'δ_j' is done using,

$$\delta_j = \frac{\delta_{Ed_p}}{\delta_{Stime}} \frac{\delta_{Stime}}{\delta x_j(S_{time})} = \frac{(D_{time} - S_{time})}{\sum_{i \in \tau_j} \sum_l w_{ij} l \frac{\delta_{yil}(S_{time})}{\delta S_{time}}} \tag{10}$$

Computation of error 'δ_i' is performed with,

$$\delta_i = \frac{\delta A_{time}}{\delta x_i(A_{time})} \sum_{j \in \tau_i} \delta_j \frac{\delta x_j(A_{time})}{\delta A_{time}} \tag{11}$$

In equation (3.19) and (3.20), 'Ed_p' denotes the pulse edge and 'δ(.)' specifies the Dirac function and 'A_{time}' represents the actual time of firing.

Step 6:

$$\Delta w_{jk} = -\alpha \frac{\delta Ed_p}{\delta w_{jk}} = -\alpha\, y_{ik}(A_{time}).\delta_j \tag{12}$$

$$\Delta w_{ji} = -\beta y_{ji}(A_{time}).\delta_i \tag{13}$$

Where, 'α' and 'β' are the learning rates.

Step 7:

$$\begin{aligned} w_{jk}(new) &= w_{jk}(old) + \Delta w_{jk} \\ w_{ji}(new) &= w_{ji}(old) + \Delta w_{ji} \end{aligned} \tag{14}$$

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Step 8: Carry out the iterative process until the terminating value is attained. The terminating criterion is the error 'Er_{mean}' attaining the least possible value or it can be a set number of iterations.

Step 9: Stop the learning procedure of the algorithm.

The above presented algorithm of the back-propagated neural network is employed to be modelled as a controller along with the fuzzy inference system module. This proposed new BPSNN is a biologically plausible model and its synaptic reactions for the signals stimulated are much faster than the regular traditional neural network models.

3.2 SMA algorithm – Process flow and Procedural steps

SMA Algorithm is used in this paper to tune the values of the newly developed neural network models and thereby perform effective control action to regulate the speed and torque of the PMSM. Generally, the algorithmic process of SMA technique is based on the concept of cytoplasm flow of slime mould and the way the slime mould moves and links the food available in the environment. The bio-oscillator forms a propagating wave when the vein reaches a source, and this raises the cytoplasm flow through the vein and the vein becomes thicker based on the faster flow of the cytoplasm. In this way of positive-negative feedback, the slime creates an optimal path to link food in a superior and effective manner.

- During the instability property of the contraction mode, an isotropy starts to appear.
- While the slime mould's contraction pattern has been non-existence with time and space, then the venous structure as well do not exist.

The fitness variation 'p' is given by,

$$p = \left[tanh \left| F(i) - F_{best} \right| \right] \tag{15}$$

In the above equation, '$F(i)$' is the fitness value of X, 'F_{best}' specifies the best fitness attained over all iterations and $i \in$ 1,2, 3, …, n. In respect of evaluating the parameter 'vb', the value of 'm' is determined using,

$$m = arctanh\left(-\left(\frac{t}{max\_t} \right) + 1 \right) \tag{16}$$

Where, 't' indicates the present iteration run of the algorithm and for determining the value of weight 'W', the equation employed is,

$$W(smell(i)) = \begin{cases} 1 + r.log\left(\frac{F_{best} - F(i)}{F_{best} - F_{worst}} + 1 \right), \ if \ F(i) Rank = fisrt half \ of \ the \ population \\ 1 - r.log\left(\frac{F_{best} - F(i)}{F_{best} - F_{worst}} + 1 \right), \qquad otherwise \end{cases} \tag{17}$$

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$$smell(i) = sort(F(i)) \tag{18}$$

In equation (18), '*r*' is a random value between 0 and 1.

The next phase is to explain how the slime mould wraps the food it has identified. Here, the contraction mode of venous structure in SMA gets executed and enhances the process. The vein becomes thicker when the food concentration is higher on contact with the vein and the cytoplasm flow is faster. In equation (18), the parameter '*r*' controls the uncertainty of contraction mode and 'log' is employed to improve change of parameter contraction frequency. When the fitness evaluated ranks within the first half of the population, this helps the slime mould for adjusting the search forms based on the food quality. The weight value is high when the concentration of food is sufficient, and the weight value becomes low when the concentration of food is low, due to which the slime mould tends to move its exploration region at different regions. In connection with this concept, the place value of the SMA gets updated using the following equation,

$$X^* = \begin{cases} rand.(upper_b - lower_b) + lower_b, \; rand < k \\ X_o(t) + vb.(WX_{r1}(t) - X_{r2}(t)), \; r < p \\ vc.X_{lo}(t), \quad r \geq p \end{cases} \tag{19}$$

In equation (20), '*upper*' and '*lower*' indicates the upper bound and lower bound of the search space, '*rand*' and '*r*' denotes the random value between 0 to 1 and the value of 'k' is between 0 to 0.1. Last step of SMA technique is to grab food from the identified location and slime mould depends mostly on the propagation wave generated by the bio-oscillator for changing the flow of cytoplasm within the veins and henceforth they inclined as a part of the concentration of food level. The weight 'W' helps the slime mould to reach the identified high-quality food faster based on its oscillation frequency at various food concentration and approaches food very slowly in case of lower food concentration levels. This improves the movement of slime mould in attaining optimal solution and thereby becomes an efficient algorithm.

In the SMA process flow, the parameter 'vb' randomly varies between *–m* to *+m* and this moves towards zero as the iteration count increases. The parameter 'vc' ranges from *-1* to *+1* and during process flow, it moves towards zero. Even though slime mould locates better food source, it tends to explore few organic food sources so as to identify further better high quality food source.

3.3 Comparative Analysis of the Control Strategies

Conventional control strategies for Permanent Magnet Synchronous Motor (PMSM) systems, such as Proportional-Integral (PI) and Proportional-Integral-Derivative (PID) controllers, face significant challenges in addressing complex system dynamics and parameter variations. These

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methods often require precise tuning to maintain stability and performance, yet they lack robustness against non-linearities and external disturbances commonly encountered in PMSM applications. For instance, PI controllers exhibit poor transient response and steady-state errors in systems with high torque ripple or load variations. Sliding Mode Control (SMC) improves robustness but suffers from chattering, which can lead to mechanical wear and increased energy consumption. Similarly, optimization-based approaches like Chaos Particle Swarm Optimization (CPSO) and Jaya algorithms enhance parameter tuning but often converge slowly and struggle to adapt to real-time changes in dynamic environments.

The proposed hybrid controller addresses these limitations by integrating the Slime Mould Algorithm (SMA) with a back-propagated Spiking Neural Network (SNN). This combination leverages the adaptive capabilities of SNNs to handle non-linearities and uncertainties, while SMA ensures efficient tuning of the network's parameters, overcoming delayed convergence. Moreover, the hybrid approach reduces steady-state error and improves speed regulation, offering superior performance compared to conventional and heuristic controllers in both static and dynamic conditions. The hybrid BPSNN-SMA model significantly enhances control precision by overcoming traditional neural network limitations, ensuring optimal weight adjustments and stable performance under dynamic conditions.

4. Design of SMA based back propagated SNN – Fuzzy PI controller for PMSM drive

The new technique developed in this section hybridizes that classic SMA and the new BPSNN network technique. The modelled new SMA – BPSNN provides optimal inputs to that of the fuzzy proportional-integral controller model. These two techniques are combined to overcome the limitations of global and local minimal occurrences and hybridized to attain better learning and generalization capability. The merits of slime mould algorithm in exploring the high-quality food using the venous structure and thicker veins achieves efficient and effective exploration and exploitation rate. Henceforth, this SMA technique with its merits is employed to compute optimal weight parameters for the back-propagated spiking neural network model. Table 1 gives the developed hybrid optimization algorithm using SMA and BPSNN technique.

Proposed Method-SMA hybrid controller

The new model rule is given by:

$$\text{IF } p \text{ is considered as } M \text{ and } q \text{ is considered as } N, \text{ THEN } Y = G \tag{20}$$

The output evaluated from the rule in equation (3.24) is the singular value 'G' that corresponds to the crisp control current value 'I_{ci}' forming the consequent of the rule.

$$Y_i = And\_Rule(H_1(p), H_1(q)) \tag{21}$$

$$Y_i = Or\_Rule(H_1(p), H_1(q)) \tag{22}$$

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With *M(.)* and *N(.)* specifying the defined membership function values. The centroid de-fuzzified process is done to evaluate the output from the Mamdani FIS model,

$$Output_{fis} = \frac{\int_{i=1}^{N} Y_i H_i}{\int_{i=1}^{N} Y_i} \tag{23}$$

The devised approach employing optimized BPSNN model – fuzzy inference controller attains the error value and based on these values the control current pertaining to the gain values is evaluated for the considered PMSM drive.

$$\begin{gathered} FIS\ Rule: IF\ (e = Y_i) \quad and \quad (\dot{e} = Y_j)\, then \\ output = \lambda_n e + \sigma_n \dot{e} + \zeta_n \end{gathered} \tag{24}$$

The computational process of the developed hybrid controller model is presented below:

Table 1 Algorithm of new SMA – BPSNN technique

Start
Given the weights and learning rate parameters of new BP-SNN model
Set the population size and other constant parameters of SMA technique
Invoke: ***New BPSNN training algorithm***
Generate the weight parameters randomly
Fed the input signals to the input layer
Perform computation and the spikes are transmitted to output units
Evaluate the output spikes values
calculate S_{time} *and set the desired firing time* D_{time}
Calculate the error Er_{mean} *with the spike firing time and desired spike flow time*
Evaluate the errors δ_j *and* δ_i
Compute the new weights using weight update rule

$$\Delta w_{jk} = -\alpha \frac{\delta Ed_p}{\delta w_{jk}} = -\alpha\, y_{ik}(A_{time}).\delta_j$$

$$\Delta w_{ji} = -\beta y_{ji}(A_{time}).\delta_i$$

Return weights (between output and spiking layer, spiking and input layer)
Invoke: ***Slime mould algorithm***
Set the initial population $\rightarrow$ *Final weights_BPSNN approach*
Set the positions of slime mould X_{lo_i} *(i=1,2,…,n)*
WHILE (Evaluated fitness_value != minimum (fitness_value))

Update Best Fitness (F_{best})
Calculate the weight W

$$W(smell(i)) = \begin{cases} 1 + r.log\left(\dfrac{F_{best} - F(i)}{F_{best} - F_{worst}} + 1\right), & if\ F(i)Rank = fisrt\,half\ of\ the\ population \\ 1 - r.log\left(\dfrac{F_{best} - F(i)}{F_{best} - F_{worst}} + 1\right), & otherwise \end{cases}$$

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FOR each search area
Update vb, vc and p
Update location of slime mould

$$X^* = \begin{cases} rand.(upper_b - lower_b) + lower_b, rand < k \\ X_o(t) + vb.(WX_{r1}(t) - X_{r2}(t)),\ r < p \\ vc.X_{lo}(t),\ \ r \geq p \end{cases}$$

END FOR
Update the iteration count $\rightarrow t = t+1$
END

While
Return Best_Fitness value (F_{best})
Continue
Weights $\leftarrow$ *Best_Fitness value-*F_{best}
Goto
BPSNN training process
Output
Global_Optimal solution
Stop

Layer 1: Fuzzification process gets initiated and triangular membership function is defined here and for both the inputs to the FIS controller the membership value is defined between 0 to 1. The membership functions get assigned to be,

$$F_{mfi\_1} = \mu Y_i(e) \qquad i = 1,2,\ldots 5 \tag{25}$$

$$F_{mfj\_1} = \mu Y_j(\dot{e}) \qquad j = 1,2,\ldots 5 \tag{26}$$

Where, F_{mfi} and F_{mfj} denotes the outputs and μY_i and μY_j specifies the membership functions defined with triangular membership function.

Layer 2: In this layer, for all the inputs received their respective product is evaluated. Here, the formation of rule is done, and it is represented using,

$$F_{mf\_2} = \mu Y_i(e)\ AND\ \mu Y_j(\dot{e}) \tag{27}$$

Layer 3: The rule firing strength here becomes,

$$F_{mf\_3} = \frac{F_{mf\_yi}}{\int_{i=1}^{N} iF_{mf\_yi}} \qquad i = 1,2,\ldots \tag{28}$$

Layer 4:

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$$F_{mf\_4} = F_{mf\_3} \int_{i=1}^{n} \lambda_i e + \sigma_i \dot{e} + \mu_i \qquad i = 1,2,...n \tag{29}$$

Layer 5: In this layer, de-fuzzified output of Mamdani FIS controller model is calculated using the centroid method and is obtained using,

$$Output_{fis} = \frac{\int_{i=1}^{N} Y_i H_i}{\int_{i=1}^{N} Y_i} \tag{30}$$

The classic SMA approach optimizes the weights of the new BPSNN model and further attains values to the fuzzy Mamdani model. During the run of SMA-BPSNN algorithm, the root mean square value (Er_{mean}) is evaluated and this is set to be the fitness function of the devised algorithm. The newly modelled algorithm is trained so that the fitness function attains the least minimum possible value during the iteration process. Fig. 3. presents the block diagram model of the proposed hybrid controller model as applicable for PMSM drive.

The hybrid SMA-BPSNN controller is integrated with a fuzzy PI controller. The combination enhances speed regulation by optimizing weight parameters and applying Mamdani fuzzy logic. The approach improves learning rates and generalization capabilities, addressing local minima and achieving efficient control. The hybrid SMA-BPSNN-Fuzzy PI controller demonstrates robust performance, combining adaptive optimization with precise decision-making for effective PMSM control.

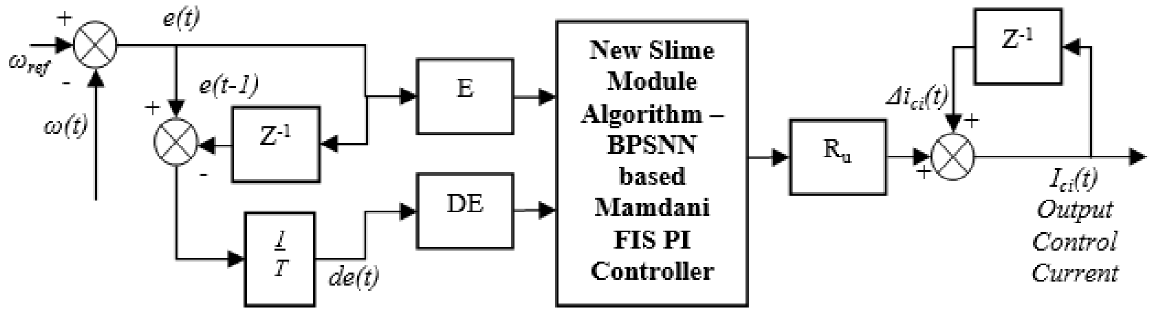

Fig.3 Block diagram of SMA BPSNN based module with controller

5. Simulated results and discussion

The error value (e) and its derivative value ($\dot{e}$) act as the inputs to the hybrid soft computing controller and the output from the designed controller is going to be the control current (I_{ci}) which is given to the designed multi-level inverter and thereby drives the motor. At the time of training progress, PI controller model simultaneously determines the optimal values for gain parameters of the PI controller (both proportional gain and integral gain). This in turn aids to carry out effective speed regulation of the permanent magnet synchronous motor drive system.

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Initial fuzzy membership function definitions and rule formulation are assigned with basic priori knowledge and subsequently definitions are modified. The developed soft computing model must set all its linear and non-linear parameter definitions before the training process gets initiated. Table 2 presents the defined values of simulation parameters of the hybrid controller model. Table 3 gives the details of the motor parameters with controller model.

Table 2 Simulation parameters of the hybrid controller model

Parameters	**Back-propagated SNN–FIS controller model**	**Parameters**	**SMA optimization approach**
Learning rate at an angle	α = 0.1, β = 0.3	Population value	39
No. of input	3	*k*	0.01
No. of Hidden Neurons	3	*r*	0.3
No. of output neuron	1	*vc*	1 (Initially)
Spiking Neuron Model	Izhikevich neuron model	Learning trials	32 runs
Weight update rule	Gradient- Descent learning	Convergence acceptance	0
Membership function	Triangular function		
No. of linguistics defined for input and outputs parameters	3		
Fuzzy inference engine	Mamdani FIS engine		
De-fuzzification	Centroid approach		

During the initial start of the controller design procedure, the training of the new BPSNN model begins employing error and derivative of error as its input parameters and here the weight coefficients are generated randomly, and the spikes get generated and passed to the output layers. With respect to the time duration of the spikes error is evaluated using,

$$E_{mse} = \frac{1}{N}\sum_{i=1}^{N}(y_{evalauted} - y_{desired})^2 \qquad (31)$$

Nine rules are formed using IF…. THEN statements as given below in equation 33and the decision-making FAM table is presented in Table 4. The de-fuzzification method employed is the centroid technique and finally it determines the controller output. The final proposed controller PI controller output is as given in equation 34.

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$$Rule\,1: IF\ (e = L)\ and\ (\dot{e} = L)\ THEN\ (I_{ci} = L)$$
$$Rule\,2\ IF\ (e = Z)\ and\ (\dot{e} = L)\ THEN\ (I_{ci} = Z)$$
$$\ldots$$
$$Rule\,9: IF\ (e = H)\ and\ (\dot{e} = H)\ THEN\ (I_{ci} = H) \quad (32)$$

$$I_{ci}(t+1) = I_{ci}(t) + K_{ci}\Delta I_{ci}(t) \quad (33)$$

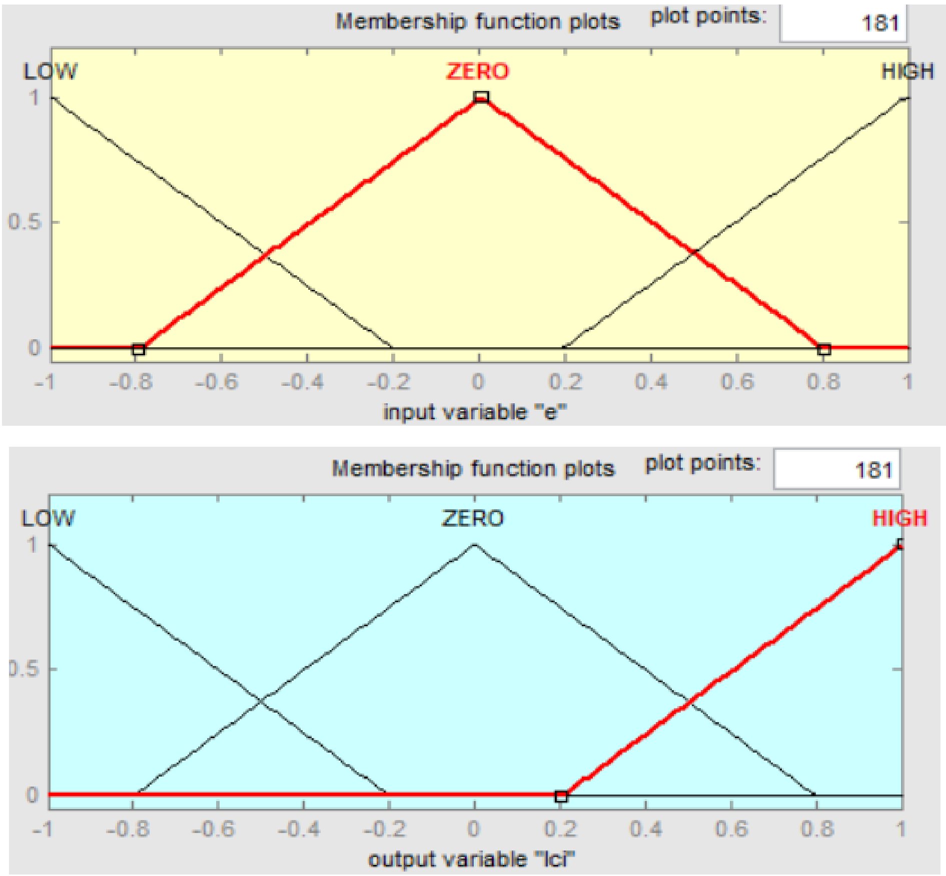

Fig. 4. Functions of input I/O variable

At the time of training, the PI gain is also tuned for their optimal values so as to improve the performance characteristics of the system. Employing the developed slime mould algorithm based BPSNN model the gain values are computed and the training error attained over 1000 iterations is presented in Fig. 5. At the 1000th iteration the training error values for proportional gain and integral gain are observed to be 0.00827 and 0.11723 respectively. The Proportional Integral controller gain values calculated during the training process is provided in Table. 5.

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Table 5. Evaluated proportional and integral gain values using given model technique

Controller	k_p	k_i
Without controller	1	0
Conventional PI controller	8.1271	0.4562
Proposed hybrid controller model (SMA-BPSNN-Fuzzy)	5.1438	0.7631

When the motor gets started, it gets accelerated from the initial speed and runs to 1500 rpm during no load condition and for attaining the rated value the current gradually increases. From Fig. 6 it has been noted that the speed has increased to only 900 rpm. During normal condition and during that the motor speed becomes equal to the rated speed and then it accomplishes the requisite frequency of the current. At this point, the starting torque of the motor tends to persist at constant rate. The PMSM drive mechanism is provided with an instant load equal to 6 Nm at the time of 0.25 seconds to the shaft and at this point the speed of the rotor tends to reduce. Fig 7. shows the equivalent current variations of the motor. Table 6 provides the metrics in respect of the performance characteristics evaluated for the PMSM drive mechanism using the proposed hybrid soft computing controller model.

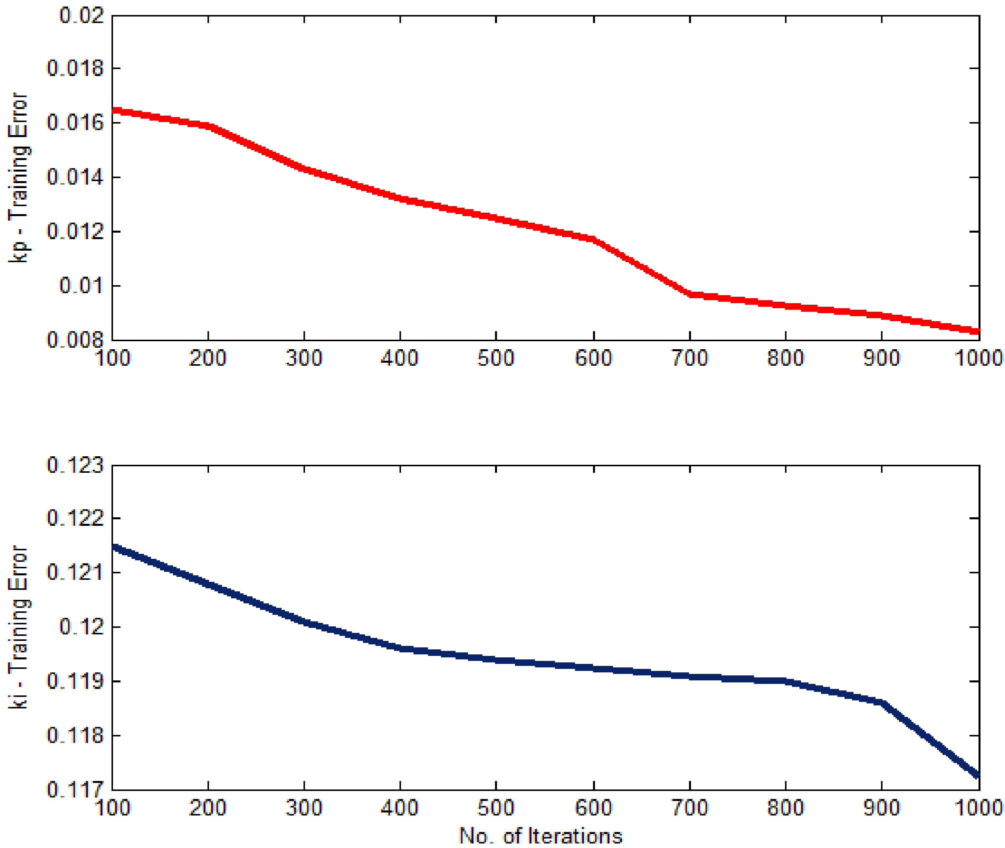

Fig. 5. Training error in respect of PI controller gain tuning

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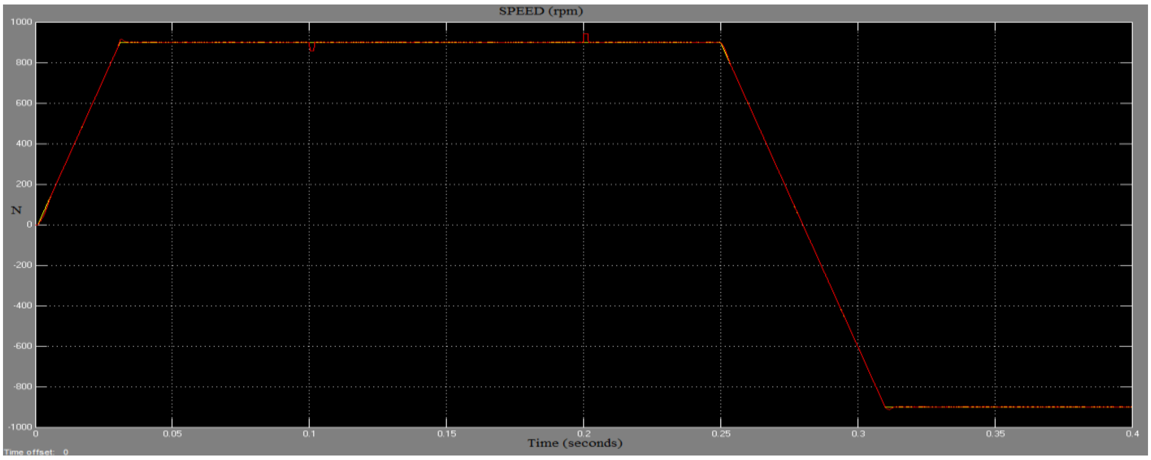

Fig. 6. Variation of speed of PMSM drive mechanism

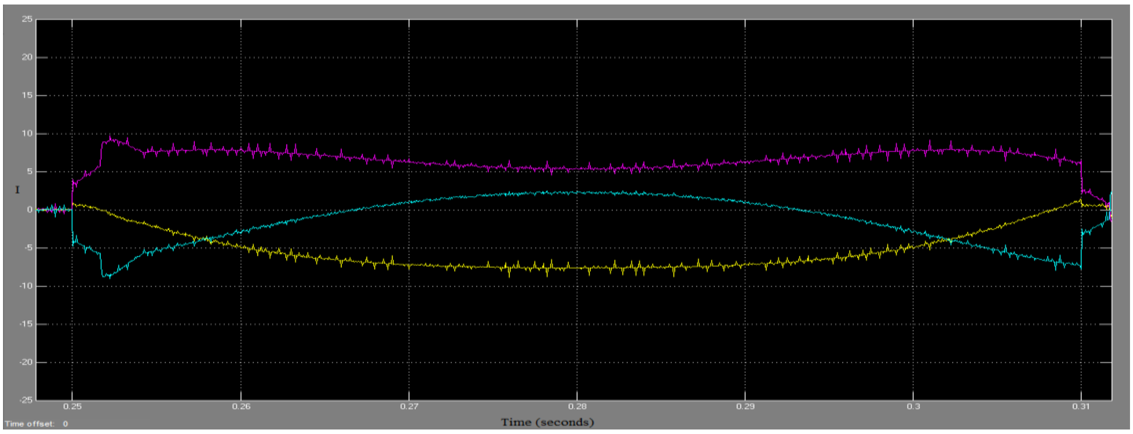

Fig. 7. Current flow in PMSM drive

Even the developed slime mould algorithm based new BPSNN – Mamdani FIS PI controller has resulted in better performance characteristics than that of the conventional PI controller. Henceforth the developed model has proved its effectiveness when the load pertaining to the PMSM is maintained at 6 Nm. Fig. 8 also proves the efficacy of the proposed soft computing controller model than that all the other methods considered for process from previous comparisons.

The simulation results are used to analyse the controller performance using three metrics-rise time, settling time, and overshoot. The SMA-BPSNN-Fuzzy PI controller outperforms traditional methods, achieving superior speed regulation and minimal error values. The optimized proportional and integral gains enhance system efficiency. To conclude, simulations have validated the proposed controller's effectiveness in achieving precise speed regulation, highlighting its superiority over conventional and heuristic models through optimal tuning and minimal error**.**

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Table 6. Performance characteristics valued using the proposed new controller model

Modelled Controllers	Performance Characteristics				
	Rise time (s)	Peak time (s)	Peak value (rpm)	Peak overshoot Value (%)	Settling time (s)
Conventional PI controller [10]	0.4362	1.0042	1506.7	0.4465	0.6926
Genetic Algorithms with Fuzzy Controller [22]	0.4359	1.0028	1518.7	0.4431	0.6923
Artificial Approach [16]	0.4532	1.0016	1515.5	0.7646	0.7073
ANFIS design [23]	0.4519	1.0022	1513.0	0.7323	0.7063
Differential Evolution [22]	0.4376	1.0035	1510.0	0.4656	0.6939
Artificial Bee Colony [21]	0.4546	1.0019	1509.0	0.8016	0.7083
New hybrid soft computing controller	0.3955	1.0014	1505.0	0.1331	0.6464

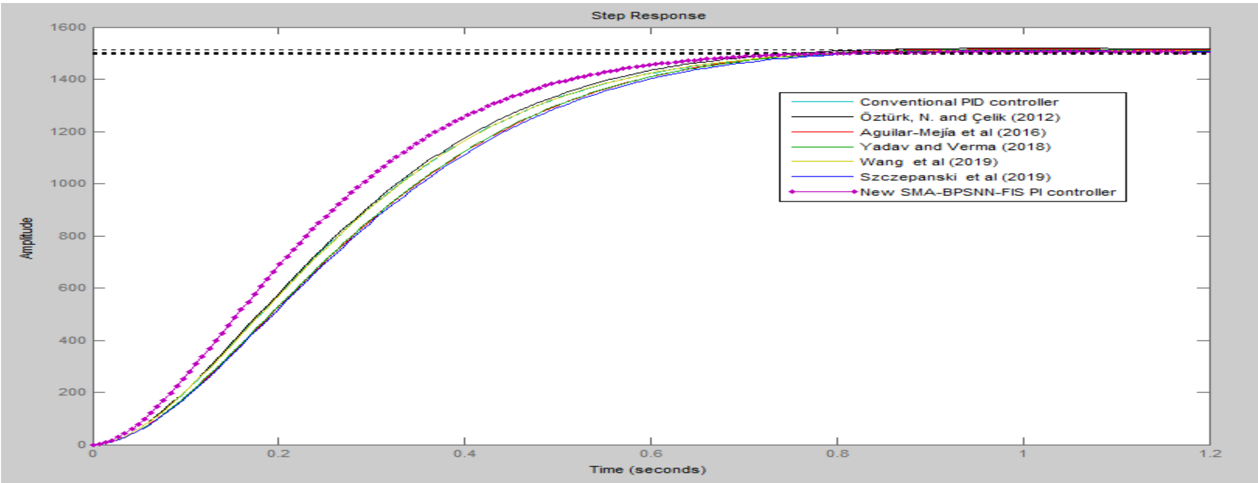

Fig. 8. Comparison of all the methods with controllers

6. Comparative Analysis

SMA algorithm is utilized for determining the optimal weights of developed new BPSNN model. SMA technique with its behaviour of enhancing and forming its venous structure locates the better solution based on its movement towards quality solution and thereby evolving more optimal weight coefficients for BPSNN model. The operation of the entire process is to minimize the mean square error, and the timing of the spikes is observed to make the network converge without any stuck at global minima occurrences. The trained and validated output from the SMA-BPSNN model is presented as input to the designed Mamdani fuzzy PI controller model. The membership function definition is made and the rules formed tend to develop control current and performs control action on the PMSM drive. The speed and torque

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variations are observed and from the performance characteristics it must be noted that speed regulation is achieved at 1505 rpm. The complete proposed controller module is run for 32 trials and then the outputs are noted and presented for analysis. During the progressive learning, the values of K_p and K_i are determined to be 5.1438 and 0.7631 and the performance curve for step input is as shown in Fig 8. Results computed as shown from the presented figures and tables prove that the proposed controller has obtained optimum solutions than the methods considered for comparison from previous studies, [24-27].

The developed soft computing controller handles randomness and employs random generation of few parameters during the training and testing process. Since the proposed controller handles randomness, it is to be validated for its guarantee on accuracy using statistical analysis. The computed statistical parameters correlation value is provided in Table 7 and from those values it is inferred to be nearer to 1. This proves the validity of the developed hybrid soft computing controller model. From Table 7, it is noted that the computational time for the run of the controller model for the system is 132 seconds. The training MSE and testing MSE computed during the learning process is provided in Figure 9 and it is clear from the table that at the end of 1000th epoch the training error and testing error is 0.13762 and 0.00907.

Table 7 Statistical validation of the developed novel controller

Type of Controller	Time Period incurred (seconds)	Co-relation value, r	Coefficient value of determination, R^2
New hybrid soft computing controller	132	0.9894	0.9901

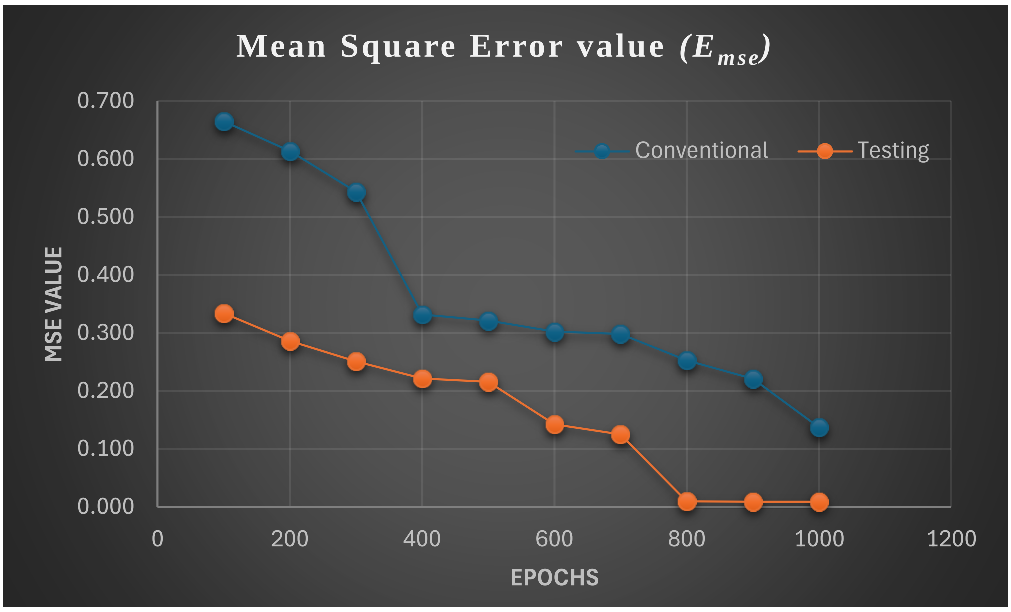

Figure 9. Evaluated error values using Proposed controller

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7. Conclusion

This study investigates advanced control strategies for Permanent Magnet Synchronous Motors (PMSMs), focusing on improving speed regulation, system stability, and energy efficiency. By integrating artificial intelligence (AI) methods, such as neural networks and fuzzy logic controllers, alongside optimization techniques like Particle Swarm Optimization (PSO) and Ant Lion Optimizer, significant advancements have been achieved in motor control performance. The research highlights the effectiveness of hybrid control approaches, combining traditional methods with AI-based solutions, to address challenges such as nonlinearity, disturbances, and parameter variations in dynamic environments.

The findings reveal several critical insights. First, sliding mode control ensures robustness against external disturbances, making it effective for PMSM systems under varying operating conditions. Second, adaptive controllers based on fuzzy logic and neural networks enhance speed regulation and system stability, particularly in renewable energy and electric vehicle applications. Third, optimization algorithms improve the design of control parameters, leading to enhanced performance and reliability. Predictive control methods, tailored to handle nonlinearity and rapid environmental changes, show promise for complex applications. Lastly, the integration of hybrid techniques achieves superior energy efficiency and operational reliability.

Within this context, several recommendations are made. Hybrid control strategies should be prioritized for their ability to balance robustness and adaptability. AI techniques, particularly neural networks and fuzzy logic, offer advanced solutions for speed regulation and should be adopted in dynamic settings. Optimization algorithms are crucial for refining controller parameters and achieving performance goals. Predictive and model-based approaches are well-suited for renewable energy systems and electric vehicle applications, and further investment in real-world testing and simulation tools is essential to validate their scalability.

Future research should explore the real-time implementation of hybrid AI-based controllers in industrial and commercial applications. The integration of PMSMs with energy storage systems for smart grids offers a promising avenue for enhancing grid stability and efficiency. Lightweight and cost-effective control solutions tailored for electric vehicles should be developed to improve their viability. Additionally, emerging optimization algorithms can be explored to further refine PMSM control strategies. The potential role of IoT and edge computing in real-time monitoring and control of PMSM systems also merits investigation. This work serves as a foundation for advancing intelligent motor control technologies, offering insights into their application across industries with high demand for energy-efficient and reliable systems.

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Compliance with Ethical Standards

Disclosure of potential conflicts of interest

The authors declare that they have no competing interests.

Availability of data and materials

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Informed consent

Not Applicable

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