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COMPUTING TECHNIQUE FOR ENHANCED BLDC MOTOR FOR E-VEHICLES

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ABSTRACT

Electric vehicles, industrial automation, and robots are using brushless DC (BLDC) motors more and more because they are more efficient, reliable, and have a better torque-to-weight ratio. However, traditional Proportional-Integral (PI) and PID controllers lack functionality as well when parameters change, loads change, or DC-link voltage changes, leading to diminished dynamic performance. This research presents a cascaded BLDC motor control system that incorporates two Adaptive Neuro-Fuzzy Inference System (ANFIS) controllers—one for speed regulation and the other for DC-link voltage stabilization—aiming for optimum parameter tuning using the Shuffled Frog Leaping Algorithm (SFLA). The optimization reduces a composite performance index that includes the Integral of Time-weighted Absolute Error (ITAE), overshoot, and DC-link ripple. Simulations in MATLAB/Simulink show that the SFLA-optimized ANFIS works better than regular ANFIS and PI controllers. It has less voltage ripple, smoother torque, more balanced phase currents, and a quicker transient response, all while keeping the steady-state error very low. The findings show that hybrid intelligent optimization works well to make BLDC drives more resilient for real-time application.

KEYWORDS: BLDC Motor Control, Adaptive Neuro-Fuzzy Inference System (ANFIS), Shuffled Frog Leaping Algorithm (SFLA); Intelligent Optimization; DC-Link Voltage Stabilization.

1. INTRODUCTION

Brushless DC (BLDC) motors are highly promoted in electric vehicles, robotics, and industrial automation because of their high efficiency, compactness, and high-tore characteristics. Nonetheless, the performance is very sensitive to changes in such parameters as load torque, DC-link voltage, and temperature [1]. Conventional controllers such as PID or PI can easily lose a robust operation due to such nonlinear and time varying conditions leading to speed ripple, distortion of torque and poor dynamic response [2] [3]. To eliminate these shortcomings, smart control approaches utilizing soft computing approaches have acquired high priority owing to their capacity to adjust and optimize the control parameters in a dynamic manner [4].

Cascaded soft computing system combines various smart methods, which include Fuzzy Logic, Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and many more within hierarchical control architecture to improve stability and accuracy of the system [5]. This compound system takes advantage of the learning and adaptive properties of these algorithms to obtain accurate speed and torque control in the uncertain situations [6]. The cascaded system will provide minimized error, enhanced efficiency, and smooth operation of BLDC drives by optimizing parameters of controllers with sophisticated algorithms, including Particle Swarm Optimization (PSO) or Shuffled Frog Leaping Algorithm (SFLA) algorithms.

Crisp Output to DAC

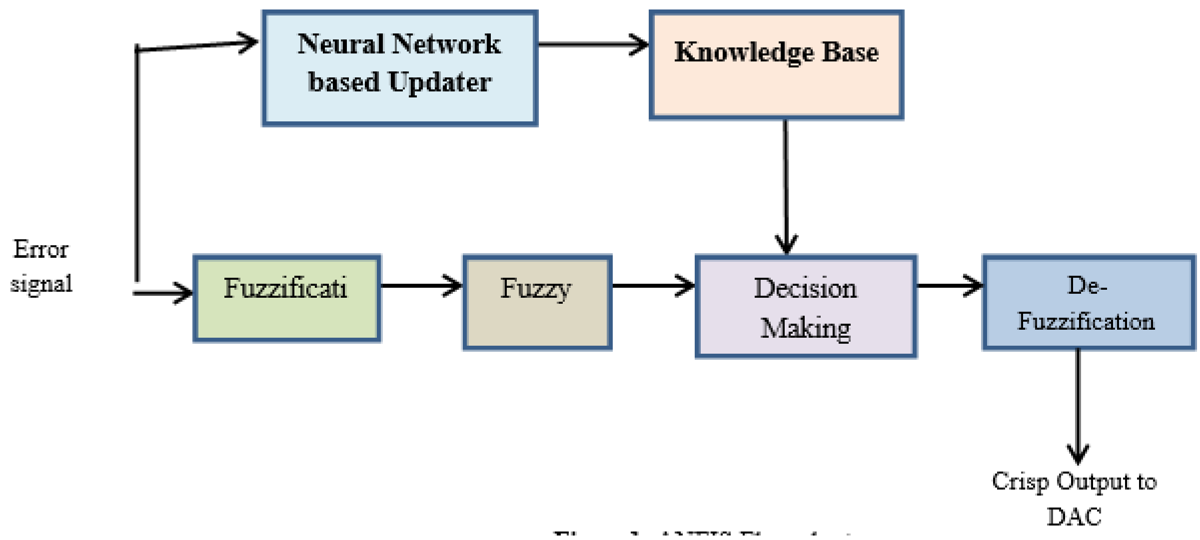

Figure 1: ANFIS Flow chart.

EV and industrial BLDC drives require powerful and flexible speed control in changing operating conditions like parameter drift and DC-link voltage sag and dynamic load disturbances - situations where traditional fixed-gain PI/PID controllers may not competently achieve the desired state [8]. These linear controllers are not adaptable to nonlinearities and parameter uncertainties of the BLDC motor dynamics, leading to poor transient response, increased overshoot, and poor voltage regulation. To address these difficulties, it uses cascaded control structure where optimized ANFIS (Adaptive Neuro-Fuzzy Inference System) controllers are used to substitute the traditional PI regulators in both the outer speed loop and the inner DC-link voltage loop [9]. The Shuffled Frog Leaping Algorithm (SFLA) is another population-based metaheuristic classifier that is based on the intelligent controller structure and parameters and is optimized with the Shuffled Frog Leaping Algorithm by virtue of high convergence speed and ability to search the global space [10]. The objective goal is to reduce ITAE (Integral of Time-weighted Absolute Error), overshoot and DC-link ripple in order to achieve more gentle torque response and improved drive stability. The novelty of this work lies in the integration of a cascaded soft computing control system that will enhance the speed as well as the regulation of the DC-link of BLDC drives under nonlinear and uncertain operating conditions. As opposed to common single-loop, or fixed-gain control approaches the discussed model employs an optimized dual-loop ANFIS control structure based on the Shuffled Frog Leaping Algorithms (SFLA); dynamic adaptability and global optimization features distinguish the proposed method from traditional methods [11]. The cascaded ANFIS–SFLA control strategy will make possible real-time adjustment of control parameters in accordance with external disturbances, such as significant parameter drift, voltage sag, and varying load torque; all of which will ensure transient response improvement, torque smoothness, and voltage stability improvement. In summary, this work proposes a synergistic combination of fuzzy intelligence and evolutionary optimizationresultinginanovelcontributiontowardintelligentandself adjusting control techniques for future EV generations as well as industrial BLDC motor drives.

2. Related Work

Cascaded soft-computing approaches to BLDC motor drives solve the long-standing problem of strong speed/torque control in the face of parameter uncertainty, load variation and DC-link variation-issue sin which fixed-gain PI/PID controllers often fail to perform. Recent attempts have integrated neuro-fuzzy controllers, metaheuristic tuning, and cascaded loop designs in order to enhance transient response, minimize torque and current ripple, and narrow DC-link control.

There are some recent studies, which have made a step forward and presented new cascaded architectures and hybrid optimization frameworks. Intidam et al. (2023) [12] designed a PI-ANFIS hybrid that is implemented on BLDC drives so that the augmentation of classical PI

structures with ANFIS can decrease the overshoot and steady-state errorinspeedregulation.SayyedBhayoetal.(2025)[13]appliedacascadedcontroller(innercurrent/ DC-link
and outer speed loop) in which the outer loop was an ANFIS, and inner loops were adjusted with a bio-inspired Snake Optimizer and reported better disturbance rejection and settling time than baseline PID. A systematic comparison of PI and ANFIS controllers in the BLDC speed control described by Subbarao (2024) [14] reported evident dynamic benefits of ANFIS in rise time and overshoot using a variety of load steps. Together with controller design, Zhao et al. (2024) [15] suggested a variant of Shuffled Frog-Leaping Algorithm (MSFLA) that enhances convergence and eliminates local optima - which is a desirable attribute when optimizing numerous ANFIS/ fuzzy-PID parameters in cascaded models. The previous seminal studies by Prem kumar (2015) [16]proved the validity of ANFIS-monitored PID/Fuzzy-PID configurations being implemented online to manage BLDC speed control to reduce windup and nonlinearities, which drives additional cascaded designs.

Other more recent works focus on sensorless operation, fault-conscious control and utilizing type-2 fuzzy or interval-based controllers within cascaded loops to achieve robustness to measure noise and parameter drift. In 2025, Rouabhi et al. [17]suggested cascade control with Type-2 fuzzy controllers to expand the robustness margins in motor drives and achieved better stability in the case of parameter uncertainty. In the study by Shenbagalakshmi et al. (2025) [18], fuzzy/ANFIS-f oriented closed-loop speed control of EV BLDC drives was studied and its benefits in terms of better tracking and disturb ancerejection demonstrated in realistic driving load profiles. Just over fault detection and control, recent ANFIS-based fault classifiers have been combined with reconfigurable control supervisors so that cascaded controllers can adjust when short-circuit or overload conditions are signaled [19].

More recent publications pointed towards the role of optimized and hybrid methods in the improvement of the performance of the BLDC. The literature on SFLA indicates that it is a useful metaheuristic in the optimization of engineering systems and has encouraged its application to controlling the gains and neuro-fuzzy parameters in motor drives [20]. Hybrid models of ANFIS (nonlinear mapping) with swarm/metaheuristic optimizers (SFLA, Bat, PSO, etc.) create controllers that do better than single-technique designs on ITAE, overshoot, and DC-link ripple in published simulations and test beds [21]. Lastly, sensorless cascaded ANFIS schemes and ANFIS + metaheuristic tuned inner converters are both tested in hardware, and the feasibility of a rapid prototyping study involving deploying cascaded soft-computing control to industrial and EV environments is demonstrated.

There is a distinct trend together, most single-loop and fixed-gain controllers, towards cascaded structures putting adaptive neuro-fuzzy controllers in outer speed/DC-link loops and using modern metaheuristics (including modified versions of SFLA) to optimize structure and parameters [22]. It is this hybrid, cascaded soft-computing scheme that underlies the methodology of the better transient behavior, better parameter drift resistance, better Vdc/torque ripple in the modern BLDC drive research.

Research Gap

Although the control of a BLDC motor has advanced substantially, currently, the control of the motor is mostly performed by fixed-gain PI/PID or single-layer intelligent controllers, which do not always succeed in maintaining optimal control in the dynamic environment caused by disturbances in load, DC-link, or controller parameters. The literature has focused on speed (or DC-link regulation), but not a combined control approach. In addition, hybrid intelligent systems have hardly been used together with optimization algorithms to generate global tuning of various loops. This leaves a research gap in the development of a cascaded soft computing framework, including ANFIS based dual-loop controller controlled by metaheuristic algorithm, to improve the dynamic response of the operating system, reduce torque ripple, and provide robust stability under different operating conditions.

3. Research Methodology

Figure 2 outlines the research methodology of the current study which is a multi-stage approach that is structured. It starts with Dataset Collection in which performance data of a three-phase BLDC motor (current, speed, torque, voltage and back-EMF) are monitored with different load and speed conditions. Following this Data Pre-processing to get uniform quality signals is carried out by standardizing and cleaning the signals through resampling, denoising and normalizing of signals. During the Feature Extraction stage, key parameters such as torque ripple, harmonic distortion and speed deviation are obtained to aid in model training. The resulting processed features are then fed to Cascaded Soft Computing Models where ANFIS controllers control speed and DC-link voltage regulation and optimize their parameters with the Shuffled Frog Leaping Algorithm(SFLA) to reduce ITAE, overshoot and voltage ripple. Lastly, MATLAB/Simulink is used to perform Simulation and Evaluation to assess the performance of the system as compared to PI and standard ANFIS controllers.

Figure 2: Flow chart of research methodology.

Dataset Collection

The BLDC Motor Performance Dataset [23] represents an organized collection of experimentally measured parameters due to the three phase Brushless DC motors running in different load, voltage, and speed combinations. It contains pre-recorded values of values of stator current, rotor speed, back-EMF, torque, winding temperature, and vibration signals at various operating conditions. All of the measurements are gathered in folders based on the operating condition (e.g., "Low Load," "Medium Load," "High Load," and "Dynamic Speed) letting them be used effectively within supervised soft computing models [24]. The data is useful in proper assessment and optimization of motor efficiency, torque ripple minimization, and speed control. Each folder holds sensor data, which is numericallycodedbasedonaparticularperformancebehavioroftheBLDCmotor,and the results of cascaded soft computing analysis might be analyzed.

Figure 3: Sample images from the BLDC Motor Performance Dataset.

Data Pre-processing

In this section, an over view of the prerequisite pre-processing functions that should be done before implementing the cascaded soft computing models would be presented and it include filtering, normalization, feature extraction, and data segmentation. Since the measured signals of the BLDC motor were recorded under various operating conditions, their lengths and noise levels were different; consequently, all current, speed, and voltage waveforms were re sampled at a constant sampling rate to provide consistency and further enhance the level of computational efficiency [25]. Electrical and sensor noise (the case offigure4) was removed by signal demising based on low-pass and moving-average smoothing. Moreover, key parameters (torque ripple, back-EMF amplitude, and harmonic distortion) were extracted through feature extraction methods, and It assist in the sound performance assessment [26]

The data set was divided into various operating conditions, namely low load, medium load, high load, and variable speed to enable quality training of the models. Table 1 presents the full distribution that enhances the modeling, prediction, and performance optimization process.

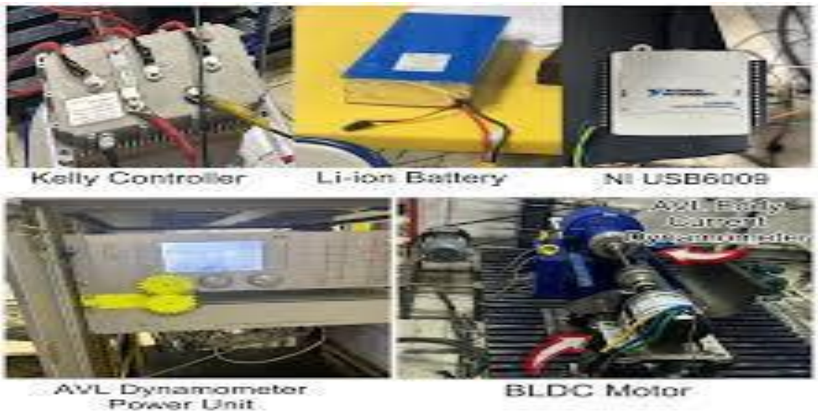

Figure 4: Pre-processing Image Sample

Table 1: Distribution of the dataset.

Operating Class	Total Samples	Train	Test
Low Load	500	400	100
Medium Load	480	384	96
High Load	450	360	90
Dynamic Speed	520	416	104
Variable Voltage	460	368	92
High Temperature	420	336	84
Torque Ripple Condition	470	376	94
Fault Condition	450	360	90
Normal Operation	500	400	100
TOTAL	**4,250**	**3,400**	**850**

Feature Extraction

This process involves extraction of key performance related features out of the sampled BLDC motor signal by use of computational models which are developed to analyze dynamic behavior [27]. In order to come up with a better performance classifier, the researcher initially filtered stator current, rotor speed, back-EMF and torque waveforms with cascading soft computing blocks, with the first fuzzy logic layer detecting nonlinear variations, and the second neural network layer tuning features patterns [28]. There are intermediate layers that are fixed or frozen to maintain former motor behavior properties to provide permanence in feature representation. The steps of further connected layers are then added and trained on the motor data to learn higher-level features like the index of torque ripple, harmonic content, speed deviation, and thermal drift. The extracted features are then utilized to maximize motor performance, increase stability, and minimize prediction error.

Classification Models

ANFIS Controller

The ANFIS controller is an intelligent hybrid controller system, a hybrid system with the human-like reasoning ability of fuzzy methods and the adaptive learning and self-adaptation skill of artificial neural networks, which can make the control system more accurate, robust, and flexible [29]. In this algorithm a set of rules and membership functions are defined using the fuzzy logic to map the input signals to the desirable outputs by relying on expert knowledge and the neural network component is utilized to automatically tune the parameters with training, making less use of manual tuning. ANFIS has a fuzzy inference structure of the Surgeon type; in general, the input is fuzzified, implemented through rule-based layers, and finally defuzzified to derive a crisp control action [30]. Algorithms like back propagation or hybrid learning are used to minimize membership functions and rule weights during training to minimize control errors. Consequently, ANFIS controller is able to respond to nonlinearities, uncertainties and dynamic changes that occur in complex systems as compared to traditional methods of control. Itis especially important in such applications as the motor control of BLDC motors, robotics, renewable energy, automobile control, and process automation when it is necessary to have a high level of control, and high resistance to disturbances. All in all, the ANFIS offers an effective, adaptable, and intelligent, yet smart control strategy utilizingtheadvantages of acombination oftheneuralnetworks and fuzzy logictoenhancetheaccuracy, efficiency, and stability of the system [31].

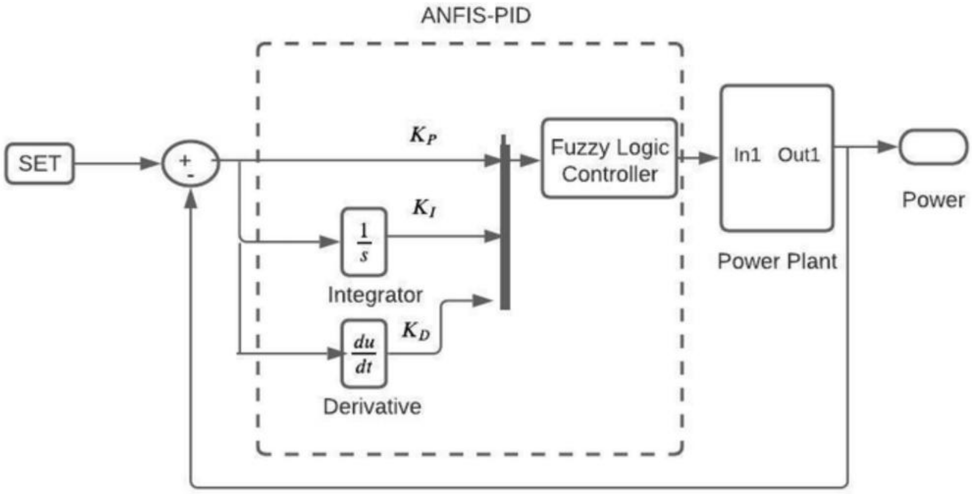

Figure 5: Block Diagram of ANFIS Controller. [32]

- **The Shuffled Frog Leaping Algorithm (SFLA)**

The Shuffled Frog Leaping Algorithm (SFLA) is ametaheuristics each algorithm optimization method based on the physical behavior of group of frogs in search of food [33] . At SFLA, there is a population of virtual frogs that symbolizes possible solutions subdivided into groups of solutions known as meme plexes. Meme plexes are the independent evolutionary processes with each needing a local search mechanism in which poorly performing frogs change their positions (solutions) and learn to do so by observing better ones. Upon repetition, the meme plexes are periodically shuffledto provide information exchange amonggroups to increase global explorationandavert Premature convergence [34].This local intensification and global diversification balance allows SFLA to effectively address complex optimization problems in engineering, scheduling and machine learning spaces [35].

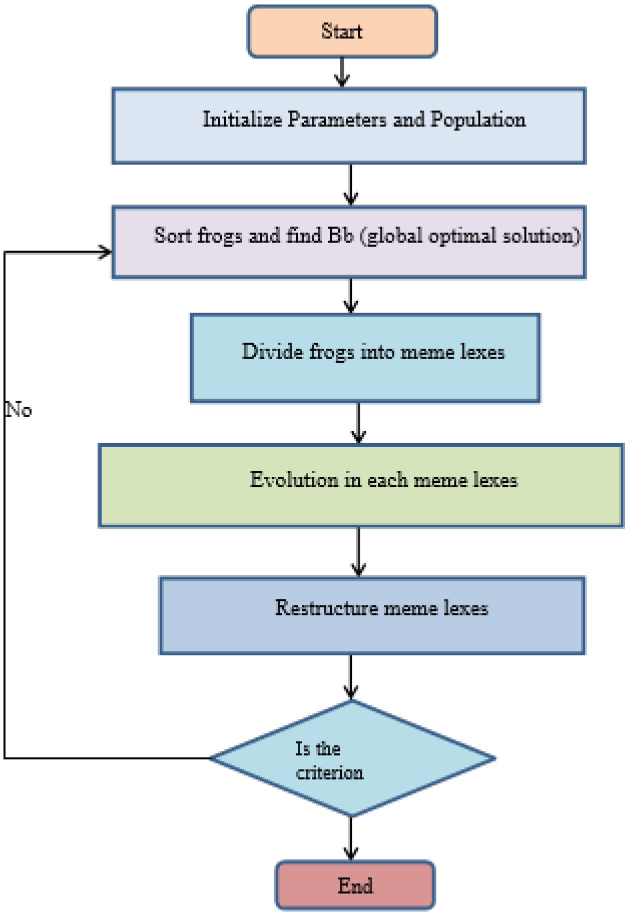

Figure 6: Flow chart of the Shuffled Frog Leaping Algorithm (SFLA).[36]

AThe mathematical enhancement phase for the most disadvantaged frog the optimal frog Xb within its memeplex is denoted as:

$$D=(rand)\times Xb-Xw \tag{1}$$

$$Xwnew=Xw+D \tag{2}$$

If unsuccessful, the update is attempted toward the global best Xg using the same formula. The use of stochastic coefficients ensures variability in movement and prevents premature convergence to suboptimal solutions.

The ANFIS controllers in the outer speed loop and inner DC-link voltage loop are optimized with the Shuffled Frog Leaping Algorithm (SFLA) and the objective of minimizing a composite performance index, comprising of steady-state, transient and smoothness of voltages. The fitness function takes into account the Integral of Time-weighted Absolute Error (ITAE) of speed regulation and DC-link voltage regulation, peak overshoot of speed response (MP), and root mean square of DC-link voltage ripple (Vrms_ripple). This provides a rapid settling, reducing over shoot and minimized energy variation during load and input variations. The objective function is expressed as:

$$min\theta J\theta = w1.ITAEw + w2.ITAEVdc + w3.MP + w4Vrms_{rippleD} = (rand)\times Xb - Xw \quad (3)$$

where θ is the vector of ANFIS parameters (membership function shapes, rule base coefficients, and scaling gains) tuned by SFLA, and w1, w2, w3, w4are weight factors reflecting the relative importance of each term. The ITAE terms are defined as:

$$ITAEw = 0Tt.|w*t - w(t)|dt.ITAEVdc = 0Tt.|Vdc*t - Vdc(t)|date \quad (4)$$

Statistical Evaluation Criterions

The effectiveness of Inception V3, DenseNet201, and hybrid models could be evaluated using four metrics: accuracy, precision, recall, and F1 score (Equations 5-8). The previously mentioned standards were employed to evaluate the predictive effectiveness of the models.

$$Accuracy = \frac{TN+TP}{FP+FN+TP+TN}$$

$$Recall = Sensitivity = \frac{TP}{FN+TP} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$F1-score = \frac{2*Precision*Recall}{Precision+Recall} \quad (8)$$

4. RESULTS AND DISCUSSION

The simulation of the suggested method is conducted in MATLAB 2021A utilizing the specified characteristics of the BLDC motor.

Table 2: Characteristics of the BLDC motor.

Winding Type	Wye-wound
Back EMF	Perfectrapezoid- Specify maximum flux
Maximum permanent magnet flux	0.0175
Rotor angle over which back EMF is constant	0.42857rad
Number of pole pairs	4
Rotor angle definition	Angle between the a-phase magnetic axis and the q-axis
Stator Self-Inductance per phase	1e-4henry
Stator Mutual Inductance	1e-5henry
Stator resistance	0.1

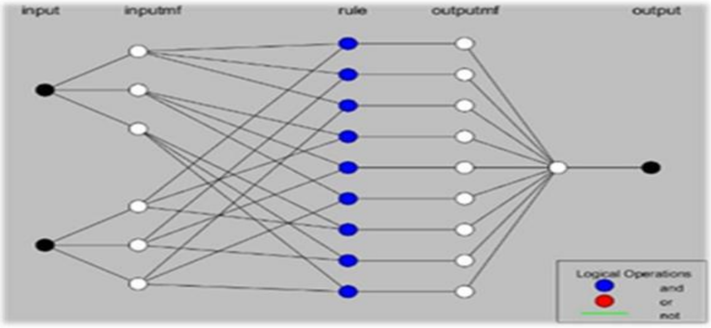

Figure 7: ANFIS-1topologyandlogicaloperations.

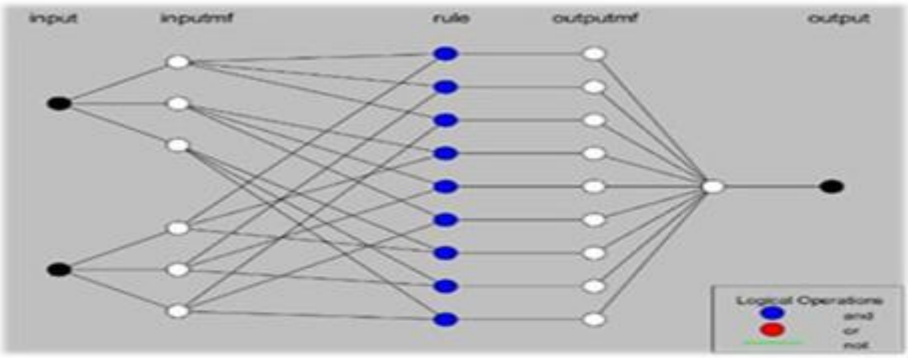

Figure 8: ANFIS-2topologyandlogicaloperations.

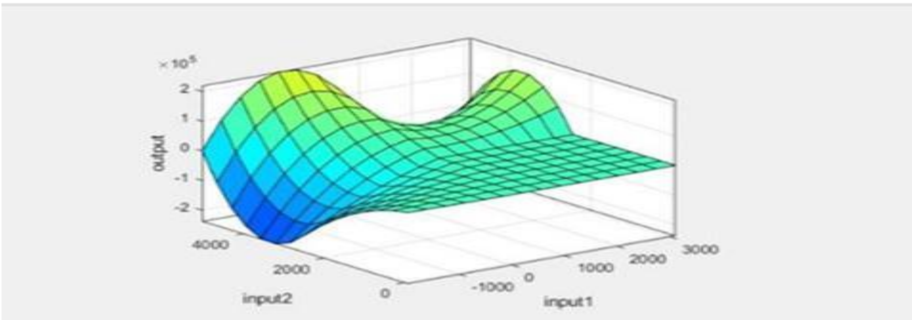

Figure 9: Learnedinput–outputsurfaceofANFIS-1.

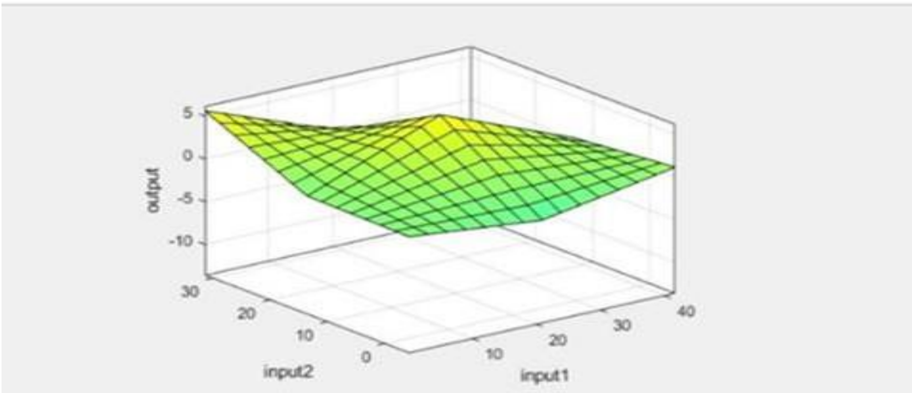

Figure 10: Learnedinput–outputsurfaceofANFIS-2.

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