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Optimized Evaluation of Brushless Motor Drive System using Adaptive Neuro-Fuzzy, PSO & Inference of Genetic Algorithm

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Abstract: A new proposed technology is introduced here, an Adaptive Neuro-Fuzzy Inference System (ANFIS) with a supervisory learning algorithm, is designed and developed here to standardize the speed and optimize the transient response of the DC (BLDC) motor drive system. The supervisory algorithm design-based ANFIS controller is applied in this proposed paper. Many industrial applications are required with high speed, high torque, high efficiency, and low volume, which will be found in the BLDC motor. This research aims to develop a complete model of the BLDC motor and design an optimal controller for its rotor position control. A PSO controller is generally designed and implemented for many control problems due to its simple structure and easy implementation. In optimizing the current distortion and torque reduction in the BLDC motor, a good genetic algorithm is proposed as a universal optimizer to find the optimized PSO particles. Therefore, this proposed concept is designed and developed in three stages to minimize the distortion where GA has implemented optimized TPBLDCM. It is also considered to evaluate and improve the effectiveness and performance issues of the BLDC motor with this proposed algorithm. Finally, this concept will be implemented in Simulink/MATLAB with a comparative analysis of the BLDC motor and its modeling. The results encourage better performance than the conventional controllers.
Index: BLDC motor, ANFIS, GA, Crossover of PSOA, Objective-function, Mutation, Performance Analysis.

I. INTRODUCTION:

Brushless DC (BLDC) motor based on permanent magnet has been improved and utilized in aerospace, automotive, household, and industrial products due to their maximum effectiveness, maximal torque, minimal maintenance & simple control. Furthermore, to lower the motor driver of BLDC cost, one of the models utilizes fewer switches & for control algorithms designed like Artificial Neural networks fuzzy inference systems (ANFIS) in the lowered inverter for generating the characteristics of required speed torque by reduced starting and torque current. On another dimension, fuzzy control has been mainly utilized in changeable speed operations for the motor of BLDC. It might be due to their optimal functions. However, current enhancements in experimental techniques would enable the application & improvement of more intricate algorithms such as fuzzy control, robust control, and a mode of sliding aimed at drive models.

FLC (Fuzzy-logic-control) exhibits a suitable controller for dealing with complicated, overloaded, and non-linear systems. On the other hand, ANN (Artificial-Neural-Networks) has a robust ability for speed, robustness, adaptation, and learning. Moreover, the benefits of both ANN and FLC have been integrated with a novel controller design. This manuscript exhibits an ANFIS development controller [1] to enhance the transient responses for reference of speed and disturbance of torque succeeding of a motor drive of BLDC. For training the controller of projected ANFIS, the ANFIS has been supervised. Experimental outcomes have exhibited the benefits and limitations of the projected algorithm compared to the traditional controller of ANN [2].

Furthermore, researchers have utilized optimization strategies for this task over an extensive period. Nevertheless, computation strategies like the Genetic Algorithm (GA) have been used for optimization [3]. Moreover, models have been claimed as more resourceful in converging towards overall minimal/maximal, evading local. Besides, they bypass the issue of initiating a search for an appropriate adaptable solution and are often encountered in traditional optimization strategies. Hence, these researchers decided to utilize GA as search equipment in optimum TPBLDCM design in this contribution.

In this manuscript, the ANFIS controllers are designed and developed from the concept of Fuzzy logic, Neural Networks. The ANFIS controllers are integrating the ideas of the intelligent control system with the FIS and ANN. The hidden layers of the neural networks will be performed as rule base membership functions to the Fuzzy control. The fuzzy logic control is designed with the IF-THEN rules and is the simple technical knowledge to control the BLDC motor. The supervisory learning procedure is used to learn for the proposed NFC instead of the traditional EBP through the system method. Finally, the proposed ANFIS controllers are implemented to determine the speed and torque of the

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BLDC motor. The performance of the ANFIS controllers is designed and described in MATLAB/Simulink software.

ANFIS Based Control

From the name itself, it says that an Adaptive Network is a network architecture comprising of directional & node links by which nodes have been interlinked. Furthermore, overall, nodes have been adaptive. Every layer outcome relies on aspects related to the node, and the rule of learning shows how such elements need to be varied to lower the pre-defined error measure.

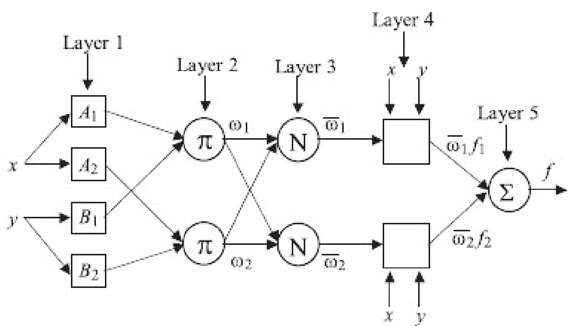

Figure 1: Adaptive Neural Network

Fundamental learning adaptive networks rule has been dependent on chain rule & gradient-descent. FLC has been prominent equipment for dealing with ill-determined, intricate & non-linear systems. On the other hand, ANN has been robust for rapidity, adaptation, etc. The benefits of both ANN, as well as FLC, are being integrated. Furthermore, ANFIS has been an adaptive networks class, a functional interference fuzzy model.

Neuro-Fuzzy Controller Framework

In minimizing the disadvantages of artificial intelligence controllers, it has been wised to utilize the integration of both, resulting in Neuro-fuzzy controllers. Therefore, fundamental NFC concepts have been primary for utilizing learning algorithms architecture to identify fuzzy logic rules and later use learning algorithms aspects for tuning the functions of membership & other elements. Furthermore, in a hybrid architecture, input & output nodes depict the output & input states to control or signal the decision in respective order and a hidden layer. Here, in figure 2, controller architecture comprises engine interference, Defuzzification part & fuzzification parts.

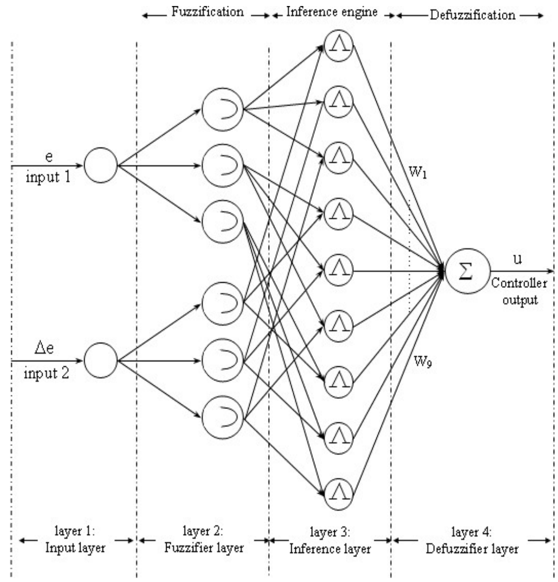

Figure 2: Neuro-Fuzzy controller structure

In this article, NFC utilizes *E* error & rate of error change ΔE as input-signal in both that having been computed through a comparator. For calculating the two input signals by fuzzy procedure, qualitative fuzzy has been conducted through non-linear quantization & membership-function (MF). In figure 3, MF has been adopted in this figure. Due to supervisory & adaptation learning, the insight variable has only three membership functions *POS*, *NEG* & *ZE*.

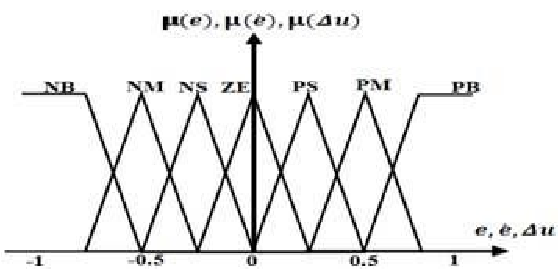

Figure 3: Input/output MF

Critic measures the NFC performance concerning error variation & error, and it produces a signal of stress in +1, [-1+1], and -1 have been resulting from planting. Also, critics have explained it as a simple control system of PD or to enhance the ANFIS training has been deliberated as a simple fuzzy system. In figure 4, fuzzy rules have been exhibited in this manuscript. It has nine rules as well as 3 MFs.

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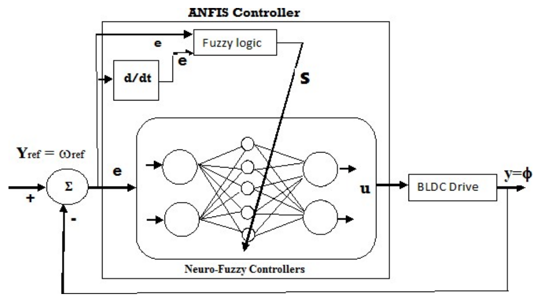

Figure 4: ANFIS controller with fuzzy supervisory learning [1]

EBP-TP (Error-back-propagation)-(Through plant) strategy has been one of the standard models aimed at neural-networks training, where the plant has passed the error of output controller and upgrading the weights law has been attained. Nevertheless, this strategy has some bugs, like sensitivity toward the noise, coefficient of learning rate & disturbance. Regardless, the knowledge about supervised learning has been accumulated towards the algorithm EBP-TP.

II. PSO CONTROL STRATEGY FOR CONVERTER

The bidirectional DC-DC converter controls the BLDC motor and maintains the constant DC voltage in different speed conditions. The algorithm is developed to produce the two current loops to retain the constant DC voltage to generate the current reference I_{ref}. In building the current as reference I_{ref}, a proportional-integral (PI) controller is designed in the HESS system. Additionally, the system will be divided to control the battery and supercapacitor (DC link) individually. The equation developed for reference current I_{ref} is given below.

$$I_{ref} = (K_P + \frac{K_I}{S}) \text{ X } V_{error} \quad (1)$$

Where K_p is proportional, and K_I is an integral gain, respectively. Then, the Kp, KI value can be determined using the Ziegler-Nichols method.

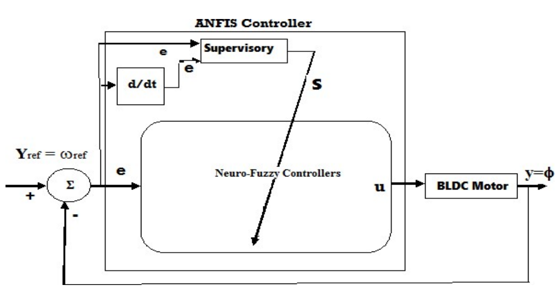

Figure 5: Supervision of Power control approach for PSO.

The SR is the reset flip-flop that receives the actual signal from the controller. This real signal decides the charging and discharging modes of the battery and supercapacitor of a converter based on the reference current I_{ref}. If the current value is more than I_{ref}, the charge will be in discharging mode, and if the real signal is less than I_{ref}, the battery will be in charging mode. Figure 5 analyzes a comprehensive explanation of the control approach of power supervision. The MAT lab investigated loop currents and designed a model to reduce the distortions.

III. DESCRIPTION OF GA OPTIMIZATION MODEL

The work [2] depicted a computer algorithm as GA, with an extensive GA implementations range that occurred in several definite regions, & GA has been proven robust enough for solving intricate issues, mainly in problems optimum of a design. Furthermore, the evolutionary algorithms of search have been considered GAs depending on natural genetics & selection mechanics. Also, the application of GA has been an optimistic approach, the fittest survival theory. The explanation for most petite fit is having minimal opportunity generated. In contrast, the maximal solution fit is reproduction. Furthermore, the search begins with a formed random population depicting chromosomes & reaches an optimal solution after a definite amount of genetic operations.

Optimization has been dependent on string architecture survival from one generation to the next, while novel enhanced generation has been formed by utilizing information genes bits of survivors of an earlier era. Moreover, an optimum design program (GA-ODEM) uses GA to be an optimization device [2], [4]. Furthermore, design variables have been depicted as vectors point of floating as in [5]. Moreover, the search begins with randomly formed strings representing chromosomes and reaches the optimal solution later, the definite number of generations, through implementing genetics operations.

The search might indefinitely continue. Hence, a stopping policy has been required to know the algorithm while it has to pause. It could be attained in several diversified approaches & is consumer & relied on the issue. Few probable models were fixing the generations could & utilizing the effective individual of overall ages in the form of optimum outcome. Therefore, the policy of stopping implementation in the GA-ODEM program has several generations.

Moreover, GA shapes aspects of the approach it runs the algorithm. Furthermore, it has been grouped into two clusters like firstly & secondly aspects. For example, size N of the population has the number of chromosomes. Therefore, one has been the initial aspect

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& the probability of crossover PC and probability of mutations have been two aspects. In table 1, values allocated for the overall theme were issue and user-dependent; moreover, these optimum design issues have been depicted. Prominent GA genetic operators, in general, were mutation, reproduction, and a crossover.

Table 1. Original GA characteristics

Parameter	Value
Production	50
Population size	50
Crossover method	distribution
The highest number of productions	0.8
method of Selection	Tournament
Probability of Crossover	0.8
Type of Mutation	regular
Probability of Mutation	0.1

A. Reproduction

Overall population working, reproduction operator forms novel generation from an earlier era. Depending on individual fitness measure & population average fitness, operator reproduction defines the copies count, which a definite individual would have in the coming generation. A fundamental concept in operator reproduction design has been to provide individuals with maximal fitness an optimal opportunity to depict incoming generation, leaving decisions variable randomly. Earlier, an extra function was applied in a computer program known as elitism. This GA-ODEM program function identifies effective solutions & transfers automatically to the upcoming generation deprived of executing operations genetically. With this function, implementing an effective solution at the time of groups has been getting rid of.

B. Crossover

The GA has a central feature, which forms a novel chromosome from two parents, and has been a crossover. Related to crossover biological, the software version integrates parents pair by randomly choosing a point, where parents pieces vectors of the count have been swapped. Regardless of utilizing changes, the crossover has been formed by arithmetical-crossover that has been determined to be a linear combination of 2 vectors x_1 and x_2 that leads to offspring that has been

$$X_1' = c.X_1 + (1-c)X_2 \quad (2)$$

$$X_2' = (1-c)X_1c + .X_2 \quad (3)$$

In former equations, c might be any amount between 0 and 1 or considered a stable count; for instance, it has been adopted for 0.5. Moreover, crossover-type has been known as arithmetical crossover uniformly & their utilization has been assured, where novel values would be in the field.

C. Transformation

A transformation is an alternate method that adds the natural random production of the desired variable in the novel population lower & upper bound field. Moreover, the initial mutation purpose has been to start variation in a population. Furthermore, this procedure has been conducted randomly & it has been done at chosen place randomly. The other process, which has been applied in optimum program design, has been fitness scaling which enhances the entire performance & results in adequate GA search reliability.

D. Scaling of Linear Fitness

The fitness of linear scaling adjusts overall chromosome fitness values so that the effective chromosome gets a stable amount of estimated offspring & hence evades it from regeneration. Moreover, the scaling model of linear fitness in this optimization process applied [5] could be depicted by the below equation

$$f_K' = a.f_k + b \quad (4)$$

Coefficients a & b might be selected in various approaches or might be determined to be:

$$a = \frac{(C-1)f_{avg}}{f_{max} - f_{avg}} \quad (5)$$

$$b = \frac{f_{avg}(f_{max} - Cf_{avg})}{f_{max} - f_{avg}} \quad (6)$$

While C has been fixed, C=1.2-2.0 & f_{avg} and f_{max} values were the average & maximal fitness for every generation.

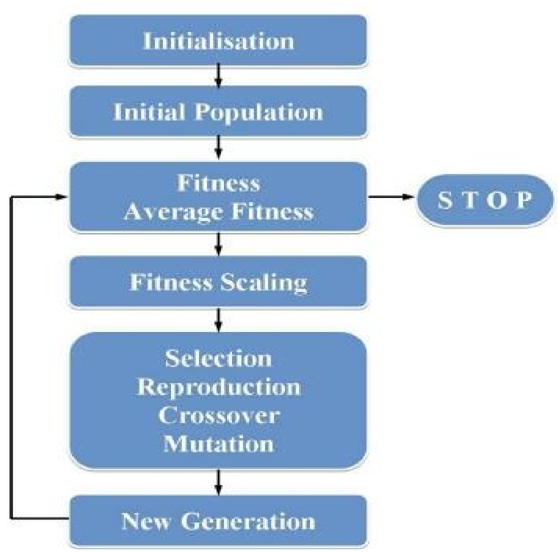

Figure 6: Significant GA-ODEM program steps

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IV. SIMULINK OF BLDC MOTOR STATE-SPACE MODEL

As stated in figure 7, mutual induction among permanent magnets in stator and rotor windings forms a trapezoidal magnetic field shape that produces EMF voltage in every BLDC motor. Moreover, an equivalent three-phase BLDC motor has been exhibited in figure 8. In table 2 and figure 9, back-induced EMF shape voltage relies on the position of the rotor, and associations have been depicted in [4]

Table II. The states of Hall Sensor

Position of Rotor in (Degrees)	State of Hall Sensor			Applied PWM Signal		Phase Currents		
						1	2	3
$0^0 - 60^0$	1	0	0	Q1	Q4	+	-	off
$60^0 - 120^0$	1	1	0	Q1	Q6	+	off	-
120^0-180^0	0	1	0	Q3	Q6	off	+	-
180^0–240^0	0	1	1	Q3	Q2	-	+	off
240^0–300^0	0	0	1	Q5	Q2	-	off	+
300^0–360^0	1	0	1	Q5	Q4	off	-	+

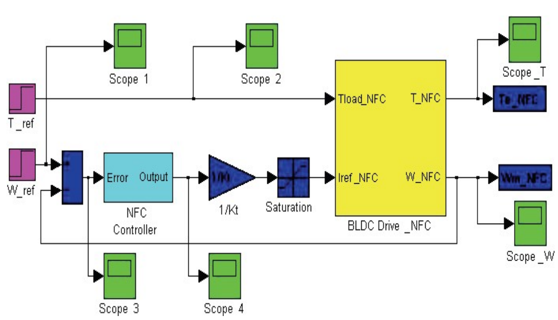

Figure 7: Overall System Block Diagram in SIMULINK[1].

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = R \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + (L-M) \begin{bmatrix} \frac{di_a}{dt} \\ \frac{di_b}{dt} \\ \frac{di_c}{dt} \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \quad (7)$$

$$\begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} = \psi_e \omega_m \begin{bmatrix} f(\phi_e) \\ f(\phi_e - \frac{2\pi}{3}) \\ f(\phi_e + \frac{2\pi}{3}) \end{bmatrix} \quad (8)$$

In each phase, the improved torque is described as

$$\begin{bmatrix} T_a \\ T_b \\ T_c \end{bmatrix} = r_t i_a \begin{bmatrix} f(\phi_e) \\ f(\phi_e - \frac{2\pi}{3}) \\ f(\phi_e + \frac{2\pi}{3}) \end{bmatrix} \quad (9)$$

$$T_e = T_a + T_b + T_c \quad (10)$$

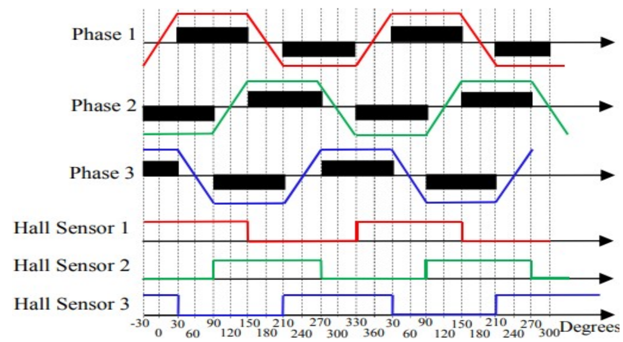

Figure 8: Trapezoidal EMF and wave patterns of Hall sensor

The field weakening rule depending on the reactive power, has been realized through the electrical-current stage as per the current instruction of torque & current speed of rotation. Angle time ahead could be attained by stator current angle opposite electromotive force counter that has been computed through d-axis device & stator current q-axis depending on reactive power concept. Also, the current peak stator is electric-current by controlling a closed loop. Field weakening control block depending on the theory of reactive power utilizing electric-current square BLDC motor has been depicted in fig-7

$$T_e - T_l = J \frac{d\omega_m}{dt} + \mu_f + \omega_m \quad (11)$$

$$\phi_e = \frac{P}{2} \varphi_m \quad (12)$$

From equations (1) and (6), the spate space representation for the BLDC motor is

$$V_{ab} = R(i_a - i_b) + (L-M) \frac{d(i_a - i_b)}{dt} + e_{ab} \quad (13)$$

$$V_{bc} = R(i_b - i_c) + (L-M) \frac{d(i_b - c)}{dt} + e_{bc} \quad (14)$$

$$\frac{di_a}{dt} = \frac{R}{L} i_a + \frac{2}{3L}(V_{ab} - e_{ab}) + \frac{1}{3L}(e_{bc} - e_{bc}) \quad (15)$$

$$\frac{di_b}{dt} = \frac{R}{L} i_b + \frac{2}{3L}(V_{ab} - e_{ab}) + \frac{1}{3L}(e_{bc} - e_{bc}) \quad (16)$$

The below equations are the BLDC motor in state-space form

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$$\begin{bmatrix} i_a \\ i_b \\ \omega_m \end{bmatrix} = \begin{bmatrix} -\frac{R}{L} & 0 & 0 \\ 0 & -\frac{R}{L} & 0 \\ 0 & 0 & -\frac{\mu_f}{J} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ \omega_m \end{bmatrix} + \begin{bmatrix} \frac{2}{3L} & \frac{1}{3L} & 0 \\ -\frac{1}{3L} & \frac{1}{3L} & 0 \\ 0 & 0 & \frac{1}{J} \end{bmatrix} \begin{bmatrix} V_{ab} - e_{ab} \\ V_{bc} - e_{bc} \\ T_e - T_l \end{bmatrix} \tag{17}$$

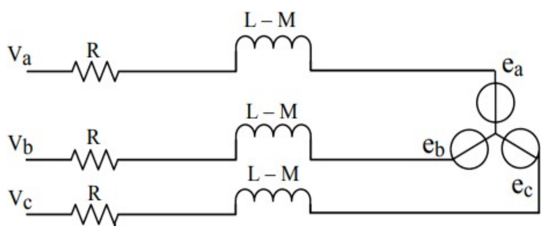

Figure 9: Three-Phase BLDC motor Equivalent circuit

$$\begin{bmatrix} i_a \\ i_b \\ i_c \\ \omega_m \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -1 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ \omega_m \end{bmatrix} \tag{18}$$

Above-stated notices have been used while constructing & designing the motor of BLDC in the simulation environment of MATLAB.

Simulation results & analysis

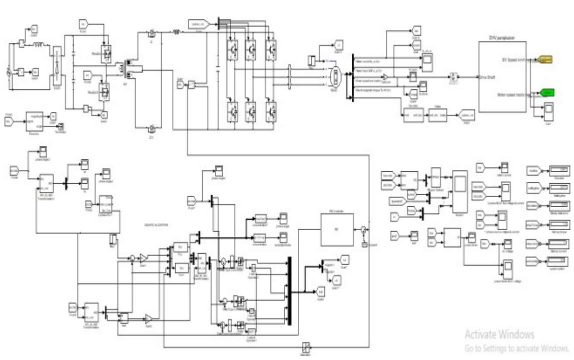
Figure 9: Simulation design of GA-based BLDCM

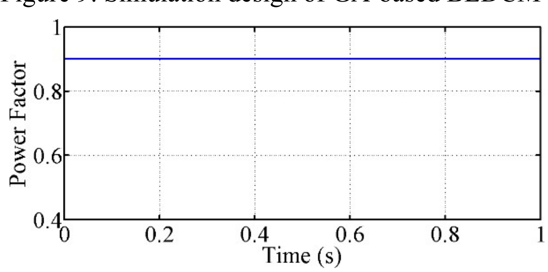

Figure 10: ANFIS designed power factor (PF 0.9)

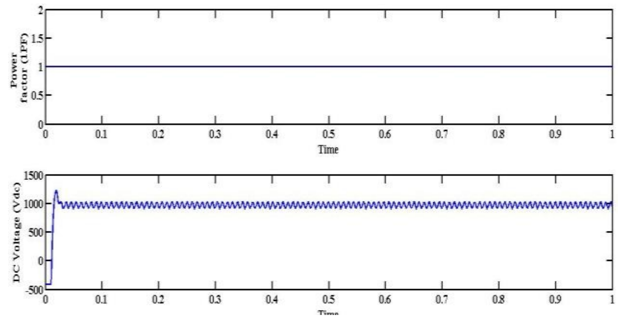

Figure 11: PSO-based power factor (PF 1.0) and DC voltage (V_{dc} 800)

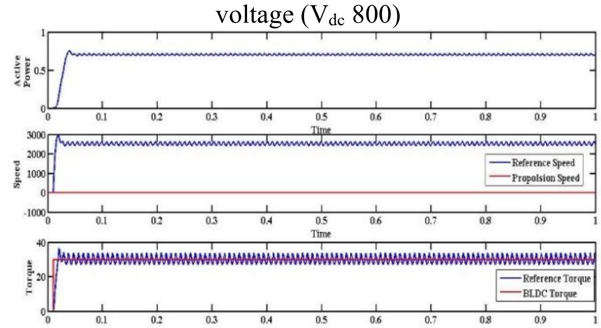

Figure 12: PSO designed (a) Active Power (b) Reference Speed & Propulsion Speed (c) Reference Torque & BLDCM torque

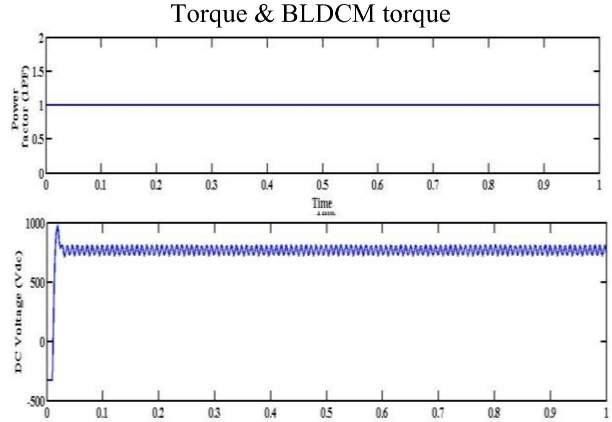

Fig 14: GA-based power factor (PF 1.0) and DC voltage (V_{dc} 900)

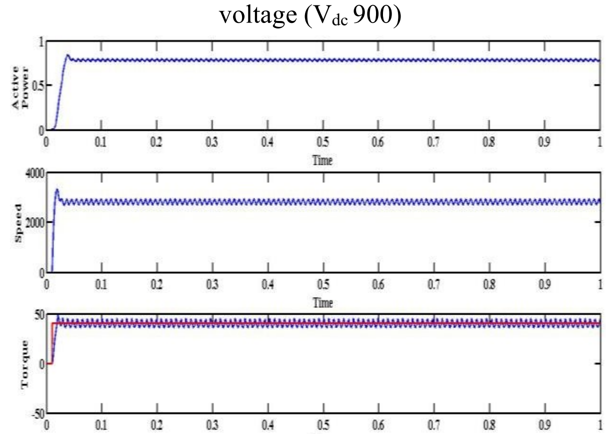

Figure 15: GA designed (a) Active Power (b) Reference

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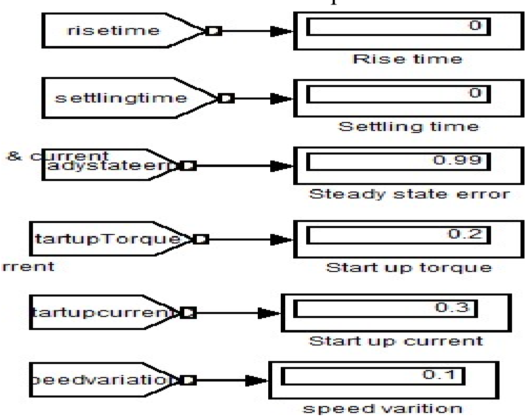
Speed & Propulsion Speed (c) Reference Torque & BLDCM Torque



Parameters		ANFIS	PSO	GA
Rise time	0-700 RPM	0.002	0.001	0
	700-900RPM	0.001	0	0
Settling time	0-700 RPM	0.016	0.011	0.002
	700-900RPM	0.002	0.001	0
Steady-state error	0-700 RPM	0.93%	0.96%	0.99%
	700-900RPM	0.93%	0.99%	0.99%
Start up torque	0-700 RPM	2.2M.M	1.2M.M	0.2 N.N
	700-900RPM	0.8N.M	0.5N.M	0.1 N.M
Start-up current	0-700 RPM	2A	1A	0.2A
	700-900RPM	0.5A	0.3A	0.1A
Speed variation		0.2%	0.1%	0.1%
Power factor		1	1	1
DC voltage		800 V_{dc}	850 V_{dc}	900V_{dc}

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Conclusion

GA-based optimization strategy has been proposed & implemented for designing a single-stage DC brushless motor. As per their outcomes and consequent examination depicted in this manuscript, it could be finalized that GA has been an appropriate device to design single-phase DC brushless motor and electromagnetic types of equipment optimization. By utilizing optimized GAs, trapping risk in local minimal or maximal has been lowered, mainly by using some search enhancements that have been intricate for eradicating in deterministic models. Furthermore, GA-optimized approach quality has been assured by primary approach data examination & solution optimization. Thus, GA solution quality is guaranteed by two motor approaches to comparative analysis utilizing a finite element model as a performance-analysis device. An empirical study on the projected contribution has been carried out in Simulink/ MAT lab. Outcomes of experimentation indicate that the estimated control strategy might enhance the response transient, robustness & stability of motor BLDC compared to traditional SMC. This concept is implemented in Simulink/MATLAB with the complete comparative analysis of the BLDC motor. The results encourage better performance than the conventional controllers.

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