Separately Excited DC Motor Speed Tracking Control Using Adaptive Neuro-Fuzzy Inference System Based on Genetic Algorithm Particle Swarm Optimization and Fuzzy Auto-Tuning PID

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Abstract. This paper presents detailed comparative studies to control the separately excited DC motor speed. The configurations of proposed methods are fuzzy auto-tuning PID and Adaptive Neuro-fuzzy inference system. The study intends to optimize the parameters of the transient speed response, for instance, the overshoot, settling time and rise time. Also, a comparison has been made between the two suggested controllers. PID tuned by Ziegler Nicholas's method utilized as a basis for the proposed controllers. Furthermore, PID model is used to extract the data set for ANFIS configuration, which has been manipulated by genetic algorithm and particle swarm optimization to ensure that it will be able to cover all operation condition possibilities. In order to investigate the eligibility of the suggested controllers, the model of the DC Motor is tested under several conditions. Finally, the results which implemented using Matlab-Simulink toolbox showed that fuzzy auto-tuning PID controller is too complicated, and has slow dynamic response comparing with ANFIS controller. Moreover, ANFIS has rapid robustness efficiency, also in the domain of the motor response characteristics. ANFIS expressed superior proficiency and better Keywords: SEDC motor, fuzzy auto-tuning PID, Adaptive Neuro-fuzzy inference system (ANFIS), genetic algorithm, particle swarm optimization, data set, and FIS. Performance under various experimental conditions.

1. Introduction

Many applications using DC motors such as electric vehicles, heavy trucks, aircraft and ships, besides small industries like toys, tools and electronic devices. DC motor categorized as two types brushed and brushless, brushed DC motor by using internal commutation directly produces the torque from the power which supplied to the motor. It has some advantages such as the cost relatively low, the control simplicity and high reliability. However, it also has a shortcoming such as the maintenance cost is a quite-high and limited operation life-cycle instead to periodic changing of brushes and related parts. Brush-less DC motor has a long life, less maintenance cost and high efficiency comparing with brushed
DC motor; however, it has some disadvantages such as, high initial cost and has complex control of the speed.

Considering SEDC motor, which is one of the most important kinds of DC motor, whenever the manufacturers are looking for variant speed, high performance and precise control; by changing the armature voltage or resistance the speed of SEDC motor, it could be controllable. The control of DC motor can be done manually by hands, or automatically by intelligent systems. The design of the motor controller for industrial purposes needs attention to high performance and ruggedness, in order to enhance the controller with high accuracy while developing robustness in ruthless operation conditions. Thus, it always attracted the attention of DC motor designers.

DC motor speed control is widely implemented by utilizing the Traditional control techniques, but still, it has some shortcomings. For instance, conventional PID cannot implement the desired and accurate speed control for DC motor [1, 2] because it has some problems with changing in load and variable speed. Resulting from that, many researchers move towards developing intelligent techniques, aiming to improve the performance of the dc motor. In [3-5] self-tuning PID using fuzzy method was utilized to control the speed, indeed in such a mechanism, ordinary PID and fuzzy logic control are combined, in order to acquire the advantages of both techniques, Where the PID control parameters values were changing online using fuzzy inference rules. Usually, the researchers compare the efficiency of their controllers with another technique, for instance, in [4] the capability of the self-tuning PID using fuzzy was compared against the performance of conventional PID tuned using Ziegler Nickola's method. A further instance of this, the fuzzy-PID efficiency and the performance of the MRAC-with-PID were compared. Indeed, merging PID and fuzzy logic increasing the control power, which is done by determining the inputs and membership functions, and then adjusting an individual set of rules-based. Where it is necessary to enhance the performance of the controller [2]. The author in [1] developed a fuzzy PD controller accomplished using the nature-inspired algorithm, while article [6] focusing on the behaviour of the controller under sudden load when the speed is constant.

Furthermore, adaptive network-based FIS (ANFIS) was utilized to control the DC motor, which also is a kind of hybrid control. It is a coupling of an intelligent-artificial neural network with fuzzy logic control concepts [7], which has been playing an essential role in enhancing the control of DC motor. In this context, the literature going to debate some previous relating work done by other researchers on ANFIS. The author in [8] developed an ANFIS configuration to control the speed; which yielded good results. It proved that ANFIS has a fast response, less overshoot and less settling time comparing with conventional PID and fuzzy control, as well as another scholar suggested neuro-fuzzy to control the SEDC motor, which PI controller used to prepare the training data for ANFIS design also tested the response of ANFIS controller under variable load at constant speeds. Furthermore, the experiment repeated under constant load with variable-speed [9]. Article [10] followed the same route of authors in [8, 9] to control the SEDC motor, where the chopper circuit is utilized and compared the efficiency with PI, PID and fuzzy. It additionally, discussed the armature temperature's effect on the motor speed. On the other hand, [11] presented a genetic algorithm for tuning the controller, and the design had been tested under both conditions; constant and varying load. Add to that; the design implemented practically using DSP processor. Even though in [12] fuzzy online tuning PID combined with the fuzzy grey predictor to design system work as a torque estimator in senseless torque control.

The ANFIS-based speed configuration for the DC motor speed regulator has been developed. The design effectiveness was compared with conventional one; simulation results showed the steady state developing [13]. Likewise, a Hybrid control has been established for DC motor; the suggested design has slowed down the response. In addition to this, the controller has a problem with changing in load [14]. Furthermore, the shortcoming with ANFIS controllers presented by [15] is the system investigated under offline mode. Most commonly used methods to control the DC motor are PID, fuzzy control, PID automatic tunings using fuzzy inference, neural network, and ANFIS. Moreover, the majority of previous studies were compared their designated controller with a conventional one. However, this study compared two techniques both classified as hybrid control; and both are built on the Fuzzy inference system basis. The article attempt to optimizing the characteristics of the transient response, and expedite
the response by implementing a perfect controller. These study contributions are: first, the comparison between most two effective strategies in this domain, second, the data set for Adaptive neuro-fuzzy inference system is extracted by two models; genetic algorithm and particle swarm optimization.

This article has been tabulated as follows: section two describes the SEDC mathematical modeling. The SEDC motor speed control techniques are presented in the third section, where it contains subsections describing fuzzy auto-tuning PID and ANFIS methodologies implemented in this study. The results obtained by this article and the discussion detailed in section four followed the conclusion in the last part.

2. Sedic motor mathematical modeling

According to figure 1 and by applying electric circuits theories on the electrical part and calculating the mathematical equation of mechanical part. Moreover, using Laplace transform to obtain the final formula, that represents the relation between the armature voltage and the rotor shaft speed; equation 1 displays the transfer function of armature-controlled SEDC motor.

\[
\frac{\omega_m(s)}{E_a(s)} = \frac{K_T}{L_a \cdot J_m \cdot s^2 + (R_a \cdot J_m + B_m \cdot L_a) \cdot s + (K_T \cdot K_E + R_a \cdot B_m)}
\]  

(1)

To find DC motor position transfer function, where the position of the motor shaft is an integral part of the speed respect to time. Shaft position is found by merging speed. Since the \( \frac{d\theta(t)}{dt} = \omega(t) \), which lead us to \( \int \frac{d\theta(t)}{dt} \ dt = \int \omega(t) \ dt = \theta(t) \).

It can be substituted by S domain equation 1, \( \theta_m(s) = \frac{1}{s} \cdot \omega_m(s) \).

As a final point, Dc motor position transfer function has obtained. Figure 2 explains the block diagram of the SEDC motor. Figure 3 clarifies the model by Matlab Simulink, and the parameters applied to the model explained in table 1.

\[
\frac{\theta_m(s)}{E_a(s)} = \frac{K_T}{L_m \cdot J_m \cdot s^2 + (R_m \cdot B_m + R_e \cdot J_m) \cdot s + (K_T \cdot K_E + R_e \cdot B_m)}
\]  

(2)
Table 1. Motor specification.

| Name                  | value            |
|-----------------------|------------------|
| Armature inductance $L_a$ | 0.1215H         |
| Armature resistance $R_a$    | 11.2 Ω          |
| Rotor inertia $J_m$        | 0.02215Kgm      |
| Viscous friction coefficient $B_m$ | 0.002953Nms/ rad |
| Back emf constant $K_s$   | 1.28Vs/rad      |
| Torque constant $K_T$     | 1.28Nm/A        |

$$\mathbf{aR}L_s + \mathbf{aL} = \mathbf{TK}$$

Figure 2. The block diagram of the DC motor.

Figure 3. The DC motor equivalent Simulink model.

3. Control the speed of sedc motor methodologies

3.1. Fuzzy Auto-tuning PID Control

The configuration proposed by this article, it could be classified as hybrid control. Where the proficiency of fuzzy control has been utilized to avoid the shortcoming of conventional PID control. The fuzzy auto-tuning PID configuration has a fuzzy system using two inputs and three outputs, as shown in figure 4. The inputs to the control system are the error E, and it is derivative $EC$; with adopting seven triangle membership function using a range $[-6, 6]$ as shown in figure 5. As for the outputs, the values represent the expected values to the PID’s outputs, respectively the proportional parameter $K_p$, integral parameter $K_i$, and differential parameter $K_d$. With Seven functions of a triangle membership are based on the $[6, 6]$ range as in Figure 6.
Fuzzy control input has seven linguistic values of input and output which fuzzified using average centroid method. Depend on the error E, and it is deviation EC, the parameters of the fuzzy PID auto-tuning Kp, Ki and Kd has been amended according to the following strategy: First, in order to make the configuration response faster when the error is big, the Kp value must be set to a large value. At the same time, reducing the value of Kd. In other words, the instantaneous increase in error leads to the appearance of differential saturation. So to avoid such situation the value of Kd must be reduced to a small value as possible, as for the integral part. If the system is going to an integral saturation, which needs to limit the integral action. The value of Ki will set to the value of zero to avoid the excess of the overshoot. Second, if the error value is medium, the value ki should be slightly smaller to reduce the overshoot. The value Kd should set to a medium value to increase the system speed response because the integral part has a great effect on the system. The value ki should set to an appropriate value. Because if it is set to a big value, it will produce integral saturation, if it is small, it will slow down the system response.

Finally, if the error is small, and to ensure the response is quite good. The system should be adjusted as follows: firstly, set Kp and Ki to big value, in case of presence of oscillation in the system response. The value of Kd needs more attention. Secondly, if the error is a very small, the value of Ki should be increased, if the error is huge, the value of Ki must be reduced.
According to the strategies as mentioned above and the definition of linguistic variables, fuzzy logic has demonstrated its ability to set the parameter values $k_p$, $k_i$, and $k_d$ according to the SEDC motor characteristics. Figures 7, 8, and 9 respectively illustrating the relations between the parameters $K_p$, $K_i$ and $K_d$ with the error $E$, and it is derivative $CE$.

Figure 7. Surface view for $K_p$ fuzzy set rules

Figure 8. Surface view for $K_i$ fuzzy set rules.

Figure 9. Surface view for $K_d$ fuzzy set rules.

Figure 10. below explains the system of fuzzy auto-tuning PID model
3.2. Adaptive neuro-fuzzy inference system

3.2.1. Adaptive neuro-fuzzy principle. The artificial neural network relatively defined as new computer information processing techniques, which handle the numeric elements and manipulate it by finding out the convergence and divergence. Indeed, Fuzzy logic is a flexible and subjectivity system. It has good capabilities of interpretation and can be easily integrated with other similar systems. Whilst ANFIS has the strong capability with the numerical level. So through hybridization (combination) both strategies; a new technique is obtained. This resulted in, the emergence of the ANFIS strategy, where the newest system acquired the gains of the two systems, leading to being a significant improvement in the modelling, nonlinear mapping, learning and pattern recognition [7].

In the context of the general structure, ANFIS and fuzzy has the same components, except ANFIS has a neural network portion, where it arranged in four major parts; as follows: fuzzification, rules(data)base, neural network, and defuzzification, as shown in figure 11.

![General structure of ANFIS controller.](image)

Neural network structure contains a set of entities organized in five connected layers. Layer 1 is a number of nodes; which represents the fuzzy input variable membership functions. Layer 2 chooses minimum input value by checking the weight of each membership function. Layer 3 is the rule's layer. Particularly it receives the input from layer 2, and each neuron implements precondition matching with the fuzzy rule. Add to that each neuron normalized by calculating it is weight. Indeed, in this stage, the number of fuzzy rules and the layers are equal. Layer 4 produces the outputs resulting from the rule's layer, where this layer named defuzzification layer. Then all inputs produced by layer 4 are summed in layer 5. Since at this stage, the system results transform to crisp values. Figure 12 illustrates the general structure of the ANFIS, where the circles and squares represent the fixed and adaptive node respectively.
3.2.2. ANFIS controller scheme

The training data set is collected built on the genetic algorithm and particle swarm optimization based on the behaviour of variables in the DC motor. Apply i/o data to model the FIS. Neuro-adaptive techniques allow the fuzzy control to learn the set of the data. Fuzzy compute the parameters and tracing the I/O data. Figure 13 illustrates the ANFIS network. The data set has been implemented using the genetic algorithm and particle swarm optimization models. And generated data operated using an algorithm, which this algorithm designated to merge the data generated by the 2 models. Finally, the data implemented in ANFIS for training. Then by using ANFIS the set of data and the membership function has modified. Furthermore, the model was validated. The system has been tested many times using different load signals and values. Figures 14, and 15 show ANFIS training error and data respectively.
Figure 15. Adaptive neuro-fuzzy inference system training data.

In this system, Adaptive neuro-fuzzy inference system controller has two inputs; each input consists of 4 triangle membership functions and one linear output type. The system has 16 rules, with error tolerance 0 and Epoch 7. Structure is automatically tuned by the hybrid optimization algorithm for training the fuzzy inference system. The ANFIS model for control the DC Motor speed has shown in Figure 16.

Figure 16. ANFIS system block diagram.

4. Result and discussion

The SEDC motor tested using fuzzy auto-tuning PID. Figure 17 shows fuzzy auto-tuning PID response. As can be seen, it covers the response in time from 0 to 2 seconds and shows that the overshoot increased steadily in the first 0.1 second, then remained steady starting from time 0.16 second. The overshoot rose steeply, throughout the time 0.04 and 0.06 second, with a rapid increase to surpass the referenced signal, and reached a peak of 4%. A sharp oscillation appears in the response, and the response reached the steady state at time 0.18 second. The figures strongly indicate that fuzzy auto-tuning PID has recovered the problems of rise time and settling time, but still, the overshoot is existing. However, in the aspect of response speed, the controller showed a quite good dynamic.

Figure 17. Fuzzy auto-tuning PID response with constant load.
Despite the positive effects of the fuzzy auto-tuning PID outlined above, there is also the overshoot issue to be considered. Consequently, the article worked hard to improve another controller, in order to avoid the problems, which encounter the fuzzy auto-tuning PID controller. Thus by utilizing an artificial intelligence controller, may is the expected solution. So secondly, the DC motor speed performance has been investigated using the Adaptive neuro-fuzzy inference system controller based on genetic algorithm and particle swarm optimization. The appropriate rule base has been developed using the hybrid optimization algorithm to obtain optimal performance, where the controller showed a perfect performance compared to the controllers introduced in the literature review or designed in this study. Figure 18 illustrates the controller response. As it can be seen, the overshoot is so small that it is difficult to measure, as for the rise time and settling time, the controller showed spectacular performance. Moreover, the controller showed a fast dynamic response with no oscillation.

![Figure 18. ANFIS response with a constant load.](image)

The system has been tested under several conditions. First, the system operated under a constant load. For fuzzy auto-tuning PID controller, a slight decline was observed at the start of the operation as shown in figure 17 but did not affect its stability. While for ANFIS, there is no change observed in speed response to the constant load as shown in figure 18. Second. A sudden light load was applied to DC motor at time 1 second. As for the fuzzy auto-tuning PID, it underwent a slight oscillation, but it did not affect the remaining operating period as shown in figure 19, and then returned to normal operation. While for ANFIS controller no change observed as in figure 20. Finally, the DC motor response tested under sudden-heavy load, where the performance of the fuzzy auto-tuning PID controller was effected, and undesired high oscillation had observed in speed response, as it is evident in figure 21. In contrary, the ANFIS controller has shown very good performance for the sudden heavy load, as it clearly seems in Figure 22. Table 2 shows the transient response characteristic for the introduced controllers.
Figure 19. Fuzzy auto-tuning PID response with small sudden load.

Figure 20. ANFIS response with small sudden load.

Figure 21. Fuzzy auto-tuning PID response with heavy sudden load.
Figure 22. ANFIS response with big sudden load.

Table 2. The transient response characteristic.

| Measured factor       | Fuzzy PID | ANFIS |
|-----------------------|-----------|-------|
| Rise time (sec)       | 0.457     | 0.054 |
| Maximum overshoot %   | 7.4       | 0     |
| Settling time (sec)   | 0.19      | 0.056 |
| Steady state error %  | 0         | 0     |

5. Conclusion
In this study, both fuzzy auto-tuning PID and ANFIS were examined under the same different conditions. The tests were evaluated using the following categories: rise time, settling time, overshoot, absorbing constant and sudden load, and steady-state error, by the two controllers to determine the efficiency. In this way, it was possible to see the convergence and divergence between the controllers, and the improvement in their ability depending on the controlling method. The output response of DC motor speed using ANFIS controller as shown in previous figures, it is distinctly observed that it has a fast dynamic performance with no overshoot and non-oscillating response. The comparison proves that the ANFIS control has a good performance, which passed all different tests conditions and showed high efficiency.

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