

Improving neural network using a sine tree-seed algorithm for tuning motor DC

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Article Info

Article history:

Received Oct 6, 2020

Revised Feb 2, 2021

Accepted Mar 23, 2021

Keywords:

DC motor

Feed-forward neural network

Sine cosine algorithm

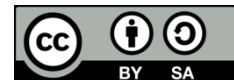
Sine tree-seed algorithm

Tree-seed algorithm

ABSTRACT

A DC motor is applied to delicate speed and position in the industry. The stability and productivity of a system are keys for tuning of a DC motor speed. Stabilized speed is influenced by load sway and environmental factors. In this paper, a comparison study in diverse techniques to tune the speed of the DC motor with parameter uncertainties is showed. The research has discussed the application of the feed-forward neural network (FFNN) which is enhanced by a sine tree-seed algorithm (STSA). STSA is a hybrid method of the tree-seed algorithm (TSA) and Sine Cosine algorithm. The STSA method is aimed to improve TSA performance based on the sine cosine algorithm (SCA) method. A feed-forward neural network (FFNN) is popular and capable of nonlinear issues. The focus of the research is on the achievement speed of DC motor. In addition, the proposed method will be compared with proportional integral derivative (PID), FFNN, marine predator algorithm-feed-forward neural network (MPA-NN) and atom search algorithm-feed-forward neural network (ASO-NN). The performance of the speed from the proposed method has the best result. The settling time value of the proposed method is more stable than the PID method. The ITAE value of the STSA-NN method was 31.3% better than the PID method. Meanwhile, the ITSE value is 29.2% better than the PID method.

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1. INTRODUCTION

DC motor (direct current) is a basic electromechanical device that has the function to convert electrical power into mechanical power. DC motor is a type of motor that is used direct voltage as its power source. By providing a voltage difference at the two terminals, the motor will be rotating in one direction. If the polarity of the voltage is reversed, the direction rotation of the motor will be reversing as well. The polarity of the voltage is applied in the two terminals to determine the direction of rotation of the motor. DC motors have reliability, flexibility, and low cost. It is the reason why DC motor is very popular in industrial applications and household appliances that requires motor speed and position control. DC motors are most compatible with level speed control and are therefore applied in many adaptable speed drives [1].

DC motors have better speed characteristics than AC motors. In addition, the DC motors have an optimal speed control for breaking and acceleration. DC motors have a longer lifetime due to adjustments and variations in implementation.

Conventional motor controllers such as PID controllers are still popularly applied [2]. This is due to the simple PID topology. The weakness of PID is to achieve high performance from a controller that has required accurate and precise control parameters. A good PID control setting will have an impact on optimal system response [3]. It is really depending on the parameter settings and the mathematical model. Classical methods have characteristics when modeling a non-linear system. This is influenced by the control equation which is complicated and required more effort.

This is stimulated the development of intelligent control technology [4]. The development of artificial intelligence is becoming an additional supplement in terms of control. In recent years, several researchers have started to apply several intelligent control methods based on artificial intelligence. Neural networks are the favorite method used because they have the ability to solve complex and non-linear problems. Several neural network methods are applied in applications such as forecasting [4], classification [5], estimation [6], and prediction [7]. Several studies on DC motor control are divided into two concepts, namely: conventional methods and artificial intelligence methods. several artificial intelligence concepts for controlling such as: Whale optimization algorithm [8], [9], Harris Hawks optimization algorithm [10], flower pollination algorithm [11], firefly algorithm [12], ant colony algorithm [13], [14], and neural network [15], [16].

Feed forward neural network (FFNN) has a simple and easy to implement network structure. FFNN is the favorite of the most widely implemented and is growing rapidly with a wide variety. Several computation methods have been widely applied to optimize neural networks such as the particle swarm optimization (PSO) method which is applied for weighting FFNN optimization [17], Genetic algorithm combined with FFNN [18], and a combination of gravitational search algorithm and FFNN [19].

Tree-seed algorithm (TSA) has the advantage that it can solve optimization problems. On the other hand, TSA has limited exploitation when dealing with complex problems. The sine-cosine algorithm (SCA) method has the advantage of balancing exploration and exploitation. The SCA can find promising areas of the search space and ultimately converge to the global optimal [20].

This research is proposing the sine tree-seed algorithm method to improve neural network skills. The limitations of the neural network in weighting will be handled by the sine tree-seed algorithm method. The method of the sine tree-seed algorithm is developed by combining the sine cosine algorithm and the tree seed algorithm [20]. The method of this research is called the STSA-NN hybrid method. The method is used to control the speed of a DC motor. The contribution of this research is to present intelligent control skills based on the Sine Tree-Seed Algorithm hybrid method and the neural network. The validation and effectiveness of the proposed method are compared with the PID, FFNN, MPA-NN and ASO-NN.

2. MATERIALS AND METHODS

2.1. A sine tree-seed algorithm

The method proposed by STSA-NN is a combination of STSA and NN methods. The STSA algorithm is an improvement in the Tree-Seed Algorithm (TSA) method using the Sine Cosine (SCA) method.

2.1.1. TSA: Tree-seed algorithm

TSA is a metaheuristic method that has a function as an intelligent optimization based on the relationship between trees and seeds. It is used to solve ongoing problems. At the start of the algorithm, the trees are planted above the ground. The location of the tree is placed with the best possible solution to the problem. The land is a representation of the search space. A control parameter called search tendency (*ST*) is used to handle trees that have the best search tendency or taken randomly. The TSA method has the advantage of strengthening and blending locally to optimal or near-optimal.

Meanwhile, a very important optimization problem is to get a clear location generated from the tree. This is the focus of the search. New trees are created by replacing existing trees with new seeds that are deemed suitable and best. The tree and seed search method will be repeating until a specified number of function criteria are accommodated. In the early stages, initialize the tree is determined by.

$$P_{i,j}^{t+1} = P_{j,min}^t + r_{i,j}^t \times (SH_{j,max}^t - SL_{j,min}^t) \quad (1)$$

$$B_{i,j}^{t+1} = P_{i,j}^t + \alpha_{i,j}^t \times (B_{j,max}^t - P_{r,j}^t) \quad (2)$$

$$B_{i,j}^{t+1} = P_{i,j}^{t+1} + \beta_{i,j}^t \times (P_{i,j}^t - P_{r,j}^t) \quad (3)$$

$$B_{j,max}^t = \min(\int(P_{i,j}^{t+1})) \quad (4)$$

Where dimension of the tree is $P_{i,j}^{t+1}$. The higher bound of the search space is $SH_{j,max}^t$. The lower bound of the search space is $SL_{j,min}^t$. The random value with range $[0,1]$ generated for each dimension is $r_{i,j}^t$. The dimension of the seed is $B_{i,j}^{t+1}$. $\alpha_{i,j}^t$, $\beta_{i,j}^t$ are the scaling element which generated in series of $[-1, 1]$ randomly. The dimension of top tree place is $B_{j,max}^t$. The dimension of a tree randomly chosen from the population is $P_{r,j}^t$. For all test, the stop state is the peak times of function evaluations ($MaxFE$) and the amount of function evaluations (FE).

$$MaxFE = M \times 10000 \quad (5)$$

$$FE = A \quad (6)$$

Where M is the dimension of a function, A is the number of trees.

2.1.2. SCA: Sine-cosine algorithm

SCA is served to solve optimization problems with unknown search spaces using the sine and cosine functions. The location of each search agent is updated to get the optimal solution. SCA has an algorithm for combining high randomness of several solutions and random solutions which is useful for obtaining promising areas in the search space.

$$V_i^{t+1} = V_i^t + r_1^t \times \sin(r_2^t) \times |r_3^t \times K_1^t - V_i^t|, r_4^t < 0.5 \quad (7)$$

$$V_i^{t+1} = V_i^t + r_1^t \times \cos(r_2^t) \times |r_3^t \times K_1^t - V_i^t|, r_4^t \geq 0.5 \quad (8)$$

Where the position of the current solution is V_i^{t+1} . The best solution obtained so far is K_1^t . r_1^t dictates the next place (or direction of movement), the distance from which the movement should move to the target or outward is r_2^t . A random weight for the goal so that stochastically emphasize ($r_3^t > 1$) or deemphasize ($r_3^t < 1$) the effect of desalination in defining the distance is r_3^t . A uniform switching between sine and cosine functions is r_4^t .

$$r_i = a - t \times \frac{a}{T} \quad (9)$$

Where t is the current iteration, T is the maximum iterations, and a is a constant.

2.1.3. STSA: Sine tree-seed algorithm

Seeds have an important role in the distribution and search for optimal value. This is not optimal due to random and simple seed production. Poor seed production will result in optimization results that are not in accordance with the optimal solution. The STSA method modifies the number of seeds (ns) value so that it can be processed according to changes in the FE value. This has an effect on the amount that impacts on the best solution finding model.

$$ratioFE = \frac{FE}{MaxFE} \quad (10)$$

$$xTheat = 0.5 \times ratioFE \times \pi \quad (11)$$

$$ns = L \times |(H - L) \times \cos(xTheat)| + 1 \quad (12)$$

$$k = 2 \times (1 - ratioFE) \quad (13)$$

Where the number of seeds is ns . L and H are the low and upper bound of the number of seeds produced by a tree. A new parameter based on the original TSA which combines the inspiration of SCA is k . k has range $[0,2]$. TSA has a weakness in the seed position updating function. Problems arise when the seed positions are separated. The position of this seed will have a large uncertainty value. This will be a factor causing the possibility of finding an optimal solution that is fast and accurate is getting smaller. On the other hand, SCA has good prowess in terms of global search capabilities. SCA has a balance in exploration and exploitation.

The STSA algorithm integrates TSA with SCA to improve the ability to find optimal global stochastic solutions in optimization problems. The (2) and () in the TSA are replaced by.

$$B_{i,j}^{t+1} = \text{tmprand} \times P_{r,j}^t + (1 - \text{tmprand}) \times B_j^t, \text{rand} < 0.5ST \quad (14)$$

$$B_{i,j}^{t+1} = P_{i,j}^t + k \times (B_j^t - P_{r,j}^t \times P_{i,j}^t) \times \sin(\pi \times \text{acos}(P_{r,j}^t)), 0.5ST \leq \text{rand} < 0.5ST \quad (15)$$

$$B_{i,j}^{t+1} = P_{r,j}^t \times P_{i,j}^t + k \times (x^t \times P_{i,j}^t - P_{r,j}^t) \times \cos(\pi \times \text{arccos}(x^t)), 0.5ST \leq \text{rand} < 0.5ST \quad (16)$$

Where k is a new parameter based on the original TSA. The supervisor parameter for controlling the search trend is ST . Higher ST supplies solid local search and accelerates convergence, and vice versa lower values lead to slow convergence but strong global search.

2.2. Feed-forward neural network

Neural networks are machine learning devices inspired by biological neural networks and capable of processing with mimic as the human brain [21]. Artificial neural networks (ANN) could construct model linear and nonlinear algorithms. They are greatly answered as potent tools for the optimization function. The feed-forward neural network (FFNN) is to approximate and control nonlinear relationships between inputs and outputs. The data model needs to move in only one direction (forward) from the input nodes, via the hidden layers, and eventually to the output node. FFNN has a topology which consists of process units, which are represented by neurons. Figure 1 is the topology of FFNN. Neurons are the most important items of the FFNN which are governed by input, hidden layers and outputs. The input (I_n) sends a signal to the hidden layer through a weighted network (W_{ij}). In this section, the hidden neuron receives a weight plus bias input. Then, the neurons are directed to the output layer (X_4). FFNN can be formulated as.

$$X_1(t) = \sum_{i=1}^j W_{ij} I_n(t) + b_1 \quad (17)$$

$$X_2(t) = f(x_1(t)) = \frac{1}{1 + \exp^{-x_1}} \quad (18)$$

$$X_3(t) = \sum_{j=1}^k W_{jk} X_2(t) + b_2 \quad (19)$$

$$X_4(t) = f(X_3(t)) = \frac{1}{1 + \exp^{-X_3}} \quad (20)$$

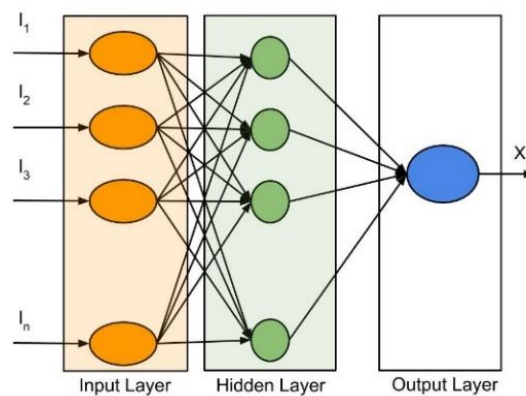


Figure 1. FFNN structure

2.3. DC motor

DC motor is a type of motor that uses speed and position control which is the armature control of the DC motor [22]. Armature control by keeping the static field current constant is key in DC motor setup [23]. The equivalent circuit is illustrated in Figure 2.

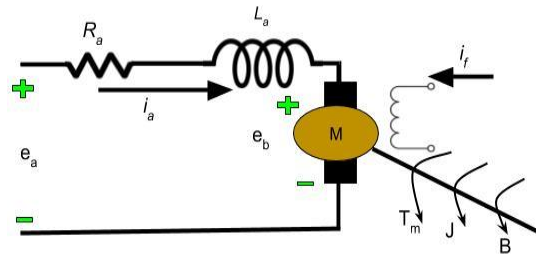


Figure 2. DC motor equivalent circuit [24]

Table 1. DC motor parameters [25]

Notation	Information
R_a	Armature resistance
L_a	Armature inductance
e_a	Armature voltage
e_b	Back electromotive force
J	Moment of inertia constant
B	Damping friction ratio
T_m	Motor torque
K_b	EMF constant
K_i	Moment constant

$$e_a(s) = (R_a + L_a \cdot s) \cdot I_a(s) + e_b(s) \quad (21)$$

$$e_b(s) = K_b \omega(s) \quad (22)$$

$$T_m(s) = J s \omega(s) + B \omega(s) \quad (23)$$

$$T_e(s) = K_i I_a \quad (24)$$

2.4. The proposed STSA-NN model

The flow chart of the STSA-NN hybrid method is presented in Figure 3 in Appendix. STSA and NN work independently. The two processes further have interacted with each other to form the STSA-NN method. In the method proposed by STSA-NN, data from the generator is taken as input and target for NN training. The data is processed and grouped. NN is set using several parameters. The weighting parameter at the beginning will be used a random value. This weight value will be increased using the STSA method. The weighted results from STSA will be stored in the NN.

3. RESULTS AND DISCUSSION

In the first step of the test, the DC motor is modeled on the MATLAB/Simulink (R2015a). DC motor modeling is regulated using the PID method. PID controller parameter values can be seen in Table 2. The necessary data were captured and grouped as a reference for the STSA-NN intelligent control training. Schematic of DC motor control using STSA-NN can be seen in Figure 4. The parameters and values used in the proposed STSA-NN method can be seen in Table 3. The convergence curve of STSA is reported in Figure 7.

In Figure 5, the convergence value of STSA stops at iteration 25. This result is obtained by entering the parameters contained in Table 3 in the STSA-NN algorithm. The next step, it is to install and test the STSA-NN controller on the DC Motor. The result of a closed loop system between the controller and the dc motor can be seen in Figure 6. Table 4 is a detail of DC Motor output wave.

Table 2. Parameter of PID controller

Parameter	Value
K_p	2
K_i	6.5
K_d	0.01

Table 3. Parameter of STSA-NN

Parameter	Value
Hidden layer	4
Training	Levenberg-marquardt
Maximum iteration number	50
Number of populations	50
Lower bound; upper bound	-1.28;1.28
ST	0.3
Upper limit of seed's number	0.1
Lower limit of seed's number	0.25

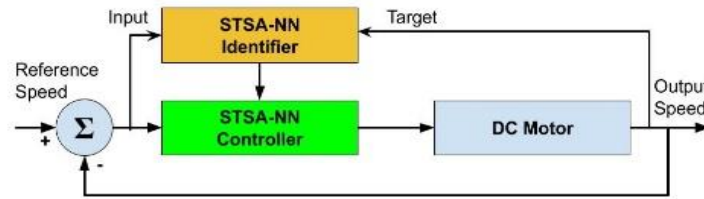


Figure 4. DC motor speed control with STSA-NN controller

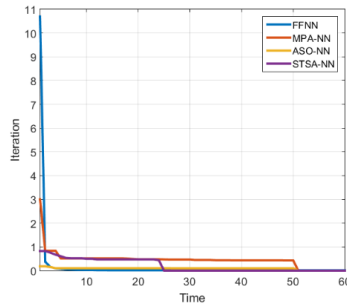


Figure 5. The convergence curve of STSA

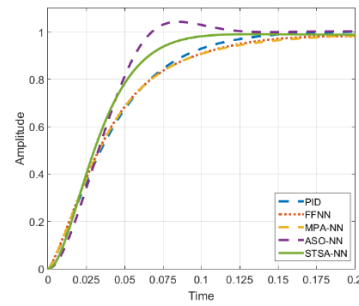


Figure 6. Speed step response of the DC motor

In Table 4, a comparative analysis of the proposed STSA-NN approach compared to PID is shown. To determine the effectiveness and validation of the proposed method, two criteria were used, namely Integral of time multiplied by squared error (ITSE) and Integral of time multiplied by absolute error (ITAE). ITSE has a supplementary time multiplier of the error function which points on the span of the error duration. This measurement is popular in the system takes quick tuning time. The ITSE index formula is given as.

$$ITSE = \int_0^{\infty} t \cdot e^2(t) \cdot dt \quad (25)$$

ITAE is integrating the absolute error multiplied by time after time. Minimizing the integral of time-weighted absolute error (ITAE) is as usual pointed to as a good achievement index in plotting controllers.

$$ITAE = \int_0^{\infty} t \cdot e(t) \cdot dt \quad (26)$$

The comparison of the ITAE and ITSE can be seen in Table 4. The ITAE value of the PID has value 0.5944. Meanwhile, the lowest ITAE value is owned by the ASO-NN method. It is 0.3357. The lowest ITSE value is owned by the STSA-NN method of 0.1423. On the other hand, the highest value of ITSE is owned by the MPA-NN method of 0.2057

Table 4. Comparison of the transient response analysis results for different controllers.

Controller	Overshoot	Settling Time (s)	Rise Time (s)	ITSE	ITAE
PID	1.0003	0.1375	0.081	0.2007	0.5944
FFNN	No overshoot	0.1375	0.08	0.2025	0.7155
MPA-NN	No overshoot	0.15	0.085	0.2057	0.7364
ASO-NN	1.042	0.13	0.04	0.1515	0.3357
STSA-NN	No overshoot	0.11	0.055	0.1423	0.4097

4. CONCLUSION

Managing control on a DC motor is a very interesting research area. DC motor control that has a setpoint value must pay attention to the efficiency of the control. The sine tree-seed algorithm and neural network hybrid method proposed in this study is used to control DC motors. From the research results, the proposed method sine tree seed algorithm-neural network (STSA-NN) has a better performance on the settling time and ITAE parameters than the performance of PID. The ITAE value of the proposed method is

0.4097. Meanwhile, the ITSE value of the proposed method has better performance than the PID value. It is 0.1423. The lowest ITAE value is owned by the ASO-NN method of 0.3357. However, the ASO-NN method has an overshoot of 1.0423. To test the performance of the STSA-NN method, it is necessary to carry out further research with more complex problems.

APPENDIX

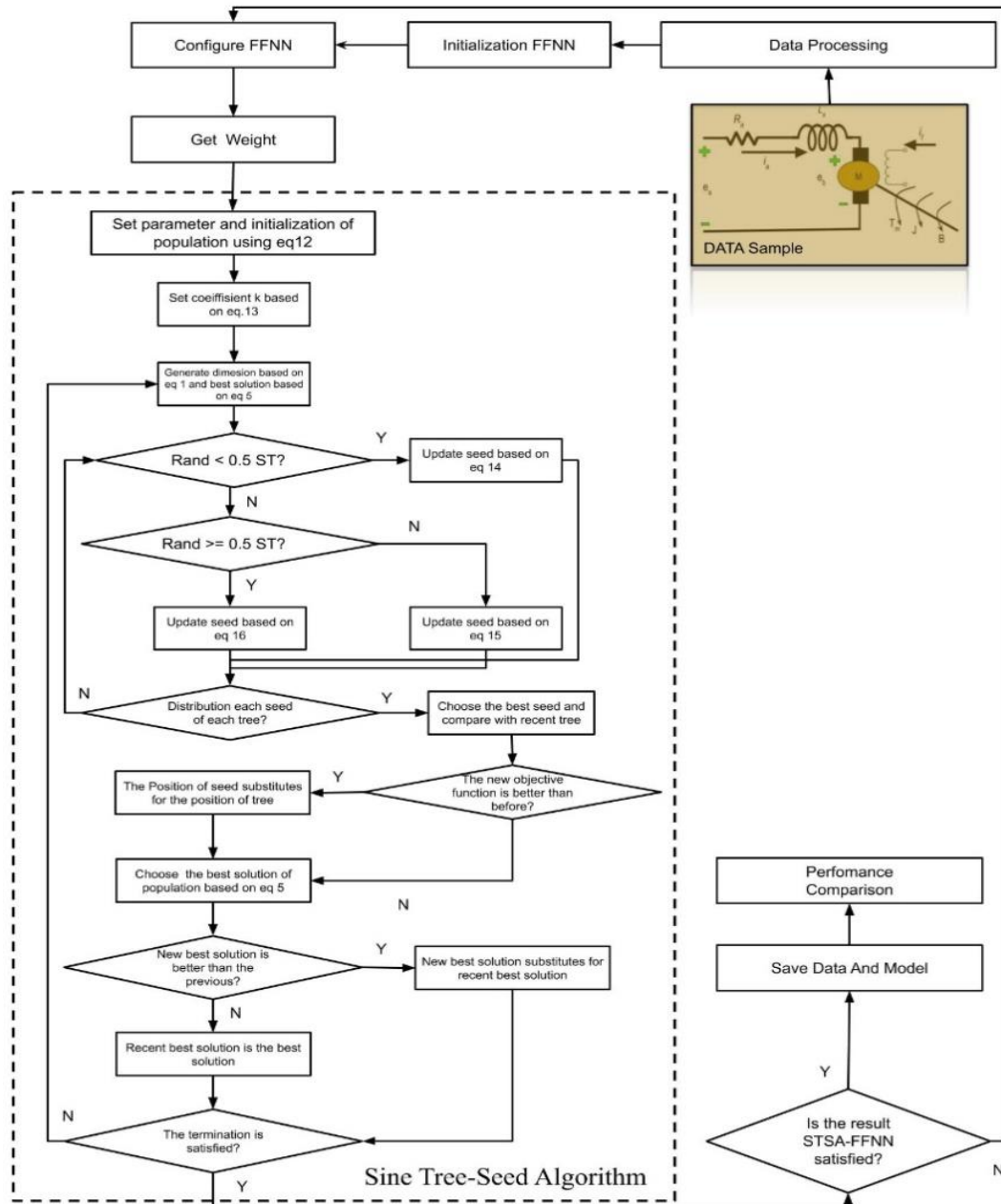


Figure 3. The proposed STSA-NN flowchart

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