



## ATOM SEARCH OPTIMIZATION – NEURAL NETWORK FOR DRIVING DC MOTOR

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### Abstract

DC motor applications are very widely used because DC motors are very suitable for applications, especially control. Thus, a proper DC motor controller design is required. DC motor speed control is very important to maintain the stability of motor operation. A recent type of metaheuristic algorithm that mimics the motion of atoms is introduced. Atom search optimization (ASO) is a mathematical model and duplicates the behavior of atoms in nature. Atoms intercommunicate with each other via the delivering contact force in the form of the Lennard-Jones potential and the constraint force produced from the potential bond length. The algorithm is simple and easy to be applied. In this study, the atomic search optimization (ASO) algorithm is proposed as a speed controller for the control dc motor. First, the ASO proposed by the algorithm is applied for the optimization of the neural network. Second, the ASO-NN proposal was the result compared to other algorithms. This paper compares the performance of two different control techniques applied to DC motors, namely the ASO-NN and proportional integral derivative (PID) methods. The results show that the proposed method has effectiveness. The calculation of the proposed ASO-NN control shows the best performance in the settling time. The ASO-NN method has the capability of settling time 0.04 seconds faster than the PID method.

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### INTRODUCTION

The basic equipment in almost all motion-related engineering applications is a dc motor. Some of the advantages of using a dc motor are simple operation using various inputs, low prices, and a variety of applications in various prototypes. For various purposes, the speed of this DC motor must be controlled to match the required speed. DC motor speed control can be done by adjusting the armature current or field current of the motor. This current regulation can be made by adjusting the motor voltage.

The main problem faced by engineers and researchers is the uncertainty of parameters. This is due to several factors, such as the erratic scope of operation, the presence of installation noise, and the gradient, which is influenced by the usage

and age of the equipment. The parameter uncertainty is due to the variation of the DC motor parameters. The condition is unpredictable and can affect the control system.

The famous traditional controller used is the Proportional + Integral + Derivative (PID) controller. PID has often been applied to fix the transient behavior and Steady State of the system [1, 2, 3].

In line with technological developments and methods, the solutions that often arise in DC motors have been sought for solutions. Designing an efficient and optimal off-line control system is one of the methods used. The method used to solve a limited series of uncertainties is to use a method that relies on the difference between the actual system and the system model [4]. It is used

to design a controller. DC motor speed regulation by various methods has been developed.

The development of artificial intelligence theory continues to increase the impact on the DC motor control system. Several methods used in DC motor control, namely particle swarm optimization [5][6], Ant Colony optimization [7][8], teaching-learning-based optimization [9][10], Jaya optimization algorithm [11][12], Harris Hawks Optimization [13][14], Flower pollination algorithm [15][16], Fuzzy [17][18], and Artificial Neural Network [19][20].

The research uses the Atom Search Optimization (ASO) method to increase the capabilities of the Feed-Forward neural network. This method is used to adjust the speed of a DC motor. The main contribution of this work is the presentation of adaptive control strategies based on metaheuristic optimization and neural networks, which prove to be efficient in compensation for the uncertainties presented in DC motors and are feasible in terms of practical experimental settings. The performance of the proposed method will be compared with the PID method and the neural network. The PID controller was chosen for comparison because it has a feedback tool.

This paper is structured as follows: the method chapter presents the atomic search optimization method, neural network, DC motor theory, and the proposed model. In the results and discussion section, the results of the proposed method on DC motors are presented. Finally, conclusions can be drawn.

## METHOD

### Atom Search Optimization

The Atom Search Optimization (ASO) method is a population-based algorithm that can be applied to break the issue. ASO is conceptually mathematics, and modeling mimics the motion of atoms in nature. Atoms have a style of interaction with other atoms. The facts are results from the potential for Lennard-jones and the resulting lifestyle potential of the bond length. ASO has an algorithm that is simple and easy to apply [21].

All matter originates from atoms that are always in motion over time. Atomic motion is based on classical techniques. According to newton's second law, it is assumed that the force

$j_i$  is the interaction force and  $k_i$  It is the limiting force acting together on the  $i$ -th atom in the atomic system. The acceleration  $a_i$  associated with  $m_i$  the mass of energy is given as (1).

$$a_i = \frac{j_i + k_i}{m_i} \quad (1)$$

The interaction force that applies to  $i$ -th atom of the  $j$ -th atom in the  $d$ -th dimension at time  $t$  is based on the Lennard-jones (L-J) potential theory, which can be formulated as (2) and (3).

$$j_{ij}^d = \frac{24\varepsilon(t)}{\sigma(t)} = \left[ 2\left(\frac{\sigma(t)}{r_{ij}(t)}\right)^{13} - \left(\frac{\sigma(t)}{r_{ij}(t)}\right)^7 \right] \frac{r_{ij}(t)}{r_{ij}^d(t)} \quad (2)$$

$$j'_{ij} = \frac{24\varepsilon(t)}{\sigma(t)} = \left[ 2\left(\frac{\sigma(t)}{r_{ij}(t)}\right)^{13} - \left(\frac{\sigma(t)}{r_{ij}(t)}\right)^7 \right] \quad (3)$$

The interaction force on the distance between atoms can be seen in Figure 1. Atoms are seen adjusting the relative distances that vary in a certain range over time due to their repulsion or attraction. The value of the change in repulsion relative to the equilibrium distance ( $r = 1.12\sigma$ ) is much greater than the attractiveness. The atoms will not converge in certain ways. This is due to the negative attraction and positive repulsion. So that (3) does not work and is revised with (4).

$$j'_{ij} = -\eta(t) \left[ 2(h_{ij}(t))^{13} - (h_{ij}(t))^7 \right] \quad (4)$$

where  $\eta$  is a function of depth to set the area of repulsion or area of attraction, which can be defined as (5).

$$\eta(t) = \alpha \left( 1 - \frac{t-1}{T} \right)^3 e^{\frac{-20t}{T}} \quad (5)$$

where  $\alpha$  is the distance weight, and  $T$  is the maximum of iterations.

Figure 2 is an illustration of the behavior of the function  $j'$  with different values following values of  $h$  in the range of 0.9 to 2. The different values of  $a$  are due to the repulsion occurring at the value of  $h$  ranging from 0.9 to 1.12. The attraction occurs when  $h$  is between 1.12 and 2, and the equilibration occurs when  $h = 1.12$ . The lower limit of repulsion and the upper limit of attraction is set in ASO. This is to increase exploration. The lower limit of repulsion is set close to  $h = 1.1$ , and the upper limit of attraction is set to  $h = 2.4$ , so  $h$  can be formulated as (6) and (7).

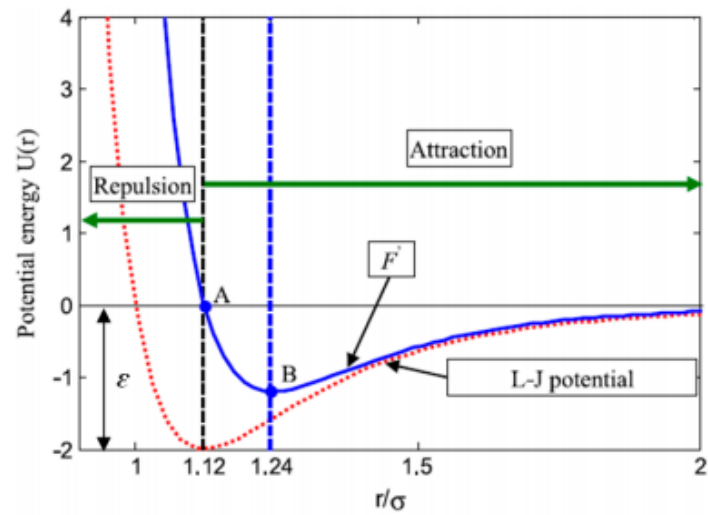
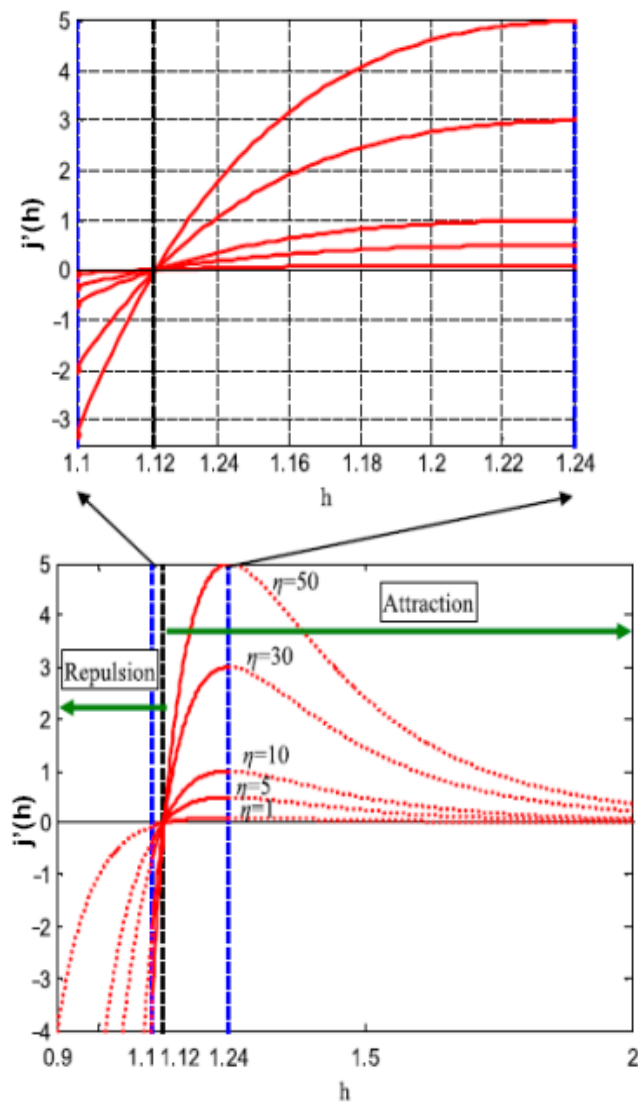


Figure 1. Atoms force interaction [21]

Figure 2. Function rule of  $j'$  with different values of  $\eta$  [21]

$$h_{ij}(t) = \begin{cases} h_{min} & \frac{r_{ij}(t)}{\sigma(t)} < h_{min} \\ \frac{r_{ij}(t)}{\sigma(t)} & h_{min} \leq \frac{r_{ij}(t)}{\sigma(t)} \leq h_{max} \\ h_{max} & \frac{r_{ij}(t)}{\sigma(t)} > h_{max} \end{cases} \quad (6)$$

$$\sigma(t) = \left\| x_{ij}(t), \frac{\sum_{g \in k_{best}} x_{ij}(t)}{k(t)} \right\|_2 \quad (7)$$

$$\begin{cases} h_{min} = g_0 + g(t) \\ h_{max} = u \end{cases} \quad (8)$$

where  $h_{min}$  and  $h_{max}$  are the lower and upper limits of  $h$ , respectively.  $K_{best}$  is a subset of an atom population, which is made up of the first  $K$  atoms with the best fitness,  $g$  is a traverse factor that shifts the algorithm from exploration to exploitation.

$$g(t) = 0.1x \sin\left(\frac{\pi}{2}x\right) \quad (9)$$

The total force that applies between atoms is the sum of the weighted components in the  $d$ -th dimension. The situation can be formulated as follows:

$$j_i^d(t) = \sum_{g \in k_{best}} rand_j j_{ij}^d(t) \quad (10)$$

where  $rand_j$  is a random number in  $[0,1]$ . As referred from Newton's third law:

$$j_{ij} = -j_{ji} \quad (11)$$

Molecular dynamics within the boundaries of geometry play a key role in the motion of atoms. The best atoms have covalence bonds with each atom according to the ASO rule. Each atom will follow the rules of the best atom ( $X_{best}$ ). The  $b_{i,best}$  is the fixed bond length between the  $i$ th atom and the best atom. Atomic constraints can be formulated as follows:

$$\theta_i(t) = [|X_i(t) - X_{best}(t)|^2 - b_{i,best}^2(t)] \quad (12)$$

The constraint force can be obtained by:

$$G_i^d(t) = -\lambda(t) \nabla \theta_i^d(t) = -2\lambda(t)(X_i^d(t) - X_{best}^d(t)) \quad (13)$$

By change of  $2\lambda$  with  $\lambda$ :

$$G_i^d(t) = \lambda(t)(X_i^d(t) - X_{best}^d(t)) \quad (14)$$

$$\lambda(t) = \beta \cdot \exp\left(-\frac{20t}{T}\right) \quad (15)$$

where  $\beta$  is the factor weight. The acceleration of the  $i$ th atom at time  $t$  can be formulated as follows

$$\begin{aligned} a_i^d(t) &= \frac{j_i^d(t)}{m_i^d(t)} + \frac{G_i^d(t)}{m_i^d(t)} \\ &= -\alpha \left(1 - \frac{t-1}{T}\right)^3 e^{-\frac{20t}{T}}, \end{aligned}$$

$$\sum_{g \in k_{best}} \frac{rand_j [2.2(h_{ij}(t))^{13} - (h_{ij}(t))^7]}{m_i(t)}, \quad (16)$$

where  $m_i(t)$  is the mass of the  $i$ th atom in the  $t$ th iteration.

$$M_i(t) = e^{\frac{Fit_i(t) - Fit_{best}(t)}{Fit_{worst}(t) - Fit_{best}(t)}} \quad (17)$$

$$m_i(t) = \frac{M_i(t)}{\sum_{j=1}^N M_j(t)} \quad (18)$$

$$Fit_{best}(t) = \min_{i \in \{1,2,\dots,N\}} \quad (19)$$

$$Fit_{worst}(t) = \max_{i \in \{1,2,\dots,N\}} \quad (20)$$

where  $Fit_{worst}(t)$  and  $Fit_{best}(t)$  are the atomic maximum and minimum fitness values at iteration  $t$ , consecutively.  $Fit_i(t)$  is the fitness values of the atomic function  $i$  in iteration  $t$ .  $N$  is the population of atoms. The position and velocity of the iterate atom ( $t+1$ ) can be formulated as follows:

$$v_i^d(t+1) = rand_i^d v_i^d(t) + a_i^d(t) \quad (21)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (22)$$

Each atom reacts with an atom with a better correspondence value under the ASO rule to improve reconnaissance in the previous iteration. Each atom reacts with the atom having the least possible better match value to improve proficiency in subsequent iterations.  $K$  gradually decreases as the iteration passes and is calculated using the formula expressed as (23).

$$K(t) = N - (N-2)x\sqrt{\frac{t}{T}} \quad (23)$$

### Feed-Forward Neural Network

Artificial neural networks or connectionist systems are machine learning tools inspired by biological neural networks and can process the same data as the human brain [22]. ANN can develop linear and nonlinear models for time series. ANN is widely accepted and applied as an effective tool for optimization and forecasting. The feed-forward back propagation neural network (FFNN) architecture consists of an input, output layer, and one or more hidden neuron layers. The FFNN architecture can be seen in Figure 3.

FFNN has efficiency in solving various types of problems. On the other hand, finding an efficient FFNN training algorithm is a challenge in itself. Solving FFNN problems can be solved by optimizing all the weights of the network. FFNN consists of an input layer that accepts input to be forwarded into the network. The input is passed to the hidden layer via neurons, and the output is computed [24][25].

In FFNN, the input data ( $I_n$ ) is multiplied by the weighting  $W_{ij}$ . The addition function is the sum of the input with weight ( $W_{ij}$ ) and bias ( $b_1$ ) on layer 1.  $X_2(t)$  is activation function.

$$X_1(t) = \sum_{i=1}^j W_{ij} I_n(t) + b_1 \quad (24)$$

$$X_2(t) = f(x_1(t)) = \frac{1}{1 + \exp^{-x_1}} \quad (25)$$

In layer 2, the output from layer 1 ( $X_2(t)$ ) is multiplied weights layer 2 ( $W_{jk}$ ). The addition

function of Layer 2 is a sum of output layer 1 ( $X_2(t)$ ) with weight ( $W_{jk}$ ) and bias ( $b_2$ ).

$$X_3(t) = \sum_{j=1}^k W_{jk} X_2(t) + b_2 \quad (26)$$

$$X_4(t) = f(X_3(t)) = \frac{1}{1 + \exp^{-x_3}} \quad (27)$$

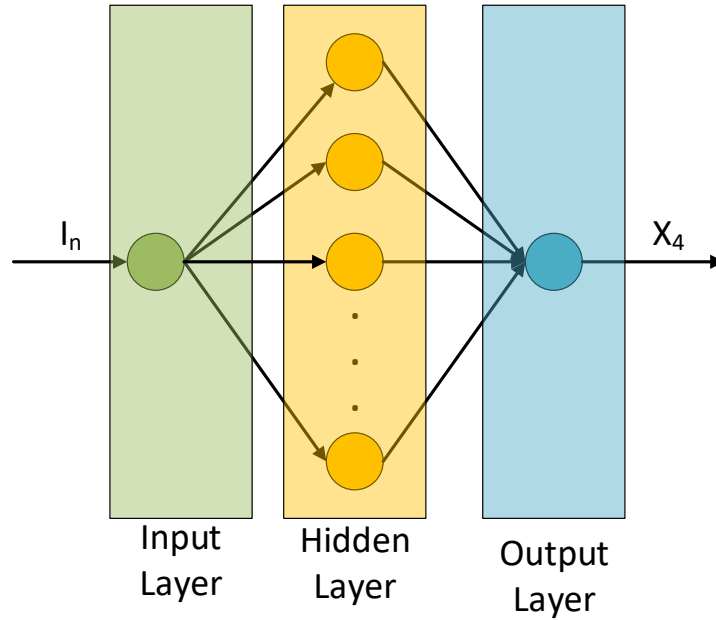


Figure 3. FFNN Structure

### DC Motor

DC motor has two controllers. The controllers are armature control and field control. DC motors require a direct voltage supply to the field coil to be converted into mechanical energy [4]. The main part of a DC motor is the stator and rotor, where the field coil on the dc motor is called the stator (the part that doesn't rotate), and the armature coil is called the rotor (the rotating part). DC motor with armature control uses the armature current as of the controlling variable. Current coils or permanent magnets can produce a stator field. When a fixed field current pours in the field coil, the motor torque ( $\tau_m$ ) i.e.

$$T_m(s) = (K_1 K_f I_f) I_a(s) = K_m I_a(s) \quad (28)$$

If using permanent magnets, then

$$T_m(s) = K_m I_a(s) \quad (29)$$

The relationship between the armature current and the input voltage in the armature circuit can be formulated as (30) and (31).

$$V_a(s) = (R_a + L_a \cdot s) \cdot I_a(s) + e_b(s) \quad (30)$$

$$e_b(s) = K_b \omega(s) \quad (31)$$

The torque in the motor is the same as the torque delivered to the load.

$$\tau_m(s) = \tau_L(s) + \tau_d(s) \quad (32)$$

The load torque for a rotating object is written as

$$\tau_L(s) = J s \omega(s) + B \omega(s) \quad (33)$$

Table 1 listed the DC motor parameter. Schematically of the DC motor are shown in Figure 4.

Table 1. DC motor parameters [23]

Notation	Information
$R_a$	Armature resistance
$L_a$	Armature inductance
$V_a$	Armature voltage
$e_b$	Back electromotive force
$J$	The inertia of the DC motor
$B$	Damping friction ratio
$\tau_m$	Motor torque
$\tau_L$	The torque connected to the load
$\tau_d$	Fault torque
$K_e$	Constant for converting the voltage on the motor to the rotational speed
$K_t$	Motor torque constant can be determined from the value of torque (T) and armature current ( $I_a$ )
$K_m$	The permeability function of the magnetic material

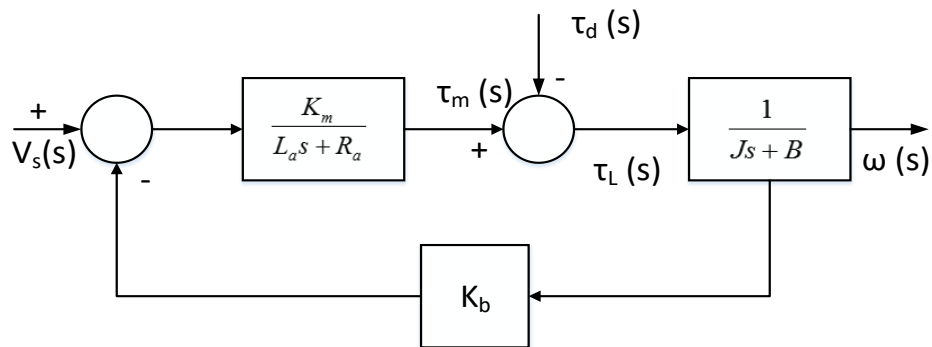


Figure 4. DC Motor System

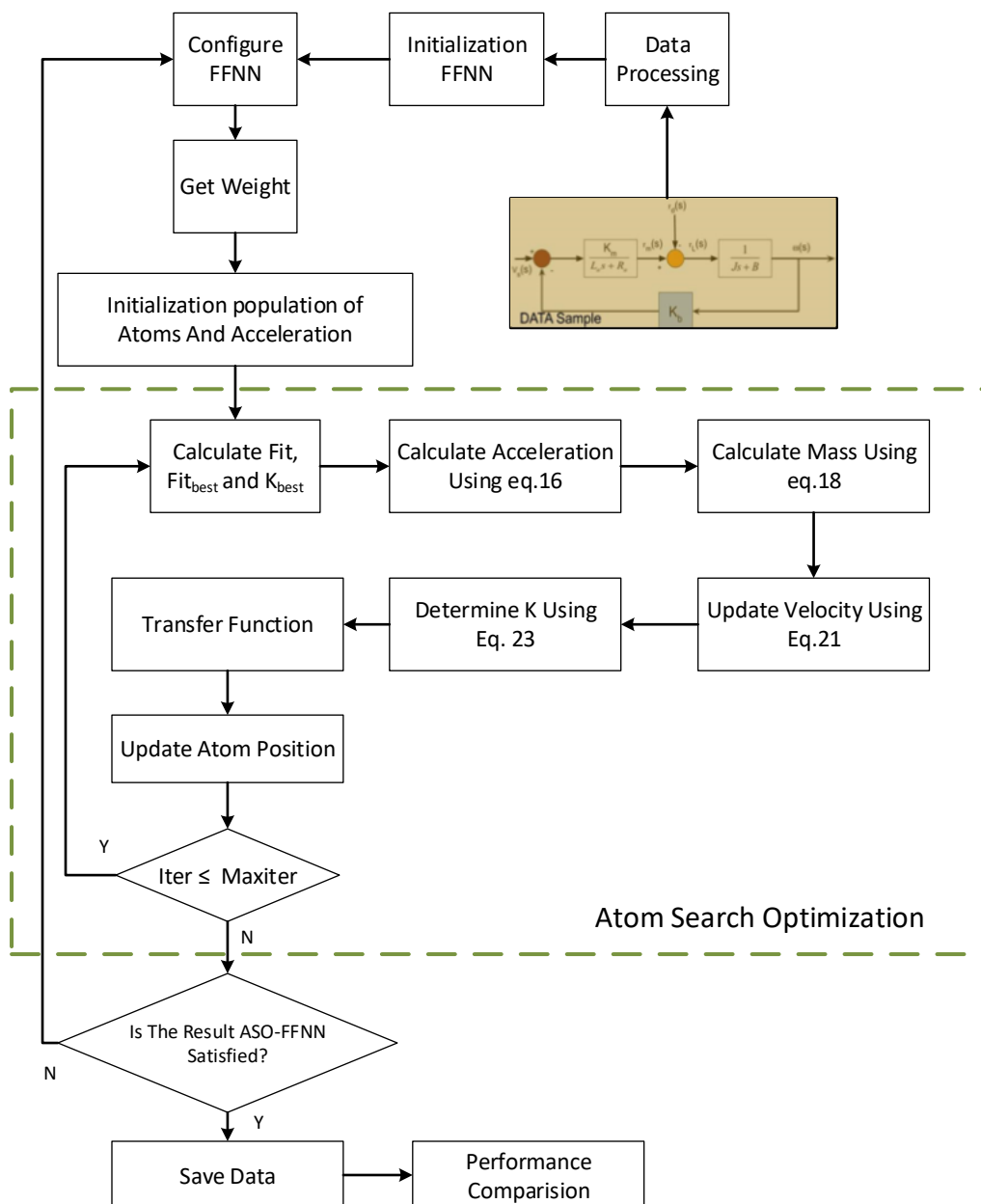


Figure 5. The Proposed ASO-NN Flowchart



### The Proposed ASO-NN Model

Data retrieved from the system is processed and mapped to be used as training data. Then, the neural network is configured and trained. The initial weighting used by the neural network is random. This value is optimized using the ASO method. The flowchart of the ASO - NN hybrid method is presented in Figure 5. ASO and NN work independently. The two processes further interact with each other to form the ASO-NN method.

### RESULTS AND DISCUSSION

DC motors with PID controllers are designed first to get the output used for training. PID controller parameters can be seen in Table 2. The ASO-NN method, response simulation, and analysis were carried out using MATLAB / Simulink software. The parameters of the ASO-NN algorithm used in this study are presented in Table 3.

The application of the proposed method is carried out using the Matlab application using data from Table 3. Figure 6 is showing the application of population variations to the ASO-NN method. The application of the 200 population has an effect on the smaller convergence value.

Table 2. Parameter of PID

Parameter	Value
$K_p$	2
$K_i$	6.5
$K_d$	0.01

Table 3. Parameter of ASO-NN

Parameter	Value
Hidden Layer	4
Training	Levenberg-Marquardt
Number of Atom (population)	200
$\alpha, \beta$	50, 0.2
Maximum Iteration Number	100

In order to see the effectiveness and advantages of the proposed ASO-NN approach, the ASO-NN controller was compared with the PID. Comparative analysis that produces the best value will be sharpened. The significant outcome of the paper is pointed in these subsections. In Figure 7, it can be seen the speed response of the DC motor for the PID and ASO-NN.

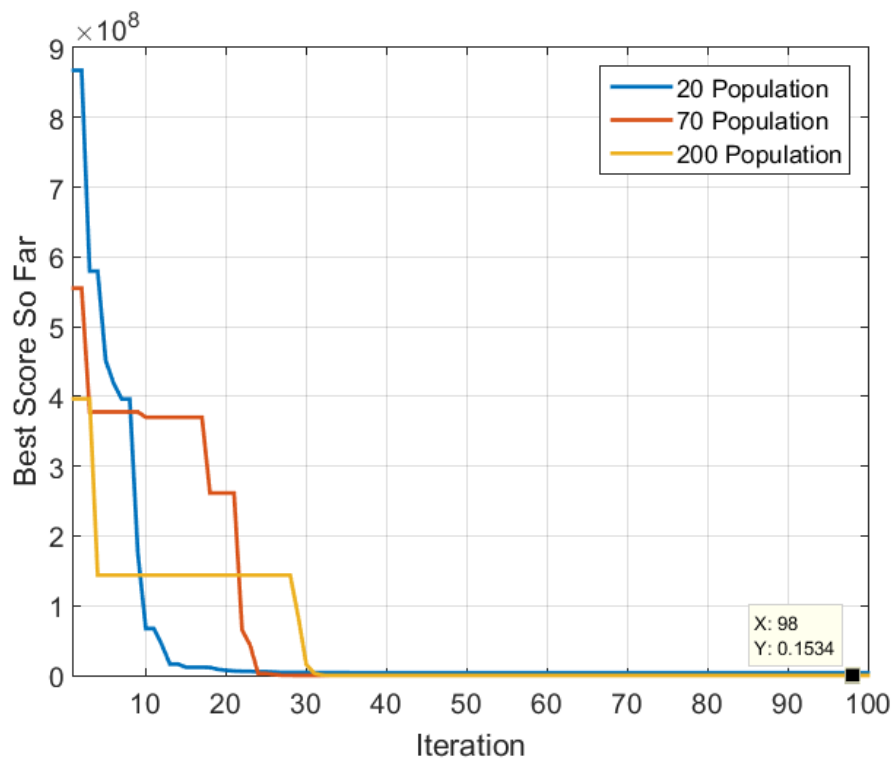


Figure 6. Convergence Curve of ASO-NN

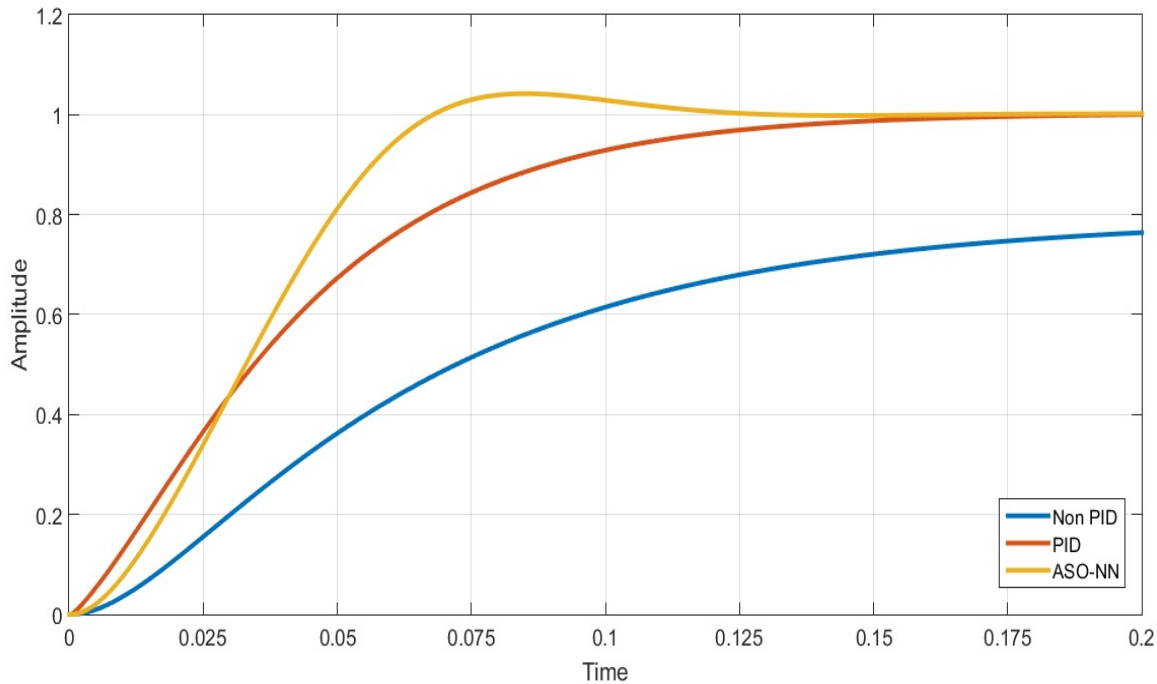


Figure 7. Output Speed of the DC motor

In Table 4, the comparative analysis between the proposed ASO-NN and PID is presented in the transient response. The results of the speed simulation using the ASO-NN controller experienced a little overshoot. The proposed method has a better stability index than the PID controller.

Table 4. Comparison for various controllers.

Controller	Overshoot	Settling Time (s)	Rise Time (s)
PID	1.003	0.2	0.02005
ASO-NN	1.042	0.16	0.0207

In this study, two performance criteria are used: Integral of time multiplied by squared error (ITSE) and Integral of time multiplied by absolute error (ITAE). The ITSE performance index was also chosen for comparison because of its wide use. ITSE has an additional time multiplier of the error function, which focuses on the length of the error duration. Therefore, this criterion is most often applied in the system requires fast setup time. The ITSE index formula is given as follows

$$ITSE = \int_0^{\infty} t \cdot e^2(t) \cdot dt \quad (33)$$

ITAE is integrating the absolute error multiplied by time after time. Minimizing integral of time-weighted absolute error (ITAE) is commonly referred to as a good performance index in designing controllers.

$$ITAE = \int_0^{\infty} t \cdot e(t) \cdot dt \quad (34)$$

Table 5. Performance indices comparison

Controller	ITAE	ITSE
PID	0.0594	0.2002
ASO-NN	0.0355	0.1501

The ITSE and ITAE results can be seen in Table 5. The ITAE and ITSE results from the proposed method have the same value as the PID method.

## CONCLUSION

Setting up the DC motor controller is a very challenging process. Setting in the predetermined setpoint value is a process that sees the condition as successful and has to be efficient. In this study, the ASO-NN method is proposed as a dc motor controller. From the research, it was found that the proposed method had a better settling time than the PID method. The index performance measurement obtained the same value between the proposed method and the PID. This research is using a simple DC motor as an object. It needs testing using a more varied and more complex object. The testing is to get the effectiveness and toughness of the proposed method at different levels of testing.

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