Comparative Study between Conventional and Intelligent methods for Speed Control of DC Shunt Motor

Dr. Jabbar Raheem Rashed
Department of Electrical Engineering
College of Engineering / Misan University
dr.jabar72@gmail.com

Abstract

This paper presents a mathematical model and Simulink model of DC shunt motor to control the speed of this motor by using conventional PID and suggested intelligent method FFWNN-PID. These approaches provide a study of a performance and speed control characteristics of motor as a classical methods with conventional controller, and then it will be compared with the proposed techniques

The main objective of this research is suggested a Wavelet Neural Networks (WNNs) as a powerful methods to control the speed of DC shunt motor. Feed Forward Wavelet Neural Network (FFWNN) is proposed. This method leads to enhance dynamic behavior of the motor drive system and an immune to load disturbance.

The parameters of PID controller and suggested methods are optimized using Particle Swarm Optimization (PSO) algorithm. The DC shunt motor drive with FFWNN-PID controller through simulation results proves a good in the performance and stability compared with traditional approach.

General Terms

Speed control of DC shunt motor

Keywords

DC shunt motor, PID, WNNs, FFWNN, PSO

الخلاصة

هذا البحث يقديم الموديل الرياضي ونموذج المحاكات لمحرك التيار المستمر ذو الاثارة التوازي للسيطرة على سرعته باستخدام مسيطرPID التقليدي والطريقة الذكية المقترحة التي تسمى FFWNN-PID . هذه الطريقتان توفر دراسة تقليدية لإداء المحرك وخصائص السيطرة على سرعته باستخدام الطريقة الكلاسيكية بواسطة مسيطر تقليدي ومن ثم تستخدم للمقارنة مع الطريقة المقترحة.

الهدف الرئيسي في هذا البحث هو تطوير الشبكات العصبية الموجية WNNs كنمط فعال للسيطرة على سرعة المحرك ويقترح الشبكة العصبية الموجية غير المتكررة FFWNN . هذه الطرق أدت الى تحسين الأداء للمحرك وتحصينه من اضطرابات الحمل.

تم اختيار بارامترات المسيطرات وبارامترات الطريقة المقترحة على أساس خوارزمية اسراب الطيور PSO. ان نتائج المحاكاة اثبتت افضل أداء واستقرار لمحرك التيار المستمر ذو الاثارة التوازي يتم مع طريقة FFWNN-PID controller بالمقارنة مع الطريقة التقليدية.

1. INTRODUCTION

The DC motors are in general much more adaptable speed drives than AC motors which are associated with a constant speed rotating field [1]. The principal advantage of a D.C. motor is that its speed can be changed over a wide range by a variety of simple methods. Such a fine speed control is generally not possible with AC motors. In fact, fine speed control is one of the reasons for the strong competitive position of DC motors in the modem industrial applications [2-3]. In this paper, the various methods of-speed control of D.C. shunt motors will be discuss.

Shunt wound motors is the most widely used as they have a linear characteristics of voltage & torque. Shunt motor has more constant and controllable speed over various loads. This type of motor runs practically constant speed, regardless of the load. It is the type generally used in commercial practice and is usually recommended where starting conditions are not usually severs. Speed of the shunt wound motors may be regulated in three ways: first, by inserting resistance in series with armature (Rheostatic control), this decreasing speed, second, by insert resistance in field circuit (flux control), the speed will vary with each change in load, and third, by varying armature applied voltage (voltage control): in the letter, the speeds are practically constant for any setting of the controller. A high-quality speed control system makes the DC motor suitable for the applications in which changeable speed variation, frequent starting, proper speed regulation, braking and reversing are required. The speed control of DC machines which used to be performed automatically has undergone a revolution as a result of advances in power electronics area. The process of variable speed drives may be achieved by armature voltage control for speeds under the rated, or by field excitation variation for beyond rated speeds. DC motor speed can be adjusted to a large extent so as to provide simple to control and high performance [4-5].

Conventional PID control is most common used method in speed control of DC shunt motor because it is structure is simple, stable, and easy adjustment. But in most industrial processes with different degree of nonlinear, tuning PID parameters is difficult, poor, robustness, therefore, it is difficult to achieve the optimal state under field conditions in the actual production [6]. In this paper, the wavelet neural network Feed Forward Wavelet Neural Network (FFWNN) is proposed with PID controller to produce modified controllers, which combines the capability of the artificial neural networks for learning form the DC shunt motor drive and the capability of wavelet decomposition for identification and control of dynamic system and also having the ability of self-learning and self-adapting.

The performance of PID controller can be further improved by making use of optimization method. In this research, the parameters of the proposed PID controller and suggested intelligent approach (FFWNN-PID) are tuned by using Particle Swarm

Optimization (PSO) method. This method is a heuristic global optimization technique, and also an optimization algorithm, which based on swarm intelligence [7].

2- Modeling of DC shunt motor

DC machines are classified according to the connection of the field circuit with respect to the armature circuit. In shunt machine, the field winding is connected in parallel with the armature winding as shown in Fig. (1).

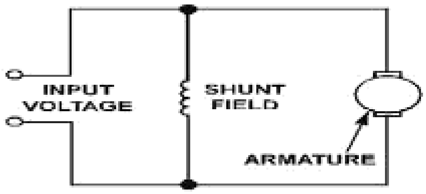

Fig. (1) DC shunt motor diagram

The mathematical model describing the dynamic behavior of the DC shunt motor are given by following equations [8-9]:

$$V_{in} = R_a i_a + L_a \frac{di_a}{dt} + e_b \quad \ldots\ldots (1)$$

$$T_m = K_T \emptyset \, i_a \quad \ldots\ldots (2)$$

$$\emptyset = K_F i_F \quad \ldots\ldots (3)$$

$$T_m = J \frac{d^2\theta}{dt^2} + B \frac{d\theta}{dt} - T_L \quad \ldots\ldots (4)$$

$$e_b = K_b \emptyset \frac{d\theta}{dt} \quad \ldots\ldots (5)$$

$$\omega = \frac{d\theta}{dt} \quad \ldots\ldots (6)$$

Where the symbols, designations and units are publicized in Table (1):

Symbols	Designations	Units
$\boldsymbol{V_{in}}$	Input voltage	[volt]
$\boldsymbol{R_a}$	Armature winding resistance	[ohm]
$\boldsymbol{i_a}$	Armature current	[ampere]
$\boldsymbol{L_a}$	Armature winding inductance	[henry]
$\boldsymbol{e_b}$	Back emf voltage	[volt]
$\boldsymbol{T_m}$	Electromagnetic torque	[N.m.]
$\boldsymbol{K_T}$	Torque constant	[N.m./Ampere]
$\emptyset$	Armature flux	[weber]
$\boldsymbol{K_F}$	Field constant	[Weber/ampere]
$\boldsymbol{i_F}$	Field current	[ampere]
$\boldsymbol{J}$	Moment of inertia of motor	[Kg.m^2/rad]
$\boldsymbol{\theta}$	Angular position	[radians]
$\boldsymbol{B}$	Frictional constant	[N.m. sec /rad]
$\boldsymbol{T_L}$	Load torque	[N.m.]
$\boldsymbol{K_b}$	Back emf constant	[Volt sec./weber rad.]
$\boldsymbol{\omega}$	Angular Speed	[rad/sec]

Table (1): Symbols, Designations, and Units of DC Shunt Motor.

3- Wavelet Neural Network Methods

Wavelet Neural Networks (WNNs) is the combination of wavelet theory and neural networks. The structure of WNN is similar to that of neural network. It represents a feed forward neural network, taking one or more inputs, with one hidden layer and output layer. The hidden layer consists of neurons, whose activation functions are drawn from a wavelet basis. These wavelet neurons are usually referred to as wavelons, whose input parameters include the wavelet dilation (a) and translation (b) coefficients. In wavelet neural networks, both position (translation) and the dilation are optimized besides the weights. The structure of WNN is shown in Fig. (2). This network approximates any desired signal f(t) by generalized a linear combination of a set of daughter wavelets $\Psi_{a,b}$ where $\Psi_{a,b}$ are generated by dilation (a) and translation (b) from mother wavelet Ψ as follows:

$$\Psi_{a,b} = \Psi\left(\frac{x-b}{a}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (7)$$

The output of the wavelet neural network is given by

$$y = \sum_{n=1}^{N} W_N \, \Psi_{a_N b_N} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (8)$$

Where W_N is the weight of the nth node in hidden layer to the output unit, a_N and b_N are the dilation factor and translation factor respectively, x is the input of the network, $\Psi_{a,b}$ is the wavelet function. In this paper, two methods of WNN are used, Feed Forward WNN (FFWNN) and Recurrent WNN (RWNN).

3.1 Feed Forward Wavelet Neural Network (FFWNN)

The feed forward wavelet neural network is a feed-forward artificial neural network with wavelet transform function in the hidden layer. The FFWNN have no feedback connection. That is, the output is calculated directly from the input through feed-forward connection [10]. There are two forms of feed-forward wavelet neural networks:

A- Radial Basis Wavelet Neural Network (RBWNN)

Radial Basis Wavelet Neural Network (RBWNN) is simplest form of the wavelet neural network and is similar to that of radial basis neural networks (RBNN) and the wavelet function instead of radial basis function. This network is a feed-forward neural network, taking one or more inputs, with one hidden layer and output layer. In this network, the weights connection are between the hidden layer and output layer only [11]. The structure of radial basis wavelet neural network is shown in Fig.(2). This network approximates any desired signal f(t) by generalizing a linear combination of a set of daughter wavelet $\Psi_{a,b}$

where $\Psi_{a,b}$ are generated by dilation (a) and translation (b) from mother wavelet Ψ as shown in equations 7 &8[12]. In this paper, the particle swarm optimization (PSO) is used select the best values of the network parameters w_N, a_N, and b_N.

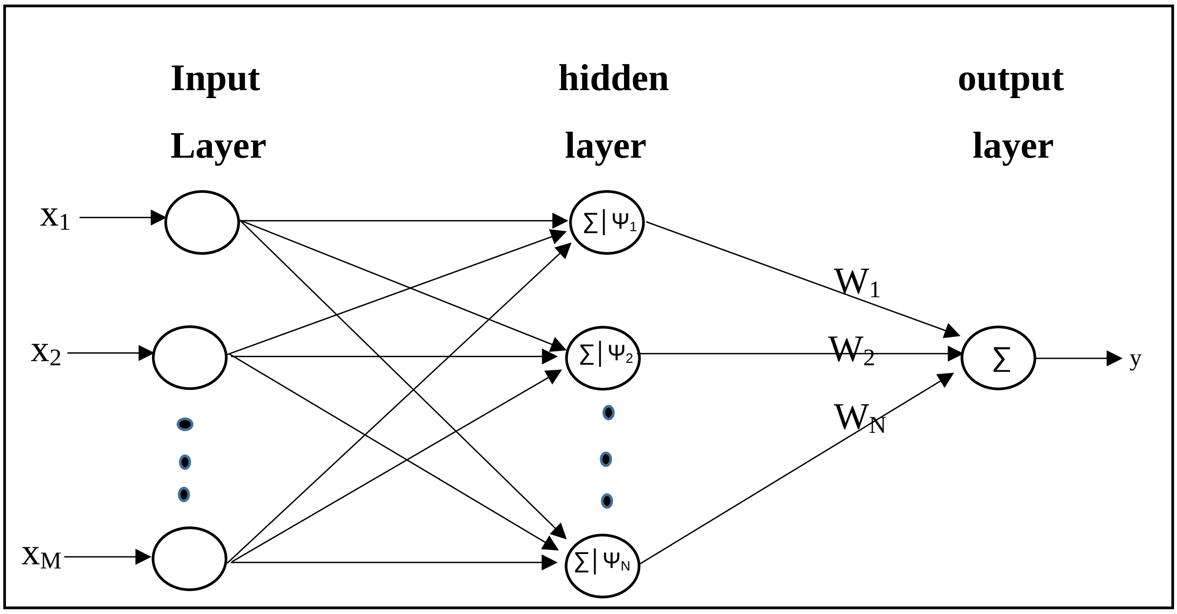

Fig.(2): The structure of RBWNN

B- Conventional Wavelet Neural Network

The conventional WNN is an extensive form of RBWNN. This network is a feed-forward network with multilayer and wavelet activation function in the hidden layer. This network contains also weights connection for each side in the hidden layer and also the output layer contain sigmoid function [13]. Fig.(3), shows the structure of the conventional WNN, the number of hidden layer and neurons are selected to construct a suitable wavelet neutral network and the parameters are optimized by PSO algorithm. The input layer can be represented by in a vector $x=[x_1,x_2,\dots\dots\dots x_M]$, the output layer represented by a vector $y=[y_1,y_2,\dots\dots\dots\dots y_k]$ and the impulse function of hidden layer is wavelet basis function. The output y_j can be given as follow [13]:

$$y_j = \sigma(u_j) = \sigma\left[\sum_{n=1}^{N} W_N\, \Psi_{a_N b_N}\left(\sum_{m=1}^{M} V_{N,M}\ X_M\right) + g\right] \dots\dots\dots\dots\dots\dots\dots (9)$$

Where j=1,2,3,4,………K, M is the number of inputs, K is the number of outputs layer, N is the number of hidden layer and $\sigma(u_j)$ is the activation function of the output layer, the most common form of activation function is sigmoid function which can be defined as follow[10]:

$$\sigma(u) = \frac{1}{1-e^{-u}} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (10)$$

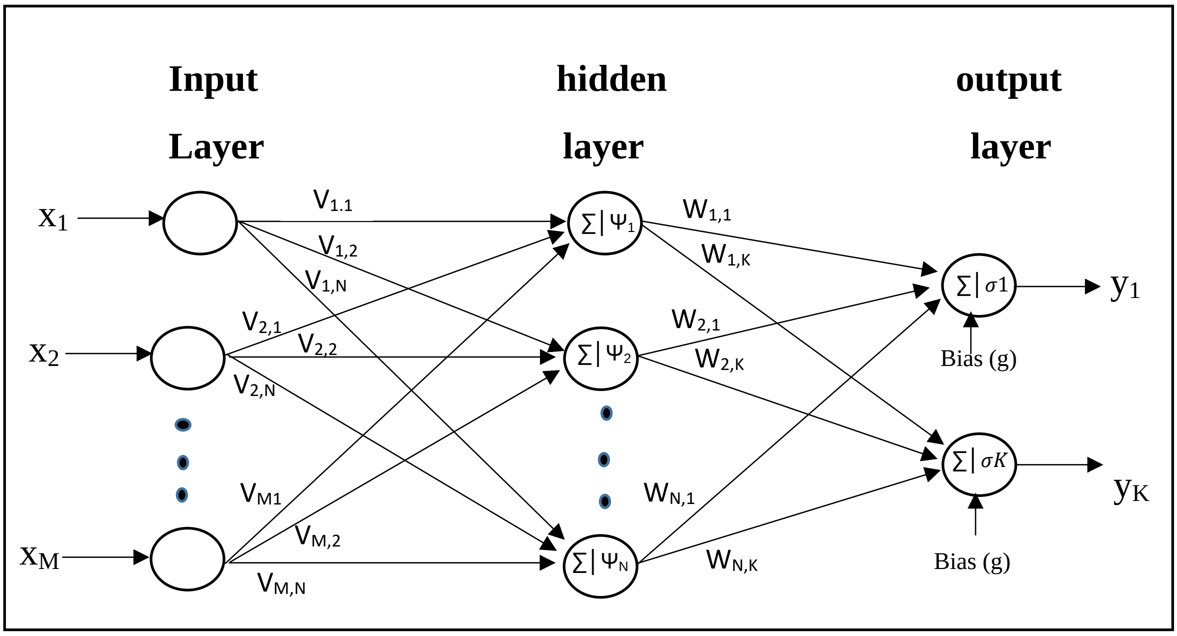

Fig.(3): Structure of conventional WNN

3-2 Recurrent Wavelet Neural Network (RWNN)

In current networks, the output depends not only on the current inputs of the network, but also on the previous outputs or states of the network. For this reason, recurrent networks are more powerful than non-recurrent networks and have important applications in nonlinear control and system identification [14-15]. Recurrent networks have feedback and are also known feedback networks. There are several types of recurrent network depends on the feedback connection. The feedback can be obtained by connecting signal from the output layer to the input layer or in one layer which is called partially feedback, or by state feedback in which each layer has feedback connection from the output to the input and also feedback from output to the input network, this type called fully connection [10].

In the recurrent wavelet network of configurations, the wavelet network input consist of delayed samples of the system x_M and the system output y(K). The number of inputs to the wavelet network increases with the order of the system being modeled. Fig.(4) shows the structure of recurrent wavelet neural network. Hence, the output for each layer can be computed as [14]:

$$\Psi_N = \Psi\left(\frac{u_N - b_N}{a_N}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (11)$$

Where a_N and b_N are the translation factors of the wavelets, respectively. The inputs of this layer for time n can be denoted as:

$$u_N(n) = x_N(n) + \Psi_N(n-1) * \varphi_N \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (12)$$

Where, φ_N denotes the weight of the self- feedback loop. The output of the network is given as follow:

$$y = \sum_{n=1}^{N} W_K \, \Psi \left(\frac{u_N - b_N}{a_N} \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (13)$$

$$u(n) = x(n - D_i) + y(n - D_O) * r_N \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where

x: the input signal.

N: the number of neuron in the hidden layer.

W_K: the output weight.

D_i & D_O : the number of delay for the input and output network.

r_N : the weight of the output feedback loop

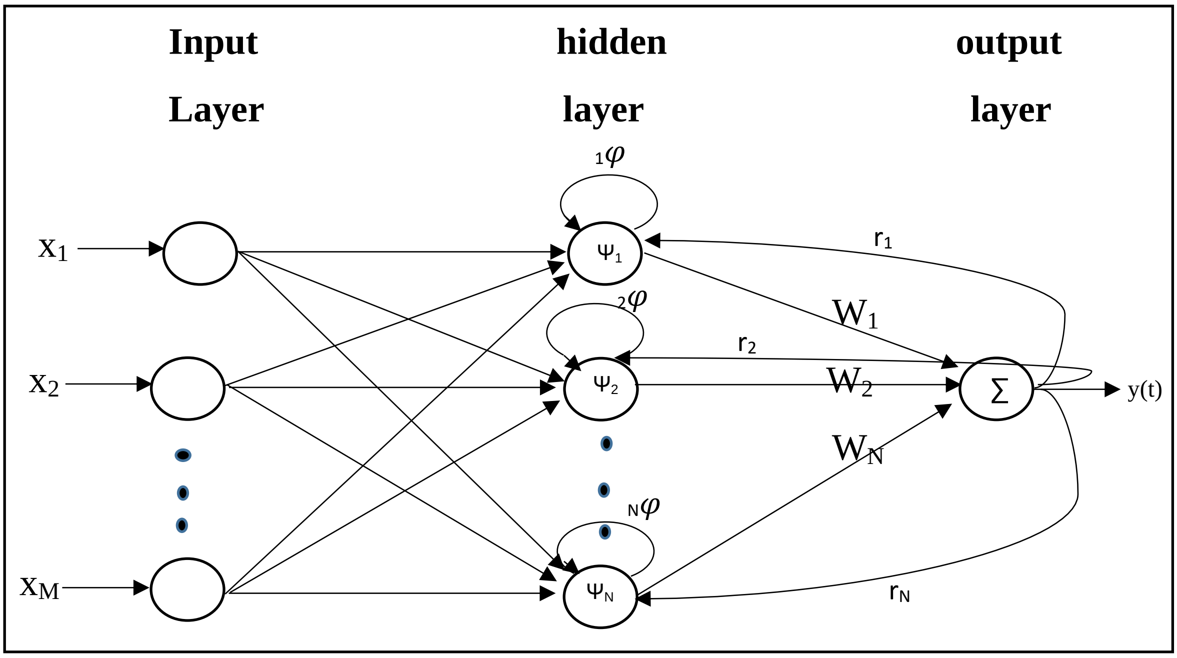

Fig.(4): The structure of RWNN

4- Particle Swarm Optimization (PSO) method

Particle Swarm Optimization (PSO) was originally developed by Kennedy and Elberhart in 1995 is a population based evolutionary algorithm [16]. It was inspired by the social behavior of bird and fish schooling and has been found to be robust in solving continuous nonlinear optimization problems.

In standard PSO, a swarm consists of N particles moving around in D-dimensional search space. The random velocity assigned to each particle. Each particle modifies its flying based on its own and companion's experience at every iteration. The *i*th particle is denoted as $X_i = (x_{i1}, x_{i2}, \dots\dots\dots, x_{iD})$, whose best previous solution *(pbest)* is represented as $P_i = (p_{i1}, p_{i2}, \dots\dots\dots, p_{iD})$. Current velocity (position change rate) is described by $V_i = (v_{i1}, v_{i2}, \dots\dots\dots, v_{iD})$. Finally the pest solution achieved by the whole swarm *(gbest)* is represented as $P_g = (p_{g1}, p_{g2}, \dots\dots\dots, p_{gD})$.

At each time step, each particle moves toward *(pbest)* and *(gbest)* locations. The fitness function evaluates the performance of particles to determine whether the best fitting solution is achieved. The particles are manipulated according to the following equations:

$$v_{id} = v_{id} + c_1 * rand(\,) * (p_{id} - x_{id}) + c_2 * rand(\,) * \left(p_{gd} - x_{id}\right) \dots\dots (15)$$

$$x_{id} = x_{id} + v_{id} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (16)$$

Where c_1 and c_2 are two positive constants, called cognitive learning rate and social learning rate respectively; *rand ()* is a random function in the range [0,1]. The velocity of the particles are limited in [V_{min} ,V_{max}]. Since the original formula of PSO lacks velocity control mechanism, it has poor ability to search at a fin grain [17]. A time decreasing inertia factor is designed by Eberhart and Shi to overcome this shortcoming in 1998[18-20].

$$v_{id} = w * v_{id} + c_1 * rand(\,) * (p_{id} - x_{id}) + c_2 * rand(\,) * \left(p_{gd} - x_{id}\right) \dots\dots (17)$$

$$x_{id} = x_{id} + v_{id} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (18)$$

Where *w* inertia factor which balance the global wide-range exploitation and the local nearby exploration abilities of the swarm. Fig.(5) shows the flow chart depicting the implementation of PSO algorithm for optimizing the parameters of FOPID controller for the given system is as follows:

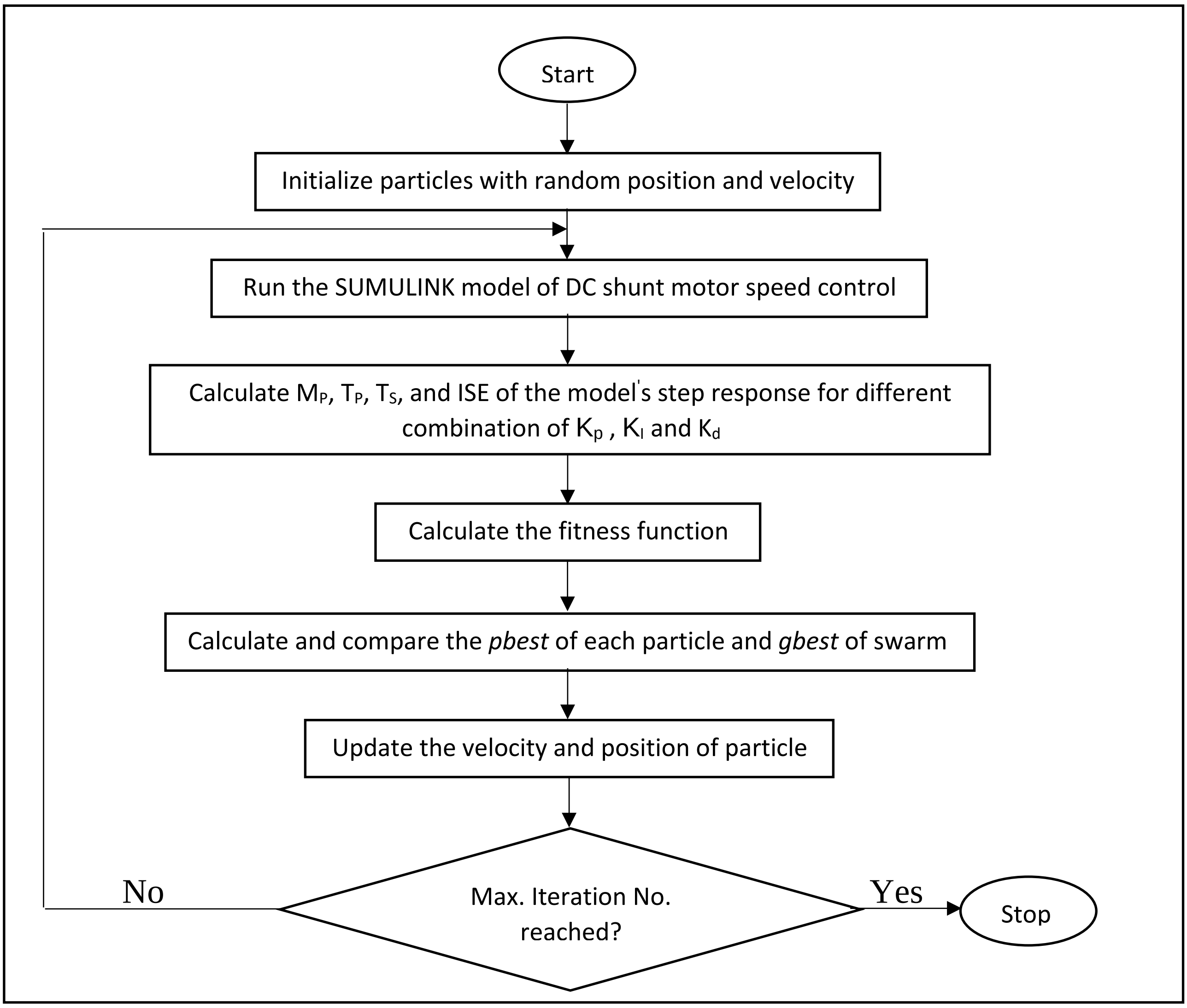

Fig.(5):Implementation of PSO in PID tuning for DC shunt motor speed control.

5- DC Shunt Motor Physical Parameters Values

Table (2) shows the physical parameters values which are used for DC shunt motor equivalent circuit.

Symbol	Value	Unit
$\boldsymbol{R_a}$	0.5	[ohm]
$\boldsymbol{L_a}$	0.0015	[henry]
$\boldsymbol{J}$	0.00025	[Kg.m^2/rad]
$\boldsymbol{B}$	0.0001	[N.m. sec /rad]
$\boldsymbol{K_b}$	0.5	[Volt sec./ weber rad.]
$\boldsymbol{K_T}$	0.05	[N.m./Ampere]

Table (2): DC Shunt Motor Physical Parameters Values

6- Simulation Results and Discussion

6 -1: Motor Drive Based on Conventional PID Controller

After applying the parameters values of DC shunt motor in table(2),The Simulink model of DC shunt motor based on equations 1 and 4 has been implemented using MATLAB/SIMULINK software as shown in Fig.(6).

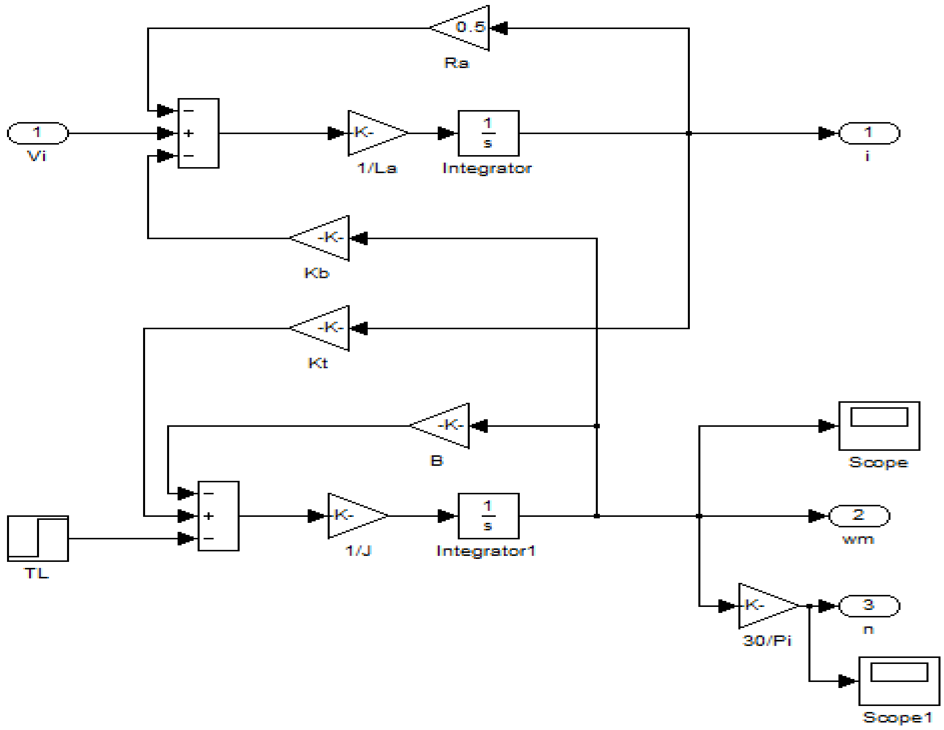

Fig.(6): Simulink model of DC shunt motor.

The speed response of DC shunt motor without controller shown in Fig. (7).This response gives an overshoot (M_p) of 1600 rpm, peak time (T_p) of 0.005 sec, rise time (T_r) of 0.002 sec, and settling time (T_s) of 0.017 sec, which is undesirable because this response is not smooth, oscillated, and peak over shoot is high, approximately (60% of reference speed). Where reference speed is 1000 rpm.

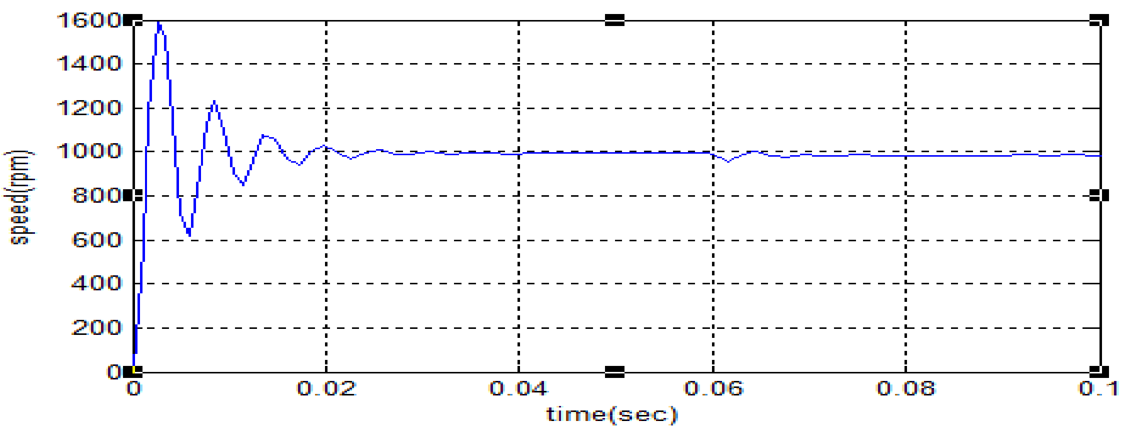

Fig.(7): The speed response of DC shunt motor without controller.

Firstly, in this study, the conventional PID controller is connected to improve the performance and tuning the different values of PID parameters as K_p, K_i, and K_d to obtain minimum overshoot, minimum settling time, and minimum rise time. The MATLAB Simulink model of PID controller shown in figure (8).

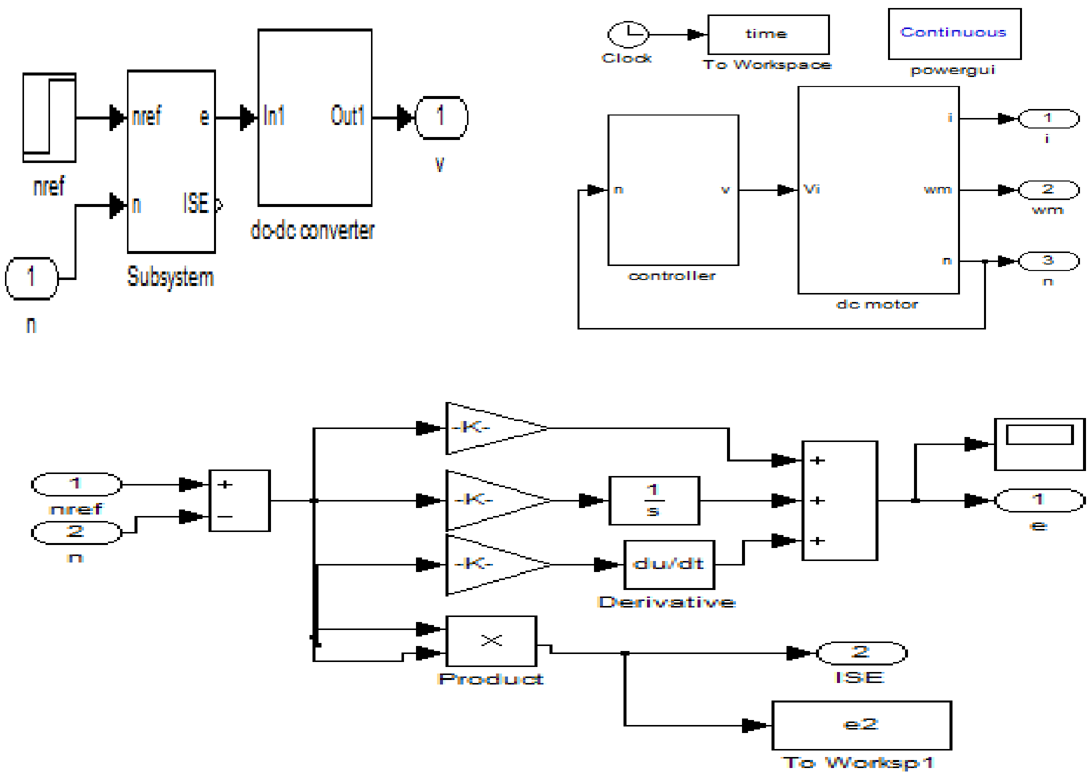

Fig.(8): PID controller by MATLAB Simulink Model

The speed response of dc shunt motor after connection PID controller is shown in figure (9). The result is undesirable too, because the rise time and settling time is increased although the overshoot is reduced to 10% of reference speed. Where the parameters of the controller are K_p= 4.858, K_i=5.457, and K_d=0.871

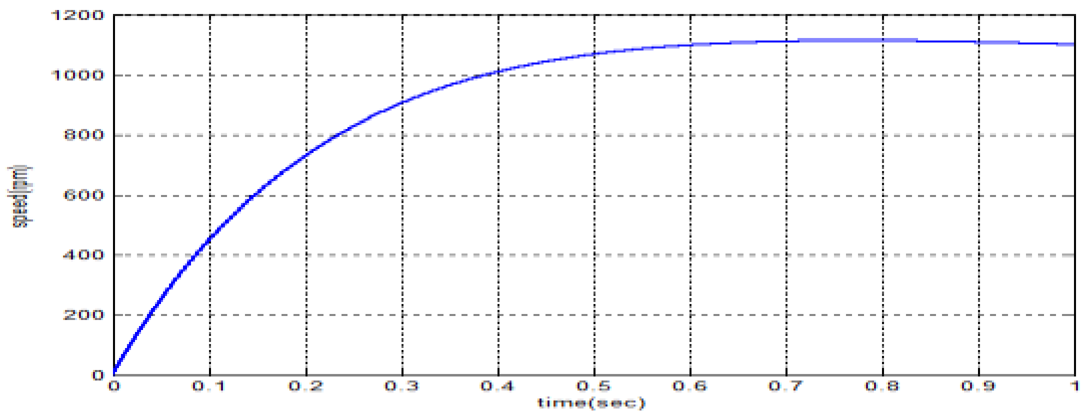

Fig.(9): The speed response of DC shunt motor with PID controller

6-2: Motor Drive Based on PID Controller modified by PSO

In this case, the parameters of controller is tuned by using PSO algorithm and the model (dc shunt motor and controller) is training to minimize all times and minimum over shoot. The response of this simulation is shown in figure (10). By comparison with conventional PID, the results are improved. Where the parameters of the controller are changed into K_p=0.84, K_i=8.7357, and K_d=0.0072.

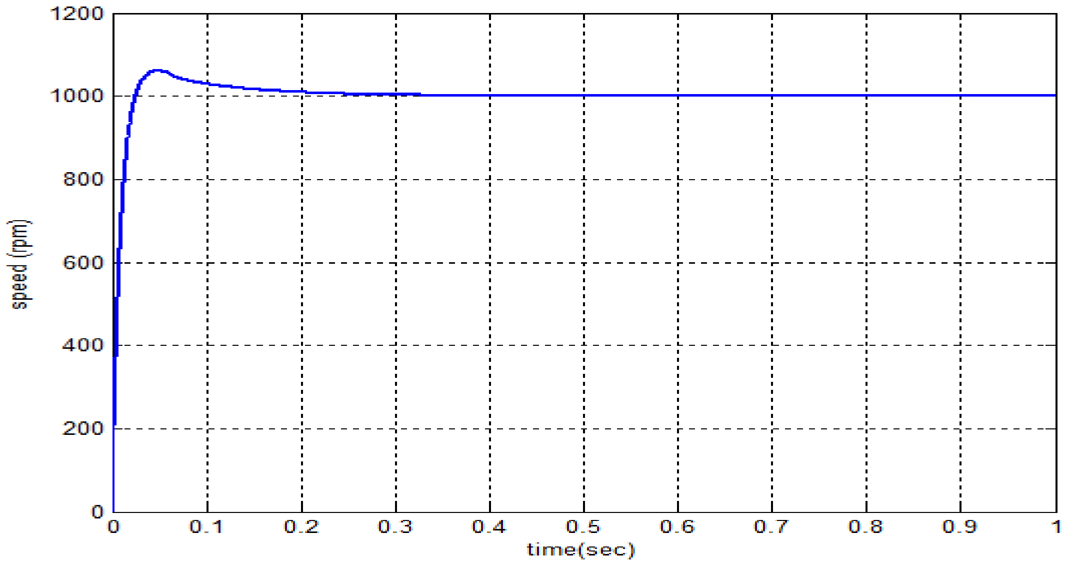

Fig.(10): The speed response of DC shunt motor with PID controller tuned by PSO.

6 -3 Motor Drive Based on FFWNN-PID method modified by PSO

The model of dc shunt motor approximately linear, therefore, the method RWNN is not used in this research because this approach more powerful with non-linear system, and the results of RWNN is not suitable with this model.

The proposed intelligent method FFWNN-PID tuned by PSO algorithm is used to obtain on much shorter times and no overshoot. The MATLAB Simulink model of this method shown in figure (11). The parameters of the controller are changed into K_p=0.84, K_i=6.7357, and K_d=0.0012 and provide better performance and better results than all methods which mentioned above. The response of this case is shown in figure (12).

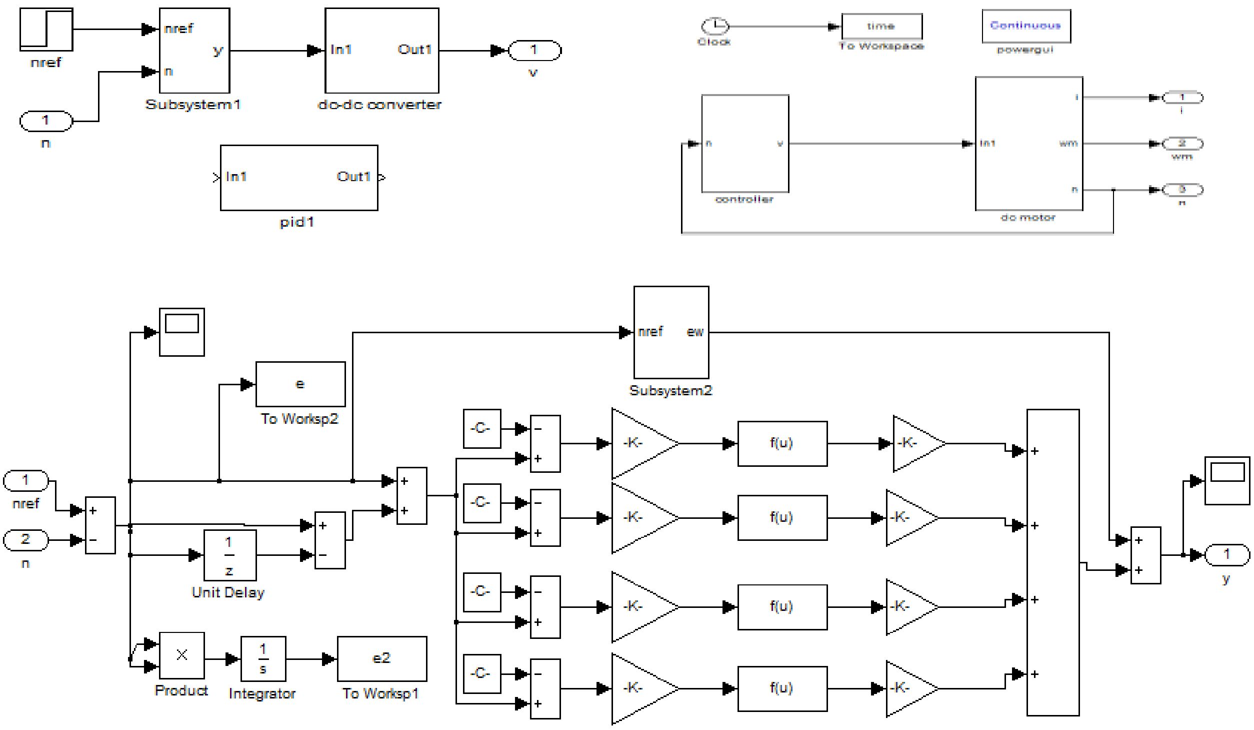

Fig.(11): FFWNN-PID method MATLAB Simulink Model

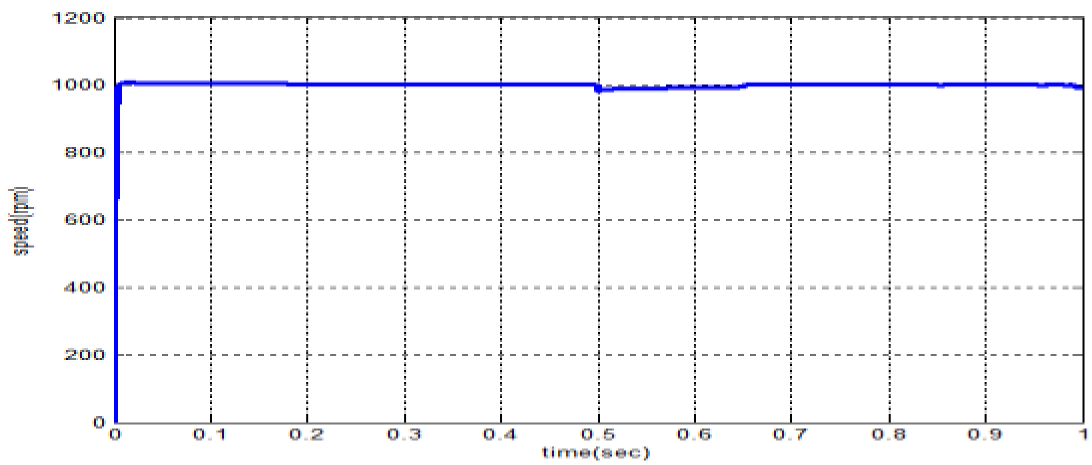

Fig. (12): The speed response of DC shunt motor with FFWNN-PID

Table (3) summarize the comparison among the methods which are used in this paper and items of performance of dc shunt motor.

Characteristics	Without PID	With conventional PID	With PID tuned by PSO	With FFWNN-PID tuned by PSO (proposed method)
Peak overshoot (%)	60	10	8	0
Peak time T_p (sec)	0.005	0.8	0.04	0.002
Rise time T_r (sec)	0.002	0.4	0.025	0.001
Settling Time T_r (sec)	0.017	3	0.1	0.005

Table (3): performance of dc shunt motor by multi methods

From the table (3), it can be seen, the proposed method has proved their excellence results and improving the steady state characteristics and better performance of dc shunt motor by obtaining shorter times and elimination of overshoot.

7- Conclusions

In this paper, a PID controller is designed based on PSO algorithm and it is tuning has been done for speed control of DC shunt motor. The simulation model of controller and motor was developed using MATLAB/Simulink. According to the results of the computer simulation, the controller with PSO is better than traditional PID without PSO algorithm. The intelligent proposed method FFWNN-PID with PSO provided flexibility and robust performance (no overshoot, very short peak time, minimal rise time, and minimal settling time). Also, the PSO algorithm is greatly succeeded to optimize of the Feed Forward Wavelet Neural Network (FFWNN-PID) parameters. Finally, the speed control model of dc shunt motor with suggested method shows optimal results compared with anther methods.

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