Comparative Study between Conventional and Intelligent Methods for Controlling on Speed of DC Shunt Motor

Dr.Jabbar Raheem Rashed
Electrical Eng. Dept.
Eng. Faculty / Misan University
dr.jabar72@uomisan.edu.iq

Abstract

Application of intelligent control methods offers the best solutions to Speed control of D.C. motors. Conventional control algorithms, though simple, have their limitations and fail in offering the required responses. In this paper, suggested a Wavelet Neural Networks (WNNs) as a powerful method to speed control of D.C.shunt motor. Feed Forward Wavelet Neural Network(FFWNN) is proposed. This method leads to enhance dynamic behavior of driving system for the motor and an immune to load disturbance. Also this proposed is compared with traditional method with conventional controller. The parameters of PID controller and suggested methods are optimized by using powerful tool is called Particle Swarm Optimization (PSO) algorithm. The D.C. 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

أن استخدام الانظمة الذكية تعتبر من افضل طرق السيطرة على سرعة محركات التيار المستمر. خوارزميات السيطرة التقليدية بسيطة ومحدودة وتفشل في تقديم الاستجابة المطلوبة. في هذا البحث ، تم اقتراح الشبكات العصبية الموجيةغير المتكررة FFWNN كطريقة فعالةللسيطرة على سرعة محرك التيار المستمر ذي الاثارة التوازي. هذه الطريقة أدت الى تحسين الأداء للمحرك وتحصينه من اضطرابات الحمل. كذلك تمت مقارنتها مع الطرق التقليدية التي تستخدم المسيطرات الكلاسيكية . تم اختيار القيم

المثاليةلبارامترات 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

Generally, there is a great difference between the Direct Current(DC) motors and Alternating Current(AC) motors because direct current motors having more adaptation in speed driving than AC motors [1]. The main advantage of a DC .motors is that, the control of speed above or below rated speed is possible by a variety of simple ways. Also, with A.C.motors, a fine speed adjustment is generally impossible. The property" fine speed adjustment" basically, is an important causes for the competitive strength of D.C.motors in the new applying of industry [2-3]. This paper will be deliberated the different techniques of speed control of D.C.shunt motors.

Shunt type of D.C.motors is having a vast use because it acts in linear properties of voltage and torque. Shunt motor is having greater permanent and adjustable speed on different loads .This kind of motor is advised to be used if starting states are not cut. Speed of this motor may be controlled in three methods: the first, by adding resistance in armature circuit (Rheostatic adjustment), the second, by adding resistance in field circuit (flux adjustment), and third, by varying armature applied voltage (voltage adjustment). A best kind of speed adjustment does the D.C.motor fit for the doing in which convertible speed assorted; repeating starting, fit speed ordering, stopping and reversing are needed. The speed adjustment of D.C.machines which is aimed to carried out automatically by benefit of the progress in power electronics field. The operation of different speed drives can be accomplished by armature voltage adjustment for less than the rated speed, or by field excitation for more than rated speed. D.C. motor speed can be control to a vast expansion so as to give simple, control and great performance [4-5].

Conventional PID control is well-known used technique in speed adjustment of DC shunt motor because it is easy, fixed, and simple regulation. But in a lot of factories operations with various degree of nonlinear, adjustment PID parameters is hard, feeble, strong; so, it is hard to accomplished the ideal condition under field area in the real output[6] .The Feed Forward Wavelet Neural Network (FFWNN) ,in this paper ,is suggested with PID controller in order to produce modified controllers, that collects the ability of the artificial neural networks for learning form the DC shunt motor drive ,the ability of wavelet detachment for identification and adjustment of dynamic system ,and the capability of self-adapting and self-learning.

The accomplishment of PID controller can be put in best equality by benefit of optimization method. In this research, the parameters of the proposed PID controller and suggested intelligent approach (FFWNN-PID) are tuned by using global optimized technique and based on intelligence. This method is called Particle Swarm Optimization (PSO) method [7]. The PSO technique has algorithm for optimizing based on swarm intelligence.

2-Modeling of D.C. Shunt Motor

Direct Current machines can be divided into three types depending on the connection between field circuit and armature circuit. Shunt ,series ,compound types .The construction of a shunt machine basically is, the field is connected in parallel with the armature as drawn in Fig.(1).

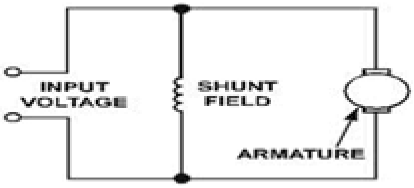


Fig.(1) D.C. Shunt Motor Diagram

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

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

3-Wavelet Neural Network (WNNs) Methods

WNNs methods are mixture between neural networks and wavelet theory. Structures of WNNs and neural network are similar. It represents a feed forward neural network (FFNN), the inputs may be one or more, hidden layer is one and output layer. The essential parts of hidden layer are called neurons; the active functions are drawn from a wavelet basis. These neurons are commonly, denoted as wavelons. The input consists of two parameters: the wavelet dilation (a) and translation (b) coefficients. In WNNs, both position (translation) and the dilation are optimized besides the weights. The structure of WNN is shown in Fig. (2). In this network, any desired signal f(t) approximates by generated an assortment of daughter wavelets $\Psi_{a,b}$ from mother wavelet Ψ as follows:

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

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

3.1 Feed ForwardWavelet Neural Network (FFWNN)

The FFWNN 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 is two forms of FFWNN as follow:

FIRST: Radial Basis Wavelet Neural Network (RBWNN)

The simplest kind of the WNN is Radial Basis Wavelet Neural Network (RBWNN) and is identical to that of radial basis neural networks (RBNN) and the wavelet function instead of radial basis function. This network FFNN has one or more inputs, one hidden layer and output layer. In this network, the weights connections are between the hidden layer and output layer only [11]. The structure of RBWNN is shown in Fig.(2). This network, any desired signal f(t) approximates by generated an assortment of daughter wavelets $\Psi_{a,b}$ from mother wavelet Ψ, where $\Psi_{a,b}$ are generated by dilation (a) and translation (b) from mother wavelet Ψ as shown in equations 7 &8[12]. The work in this search used (PSO) method to choose the best values of the network parameters w_N, a_N, and b_N.

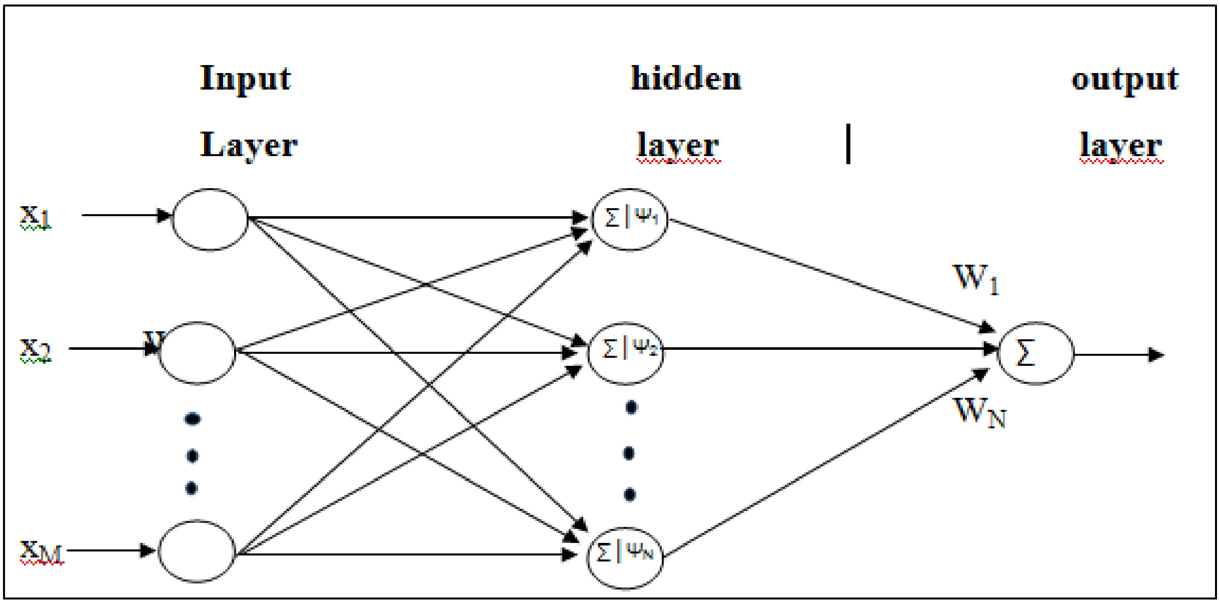


Fig.(2): The structure of RBWNN

Second- Conventional Wavelet Neural Network

The conventional WNN is an extensive form of RBWNN. In this net, the hidden layer consists of multi-layer with feed-forward network and wavelet activation function. Output layer and hidden layer contain sigmoid function and weight connection respectively[13] .The structure of the conventional WNN is shown in Fig.(3), the number of neurons and hidden layer are selected to put up a suitable wavelet neutral network and the parameters are optimized by PSO algorithm. A vector $x=[x_1,x_2,\ldots\ldots\ldots x_M]$ represents the input layer, a vector $y=[y_1,y_2,\ldots\ldots\ldots\ldots y_k]$ represents the output layer and the hidden layer include impulse function whose which that a wavelet basis function. The output y_j can be given as follow [13]:

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

Where j=1,2,3,4,………K, M, and N are the number of output layers , the number of inputs, the number of hidden layers respectively. The activation function denoted by$\sigma(u_j)$, in generality, the common form of activation function is sigmoid function which can be defined as follow [10]:

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

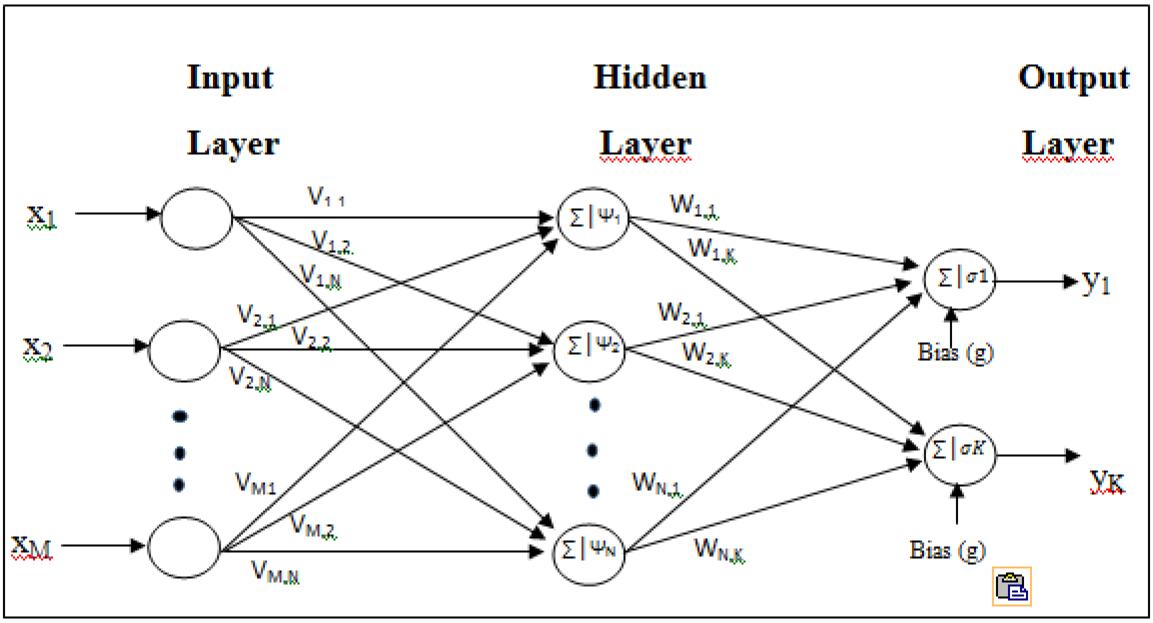


Fig.(3): Structure of conventional WNN

3-2 Recurrent Wavelet Neural Network (RWNN)

The main reasons for preferring RWNN on other methods because this method depends on previous and current inputs, also these networks are more powerful in the applications and identification of nonlinear control system [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 WNN input consist of delayed samples and the output which that denoted by x_M and y(K) respectively. The numbers of inputs are proportional with order of the system. Fig.(4) shows the structure of RWNN. Hence, the output for each layer can be computed as [14]:

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

Where a_N and b_N are the translation factors of the wavelets, respectively. Equation (12) represented input layer for n time as follow:

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

the self- feedback loop weight denoted by φ_N .The output of the network is given as follow:

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

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

Where

x:the input signal.

N :No. of neuron in the hidden layer.

W_K: output weight.

D_i&D_O :No. of delay for the input and output network.

r_N : the weight of the output feedback loop

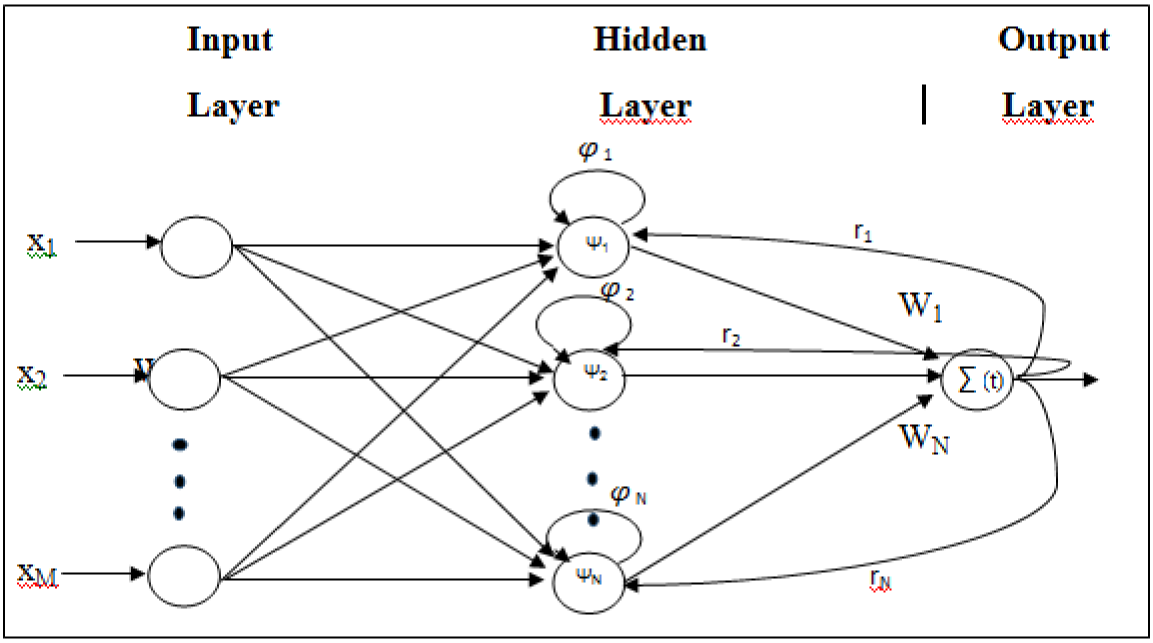


Fig.(4): The structure of RWNN

4-Particle Swarm Optimization (PSO) method

Elberhart and Kennedy in 1995 had put the (PSO) method in advanced state and it became well-known depending on the algorithm of evolutionary [16]. This state was given by the traditional conduct of swarm for fish or bird .It has been obtained to be effective in solution of problems which it needs continuous nonlinear optimization.

A search space ,in PSO technique ,consists of D-dimensional and N particles in the swarm they are moving around it. Each particle has a random velocity. The flying of every particle changes depending on its own and comrade's experience at every iteration .A $X_i = (x_{i1}, x_{i2}, \dots \dots \dots, x_{iD})$ represents the *i*th particle. $P_i = (p_{i1}, p_{i2}, \dots \dots \dots, p_{iD})$ represents best previous solution *(pbest)* of ith particle. $V_i = (v_{i1}, v_{i2}, \dots \dots \dots, v_{iD})$ portrays current velocity (position change rate) .At last, $P_g = (p_{g1}, p_{g2}, \dots \dots \dots, p_{gD})$ symbolizes to best solution accomplished by the entire swarm *(gbest)*.

Every particle, at each period, locomotes toward best solution and entire position. The suitable formula assesses movement of the particles to define whether the most excellent solution is accomplished. The particles are handled skillfully by equations (15) and (16) :

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

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

from equations (15-16) ,c_1 is positive constant ,called cognitive learning rate ,c_2 is positive constant ,called social learning rate ,and random function rand( ) in the range [0,1] .The particles have limited velocity in [V_{min},V_{max}] .The primitive expression of PSO needs mechanism of controlling on velocity, this expression has week capability to find a fin grain [17] .In 1998 , Eberhart and Shi conquer this lack by arranging factor is called time decreasing inertia [18-20].

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

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

the relation between the worldwide used and the regional used capabilities of the swarm is balanced by inertia factor w .The flow chart in Fig(5) ,displays optimizing of parameters of FOPID controller after implementation of algorithm in PSO for the given system is as follows:

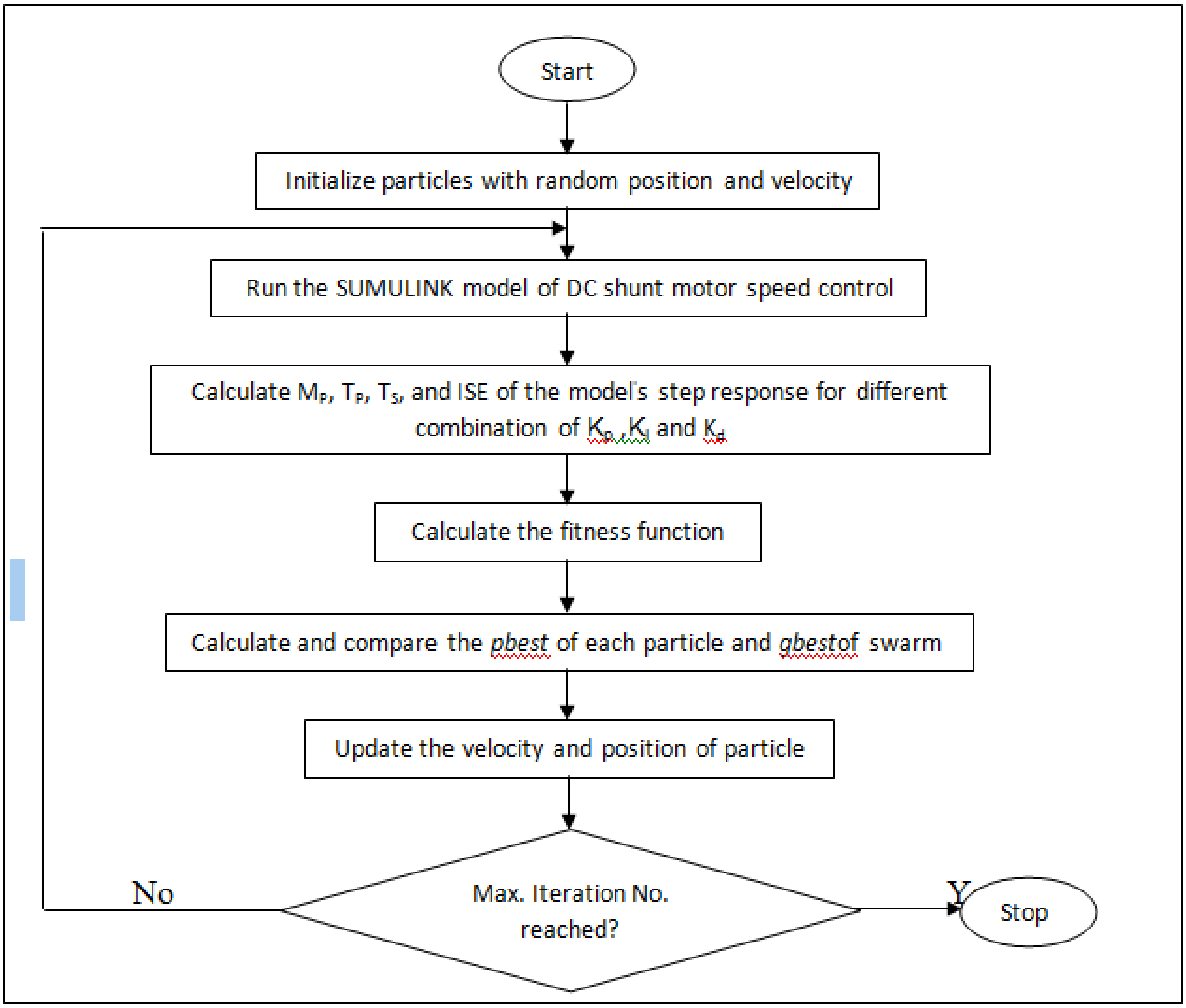


Fig.(5):Implementation of PSO in PID tuning for DC shunt motor speed control.

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
R_a	0.5	[ohm]
L_a	0.0015	[henry]
J	0.00025	[Kg.m^2/rad]
B	0.0001	[N.m. sec /rad]
K_b	0.5	[Volt sec./weber rad.]
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 using the parameters values of D.C.shunt motor in table(2),The Simulink model of D.C. shunt motor based on equations 1 and 4 has been implemented using MATLAB/SIMULINK software as shown in Fig.(6).

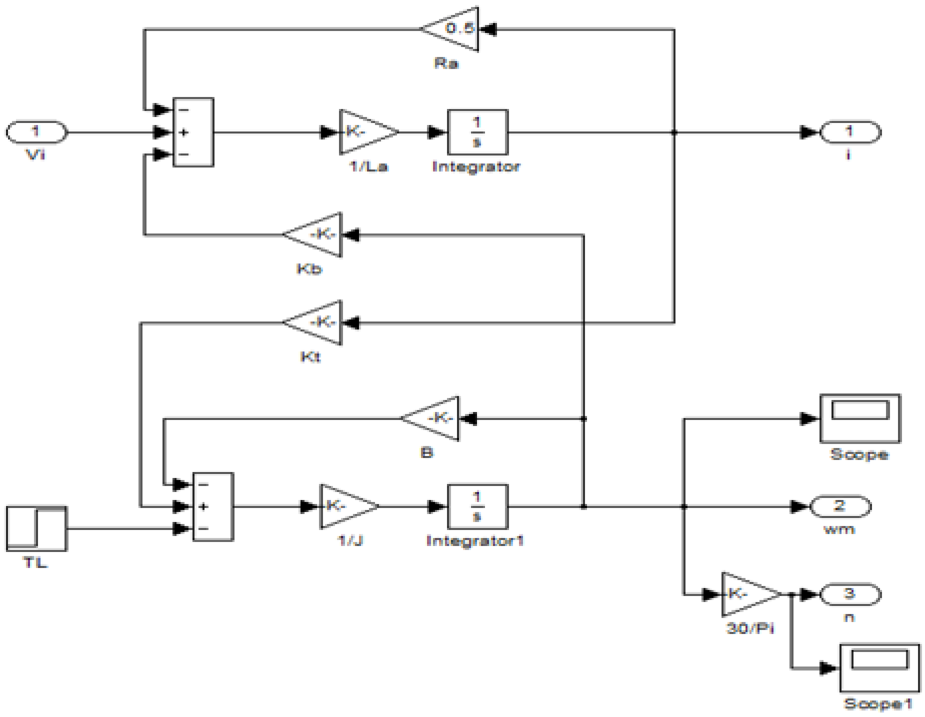


Fig. (6): Simulink model of DC shunt motor.

The response of speed of direct current 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 the reference speed is 1000 rpm.

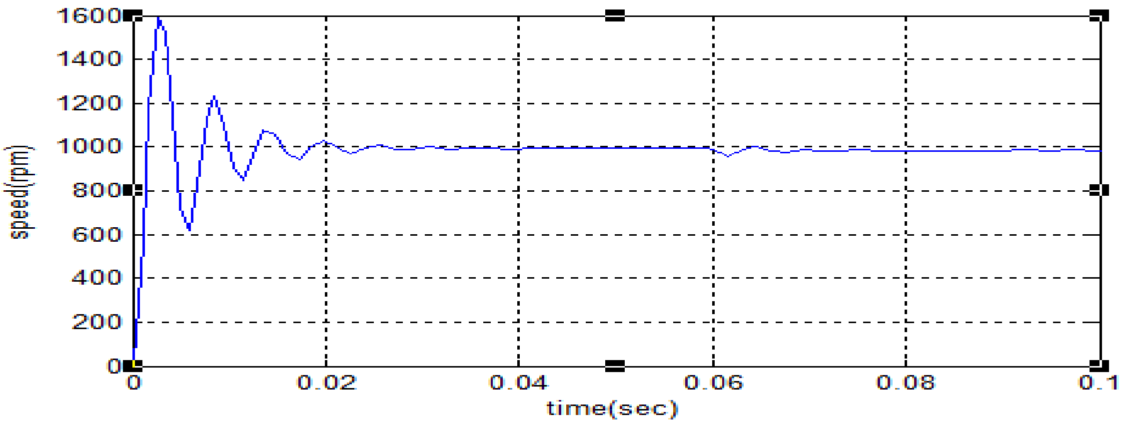
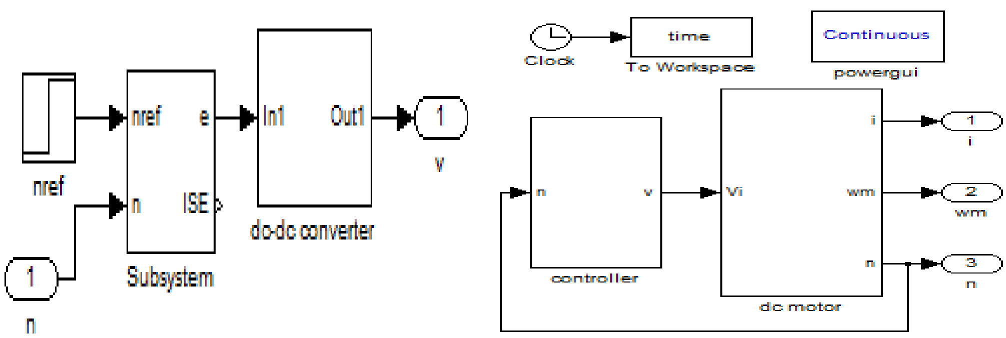


Fig.(7):The speed response of DC shunt motor without controller.

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 by obtaining minim values for overshoot, settling time, and rise time .Figure (8) shows the model of PID controller by using MATLAB program.



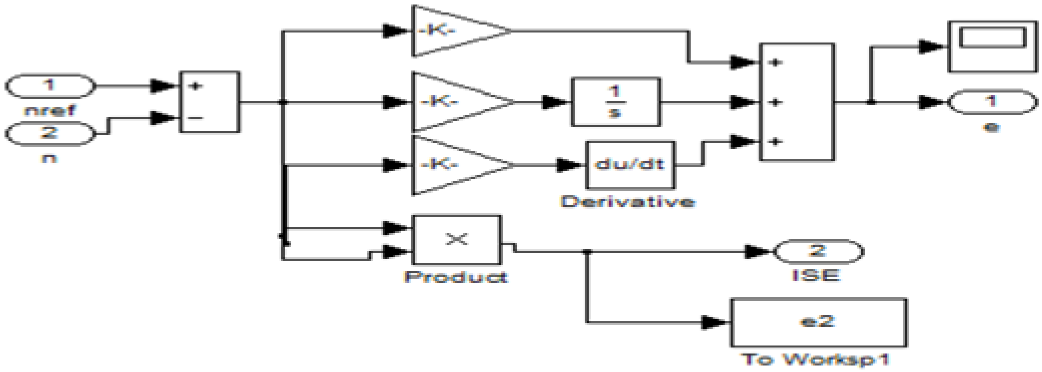


Fig. (8): PID controller by MATLAB Simulink Model

The response of speed of direct current 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

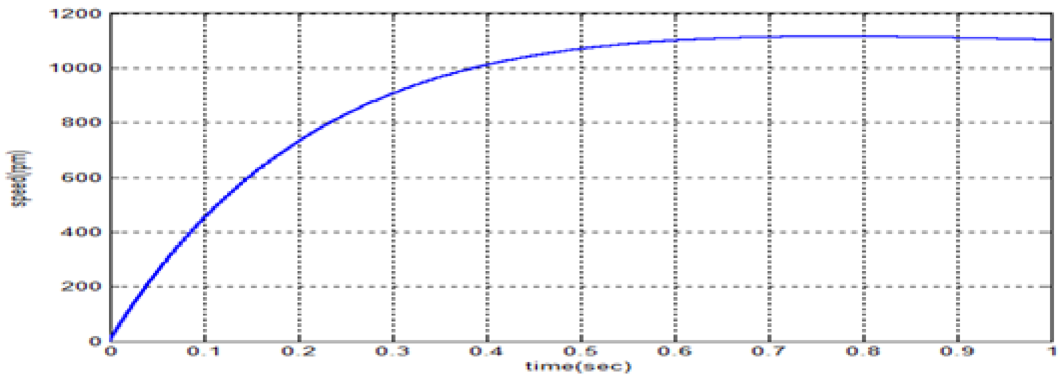


Fig. (9): The speed response of DC shunt motor with PID controller

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

In this case, by PSO algorithm and the model (dc shunt motor and controller) training, the controller parameters are tuned 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.

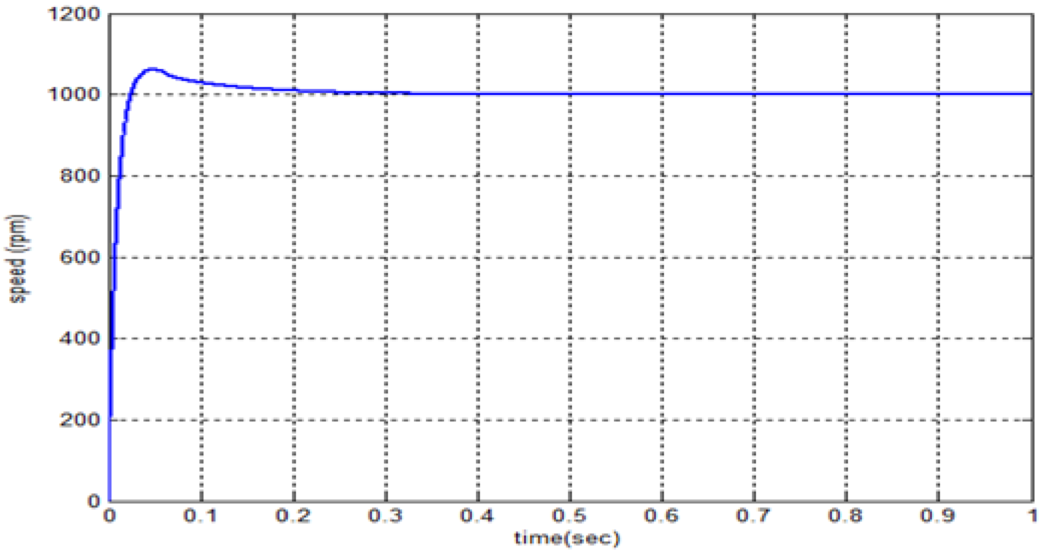
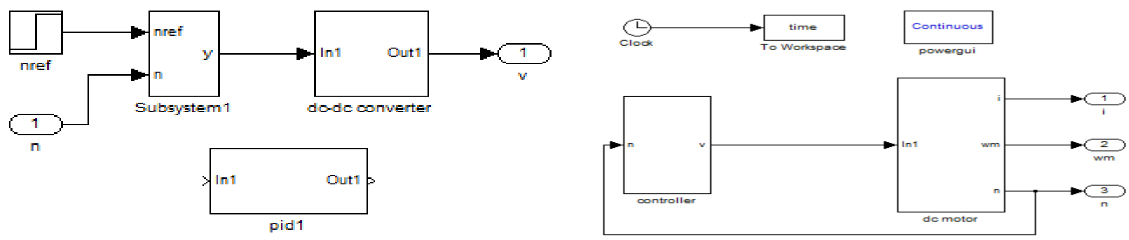


Fig. (10): The speed response of DC shunts motor with PID controller tuned by PSO.

6 -3Motor 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).



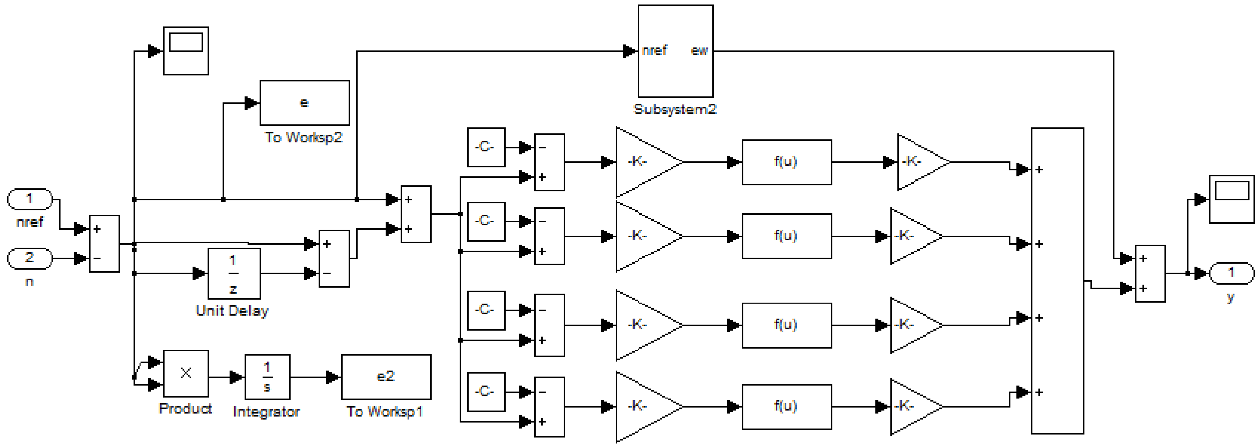


Fig.(11): FFWNN-PID method MATLAB Simulink Model

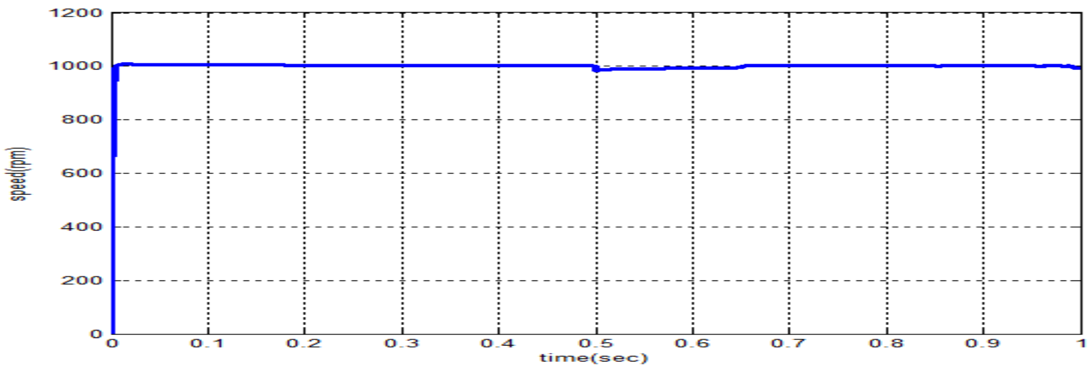


Fig.(12): The speed response of DC shunt motor with FFWNN-PID

Table(3) summarize the comparison among the methods which are used in this paper and items of performance of direct current 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

In 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, presents simulation studies on traditional method and intelligent method of controllers for FFWNN-PID with PSO. The simulation model of controller and motor was developed using MATLAB/Simulink. A PID controller is designed based on PSO algorithm and it is setting has been done for controlling on speed of direct current shunt motor. According results from the computer simulation, trough the results is found the controller with PSO is better than traditional PID without PSO algorithm. Also 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 using of PSO algorithm is achieved greatly succeeding in optimization of the (FFWNN-PID) parameters. Finally, the suggested method shows optimal results of direct current shunt model for controlling on its speed compared with anther methods.

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