ANN - Control System DC Motor

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***Abstract*—This paper introduces the new ability of Artificial Neural Networks (ANNs) in estimating speed and controlling the separately excited DC motor. The neural control scheme consists of two parts. One is the neural estimator which is used to estimate the motor speed. The other is the neural controller which is used to generate a control signal for a converter. These two neurals are training by Levenberg-Marquardt back-propagation algorithm. ANNs are the standard three layers feed-forward neural network with sigmoid activation functions in the input and hidden layers and purelin in the output layer. Simulation result are presented to demonstrate the effectiveness of this neural and advantage of the control system DC motor with ANNs in comparison with the conventional scheme without ANNs.**

Keywords:DC motor, artifical neural networks, control system.

I. INTRODUCTION

Nowadays, the field of electrical power system control in general, and motor control in particular have been researching broadly. The new technologies are applied to these in order to design the complicated technology system. One of these new technologies is Artificial Neural Networks (ANNs) which base on the operating principle of human being nerve neural.

There are a number of articles that use ANNs applications to identify the mathematical DC motor model. And then this model is applied to control the motor speed [1]. They also uses inverting forward ANN with two input parameters for adaptive control of DC motor [4].

However, these researches were not interested in the ability of forecasting and estimating the DC motor speed.

ANNs are applied broadly because of the following special qualities:

1. All the ANN signals are transmitted in one direction, the same as in automatically control system.
2. The ability of ANNs to learn the sample.
3. The ability to creating the parallel signals in Analog as well as in the discrete system.
4. The adaptive ability.

With the special qualities mentioned above, ANNs can be trained to display the nonlinear relationships that the conventional tools could not implemented. It also is applied to control complicated electro- mechanic system such as DC motor and synchronous machines [5].

To train ANNs, we have to determine the input and output datasheets first, and then design the ANNs net by optimizing the number of hidden layers, the number of neural of each layer as well as the input/output number and the transfer function. The following is to find the ANNs net learning algorithm.

ANNs are trained relying on two basic principal: supervisor and unsupervisor. According to supervisor, ANNs learn the input/ output data (targets) before being used in the control system.

In this paper, the author would like to present the new ANNs application in speed estimating and controlling separately excited DC motor. The motor speed is controlled by forecasting method and forecasting task which ANNs undertake from the terminal voltage parameter, armature current and a reference speed.

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II. DC MOTOR CONTROL MODEL WITH ANNS

The DC motor is the obvious proving ground for advanced control algorithms in electric drives due to the stable and straight forward characteristics associated with it. It is also ideally suited for trajectory control applications as shown in reference [1-3]. From a control systems point of view, the DC motor can be considered as SISO plant, thereby eliminating the complications associated with a multi-input drive system.

A. *Matematical model of DC motor*

The separately excited DC motor is described by the following equations:

$$KF\omega_p(t) = -R_a i_a(t) - L_a[di_a(t)/dt] + V_t(t) \quad (1)$$

$$KFi_a(t) = J[d\omega_p(t)/dt] + B\omega_p(t) + T_L(t) \quad (2)$$

where,

$\omega_p(t)$ - rotor speed (rad/s)

$V_t(t)$ - terminal voltage (V)

$i_a(t)$ - armature current (A)

$T_L(t)$ - load torque (Nm)

J - rotor inertia (Nm^2)

KF - torque & back emf constant (NmA^{-1})

B - viscous friction coefficient (Nms)

R_a - armature resistance (Ω)

L_a - armature inductance (H)

From these equations we can create mathematical model of the DC motor. The model is presented in Figure1.

Where,

T_a -Time constant of motor armature circuit and T_a=L_a/R_a (s)

T_m – Mechanical time constant of the motor T_m=J/B (s)

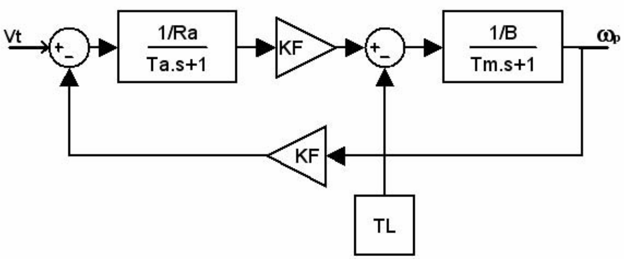

Figure 1. The mathematical model of a separately DC motor

B. The conventional control systems of DC motor

There are different methods to synthesize a control systems of DC motor, but for a comparison with method used ANNs authors presented a conventional control system of DC motor, where the regulator current and regulator speed are synthesized by Bietrage-optimum to reduce the over-regulation [6].

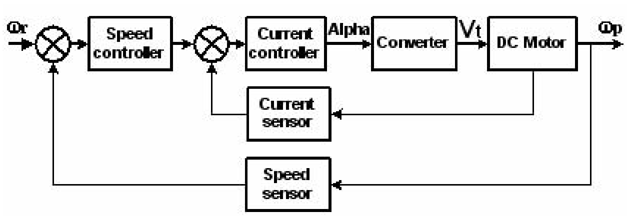

Figure 2. Conventional model of control system DC motors

In the conventional model current and voltage sensors are very important elements and they are a main role during regulation of speed alongside with regulator current and regulator speed.

C. The control system of DC motor using ANNs

The control system of DC motor using ANNs is presented in the Figure3, where ANN1, ANN2 are trained to emulate a function: ANN 1 to estimate the speed, ANN2 to control terminal voltage.

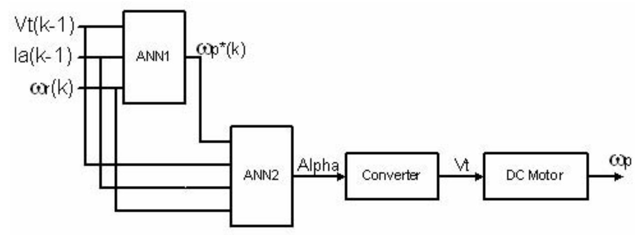

Figure 3. DC motor control model with ANNs

D. The structure and the process of learning ANNs.

ANNs have been found to be effective systems for learning discriminates for patterns from a body of examples [5]. Activation signals of nodes in one layer are transmitted to the next layer are through links which either attenuate or amplify the signal.

An ANNs are trained to emulate a function by presenting it with a representative set of input/output functional patterns. The back-propagation training technique adjusts the weights in all connecting links and thresholds in the nodes so that the difference between the actual output and target output are minimized for all given training patterns [1].

In designing and training an ANN to emulate a function, the only fixed parameters are the number of inputs and outputs to the ANN, which are based on the input/output variables of the function. It is also widely accepted that maximum of two hidden layers are sufficient to learn any arbitrary nonlinearity [4]. However, the number of hidden neurons and the values of learning parameters, which are equally critical for satisfactory learning, are not supported by such well established selection criteria. The choice is usually based on experience. The ultimate objective is to find a combination of parameters which gives a total error of required tolerance a reasonable number of training sweeps [1,2,3].

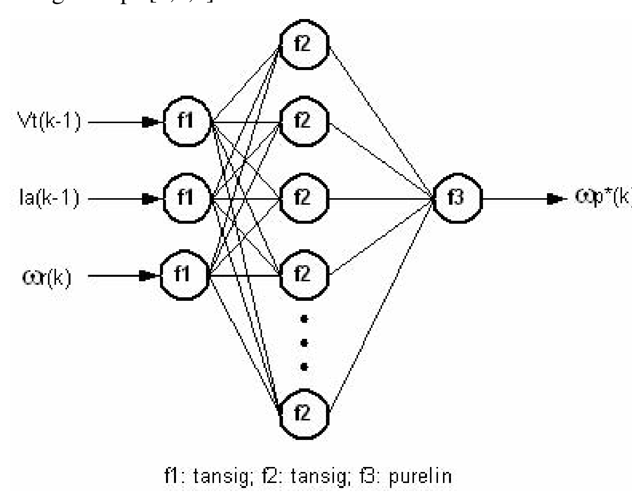

Figure 4. Structure of ANN1

The ANN1 and ANN2 structure is shown in Figure4, and Figure5. It consists of an input layer, output layer and one hidden layer. The input and hidden layers are tansig-sigmoid activation functions, while the output layer is a linear function.

Three inputs of ANN1 are a reference speed $\omega_r(k)$, a terminal voltage $V_t(k-1)$ and an armature current $i_a(k-1)$. And output of ANN1 is an estimated speed $\omega_{p*}(k)$.

The ANN2 has four inputs: reference speed $\omega_r(k)$, a terminal voltage $V_t(k-1)$, an armature current $i_a(k-1)$ and an estimated speed $\omega_{p*}(k)$ from ANN1. The output of ANN2 is the control signal for converter Alpha.

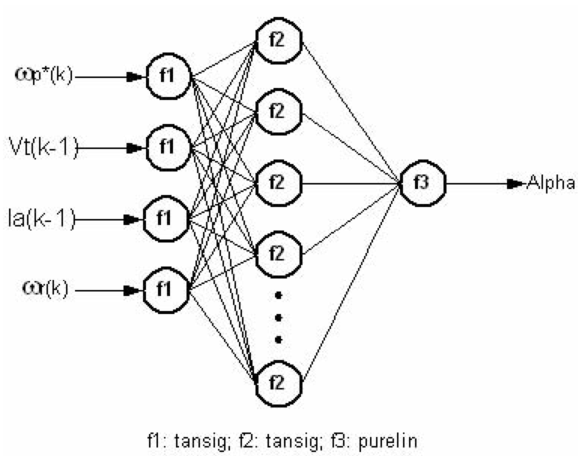

Figure 5. Structure of ANN2

The ANNs are trained off-line using inputs patterns of $\omega_r(k),V_t(k),i_a(k)$ - for ANN1, and of $\omega_r(k),V_t(k),i_a(k),\omega_{p*}(k)$ – for ANN2. The reference speed – training data $\omega_r(k)$ is shown in Figure 6. Other inputs patterns are taken from actual hardware and the corresponding output target is shown in Figure 7.

The motor speed is estimated by the trained ANN predictor as :

For ANN1 $\quad \omega_{p*}(k) = f[\omega_r(k),V_t(k-1),i_a(k-1)] \quad (3)$

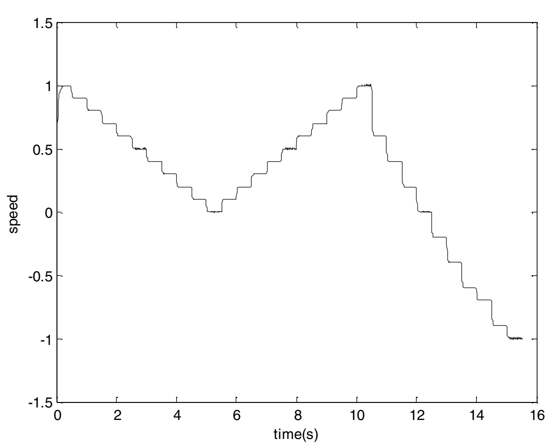

Figure 6. The Reference speed DC motor

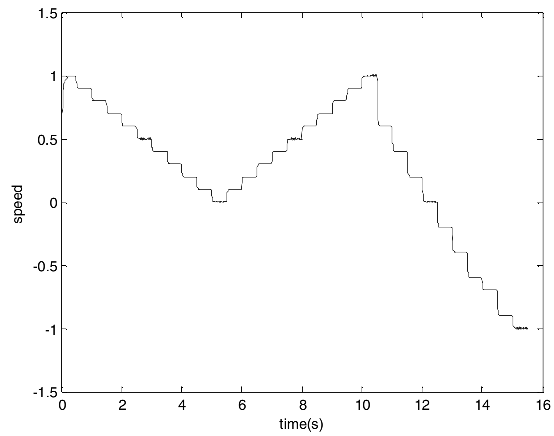

Figure 7. The target speed DC motor

For ANN2 $\quad Alpha = f[\omega_r(k),V_t(k-1),i_a(k-1),\omega_{p*}(k)] \quad (4)$

The training program of ANN1 and ANN2 are written in the Neural Network of Matlab program under m-file and it uses the Levenberg – Marquardt back propagation. There is no any reference that mention to the optimal number of neural in each layer, so collecting the neural networks becomes more complicated.

In order to choose the optimal number of neural, the neural network is trained by m-file program, reducing the number of neural in ANNs hidden layer until the learning error can be accepted.

The ANNs and the training effort are briefly described by the following statistics.

TABLE 1 THE RESULTS OF THE ANN TRAINING

Network	ANN1	ANN2
Number of input	3	4
Number of output	1	1
Number of hidden layer	1	1
Number of hidden neurons	3	4
Number of training patterns	1215	1215
Number of training sweeps	5000	5000
Learning error	1e-7	1e-8

III. SIMULATION OF CONTROL SYSTEMS DC MOTOR

To simulation the conventional control system and control system with ANNs we used A Simulink/Matlab program the toolbox of Neural-network. The DC motor , which is used in models has the follows parameter 5HP, 240V, 1750 RPM, field 150V, J=0.02215 Nm^2, KF=1.976 NmA^{-1}, B=0.002953 Nms, R_a=11,2 Ω, L_a=0.1215 H.

To compare the quality of two control systems we consider different operating modes of the DC motor:

a) When parameters of the DC motor are constant.

The start of DC motor and regulation of DC motor speed for two models of control systems is shown in Figure 7,8,9,10. The results show that both models have a good performance and the control quality is same for two models.

2) When parameters of the DC motor are not constant.

Figures 11,12,13 show a start of the DC motor for conventional model and model with ANNs when mechanical time constant of the motor reduces and gives : $T_{m1}=75\%T_m$; $T_{m2}=50\%T_m$; $T_{m3}=30\%T_m$. Where T_m is the mechanical time constant of the motor when parameters of the DC motor are constant.

Figures 14,16 show a regulation of speed for conventional model when $T_{m2}=50\%T_m$; $T_{m3}=30\%T_m$. Figures 15,17 show a regulation of speed for model with ANNs when $T_{m2}=50\%T_m$; $T_{m3}=30\%T_m$. Obviously, that model with ANNs has the better performance when T_m is variation. Thus, in the conventional model a speed of the DC motor is fluctuating and the system may be instability.

IV. THE SIMULATING RESULTS

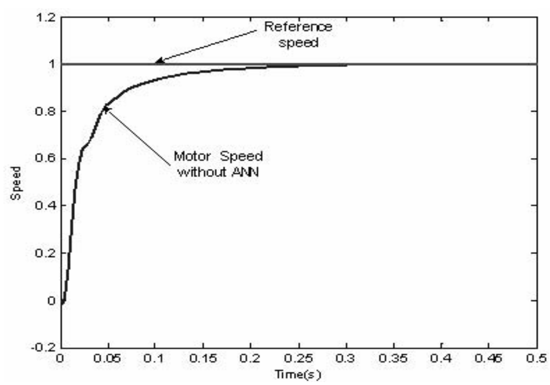

Figure 8. Starting the DC motor – Conventional model

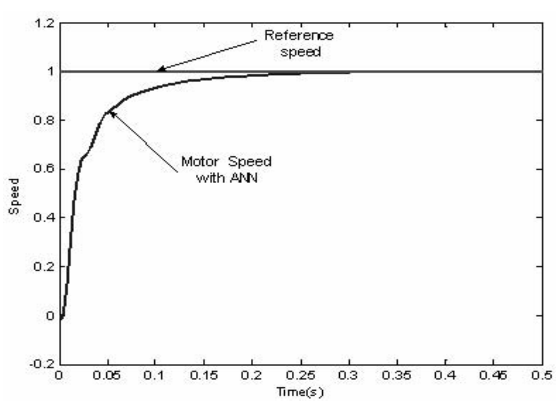

Figure 9. Starting the DC motor – Model with ANNs

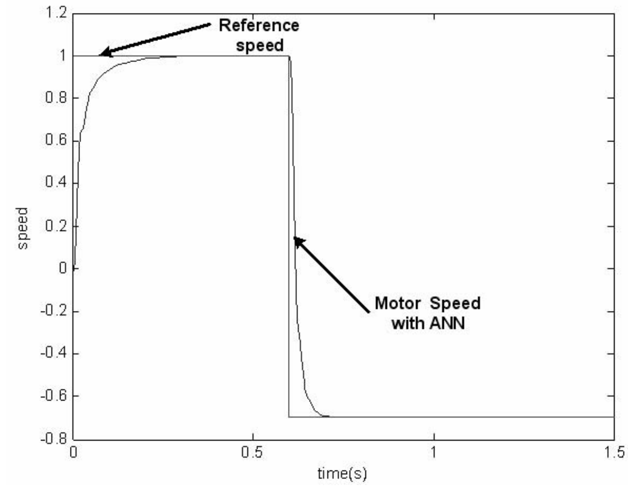

Figure 10. Reverse the DC – motor with ANNs

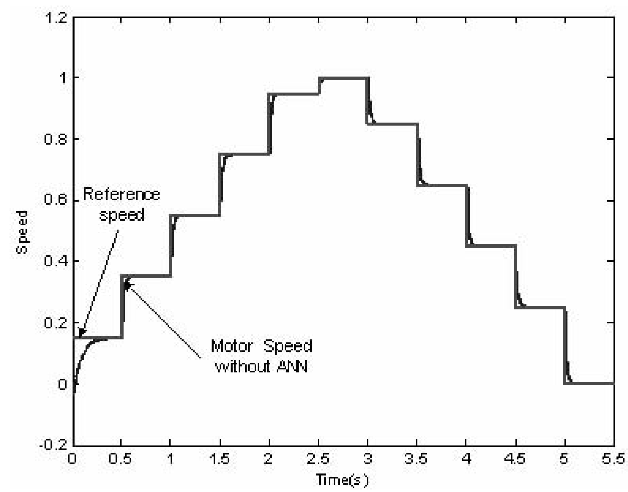

Figure 11. Regulation of DC motor speed - Conventional model

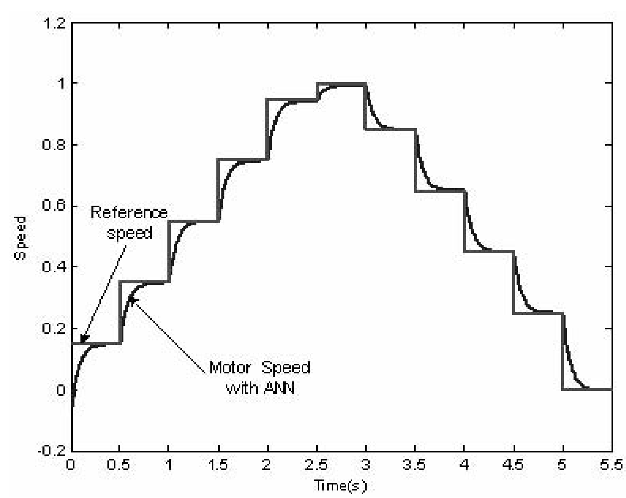

Figure 12. Regulation of DC motor speed – Model with ANNs

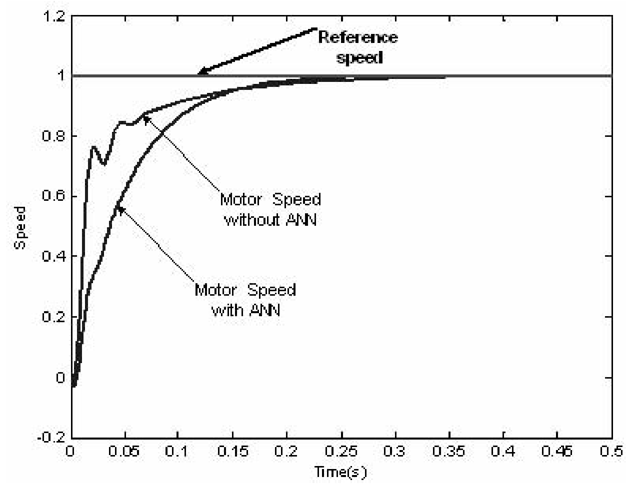

Figure 13. Starting the DC motor. $T_{m1}=75\%T_m$

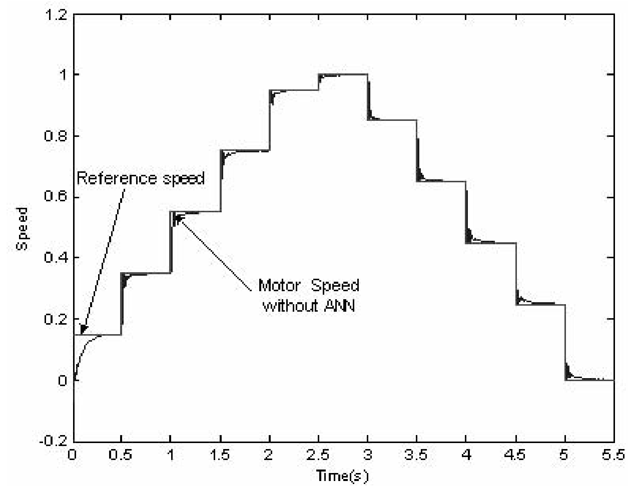

Figure 16. Regulation of DC motor speed - Conventional model. $T_{m2}=50\%T_m$

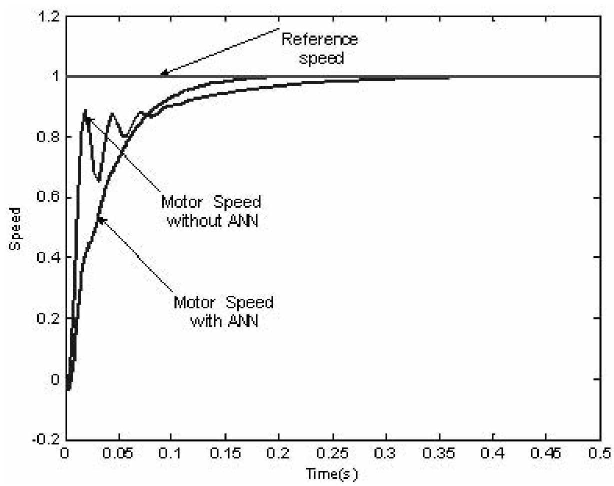

Figure 14. Starting the DC motor. $T_{m2}=50\%T_m$

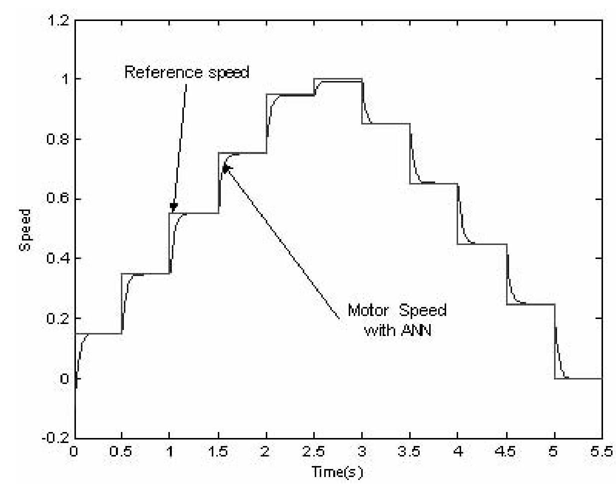

Figure 17. Regulation of DC motor speed – Model with ANNs. $T_{m2}=50\%T_m$

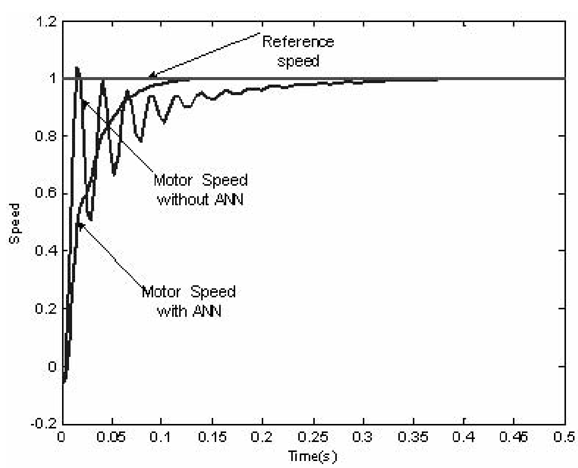

Figure 15. Starting the DC motor.$T_{m3}=30\%T_m$

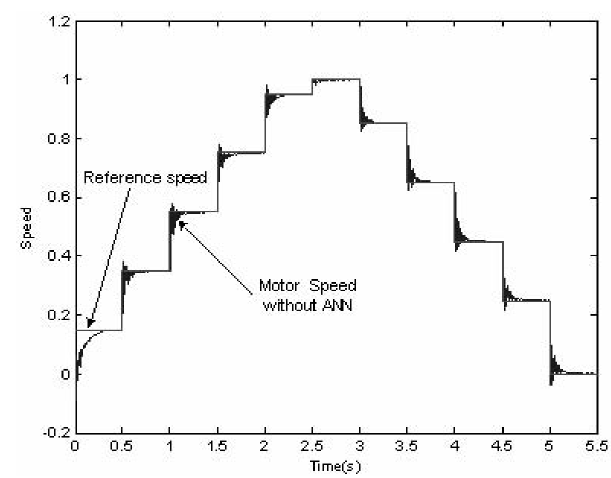

Figure 18. Regulation of DC motor speed - Conventional model.$T_{m3}=30\%T_m$

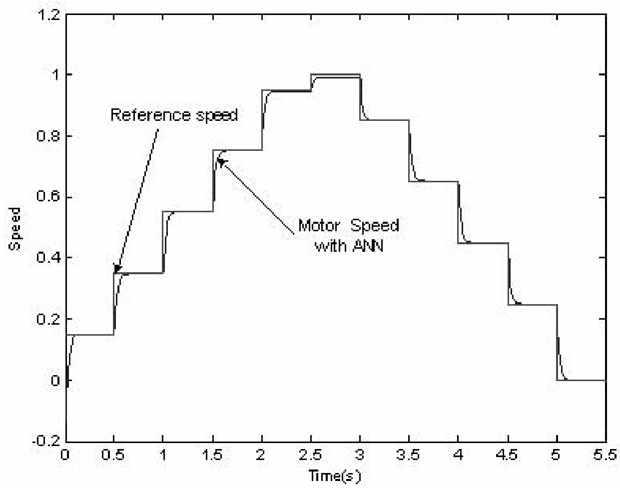

Figure 19. Regulation of DC motor speed – Model with ANNs.T_{m3}=30%T_m.

V. Conclusion

The DC motor has been successfully controlled using an ANN. Two ANNs are trained to emulate functions: estimating the speed of DC motor and controlling the DC motor, Therefore , and so ANN can replace sensors speed in the model of the control systems. Using ANN, we don't have to calculate the parameters of the motor when designing the system control.

It is shown an appreciable advantage of control system using ANNs above the conventional one, when parameters of the DC motor is variable during the operation of the motors. The satisfied ability of the system control with ANNs is much better than the conventional system control. ANN application can be used in adaptive controlling in the control system machine with complicated load. Nowadays, in order to implement the control systems using ANNs for DC motor on actual hardware, the ANN micro processor is being used.

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