تصميم وتمثيل مسيطر ضبابي- مويجي - عصبي لانظمة الفولتية الاوتوماتيكية

Design and Simulation of Adaptive Fuzzy Wavelet Network Controller For Automatic Voltage Regulator System

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Abstract

In recent years the world was directed towards the intelligent control technique. It is well known that the intelligent control techniques are powerful tools for handling problems of large dimensions. The integration of fuzzy logic, wavelet transform and artificial neural networks theories enable a tool condition monitoring system to have a high monitoring success rate and fast response. An Auto Tuning Adaptive Fuzzy Neural Wavelet Network (ATAFNWN) controller is proposed. To overcome offline learning and to perform efficient tracking behavior for the Automatic voltage regulator system (AVR). The simulation results are compared with another controller to prove the controller efficiency with this plant

الملخص

أتجه العالم في السنوات الاخيره باتجاه تقنيات السيطرة الذكية . ومن المعروف بأن السيطرة الذكية هي اداه جيده لحل المشاكل ذات الابعاد الكبيرة . التكامل بين الانظمة الضبابيه الغامضه وتحويلات المويجة والشبكات العصبية انتج انظمة متابعة عالية وذات استجابة عالية وقد تم تحضير مسيطر ضبابي-عصبي ذو المتغيرات التلقائية (ATAFNWN) لتجاوز مشكلة التعليم (offline) ولحصول على متابعة كفوءة لنظام الفولتية الاوتوماتيكي (AVR) وقد تم مقارنه الاستجابه الحاصله من هذا المسيطر مع مسيطرات اخرى واوضحت المقارنة كفاءة المسيطر المقترح .

1- Introduction

In recent years, controller design for systems having complex nonlinear dynamics becomes an important and challenging topic. Many remarkable results in this area have been obtained owing to the advances in geometric nonlinear control theory, and in particular, feedback linearization techniques [1]. Fuzzy controllers are used to control consumer products, such as washing machines, video cameras, and rice cookers, as well as industrial processes, such as cement kilns, underground trains, and robots. Fuzzy control is a control method based on fuzzy logic. Just as fuzzy logic can be described simply as computing with words rather than numbers", fuzzy control can be described simply as control with sentences rather than equations [2]. Fuzzy Wavelet Network (FWN) is based on the integration of fuzzy logic, wavelet transform and artificial neural networks theories. This new schemes give an ability of self learning and self organizing, it can merge these techniques within the same system. It is shown here that it is possible to train WN learning and interpret the knowledge that is acquired from linguistic form, as well as it is very easy to define the initial values of parameters in WN form linguistic rules [1].This paper is organized to, after introduction, the AVR system and controller types are explained , finally the simulation result with (ATAFNWN) controller is tested.

2- Automatic Voltage Regulator (AVR) System

The basic work of an AVR is to hold the output terminal voltage magnitude of a synchronous generator at a limited level. Generally the A VR system consist of four main components, namely(Amplifier, Exciter, Generator, and Sensor). For mathematical modeling and transfer function of the four components, these components must be linearized , which takes into account the major time constant and ignores the saturation or other nonlinearities [3,4].The generator excitation system maintains generator voltage and controls the reactive power flow using an automatic voltage regulator (AVR). The role of an AVR is to hold the terminal voltage magnitude of a synchronous generator at a specified level. Hence, the stability of the AVR system would seriously affect the security of the power system [5,6]. The following model in Figure (1) provides an AVR compensated system

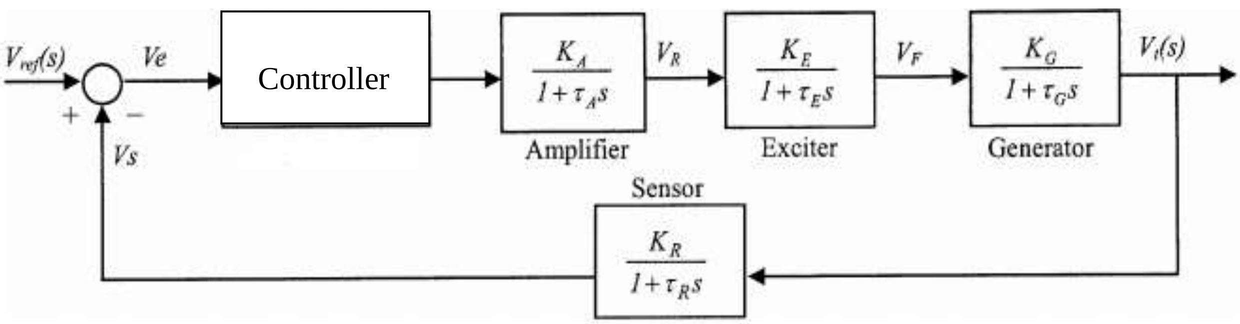

Figure (1): Block diagram of an AVR system with controller.

The reasonable transfer function of these components may be represented, respectively, as follows [5,6].

-Amplifier model.

The amplifier model is represented by a gain K_A and a time constant τ_A the transfer function is:

$$\frac{V_R(s)}{V_e(s)} = \frac{K_A}{1+\tau_A s}.$$

Typical values of K_A are in the range of 10 to 400. The amplifier time constant is very small ranging from 0.02 to 0.1 s.

- Exciter model.

The transfer function of a modern exciter may be represented by a gain K_E and a single time constant

Typical values of K_E are in the rang

$$\frac{V_F(s)}{V_R(s)} = \frac{K_E}{1+\tau_E s}.$$

constant is in the range of 0.5 to 1.0 s.[5]

-Generator model.

In the linearized model, the transfer function relating the generator terminal voltage to its field voltage can be represented by a gain K_G and a time constant τ_G .

These constants are load dependen

$$\frac{V_t(s)}{V_F(s)} = \frac{K_G}{1+\tau_G s}.$$

0.7 to 1.0, and τ_G between 1.0 and 2.0 s from full load to no load.

-Sensor model.
The sensor is modeled by a simple first-order transfer function, given by

$$\frac{V_s(s)}{V_t(s)} = \frac{K_R}{1+\tau_R s}.$$

τ_R is very small, ranging from of 0.001 to 0.06 s [6]
In general, the controller design method using the integrated absolute error (IAE), or the integral of squared-error (ISE), or the integrated of time-weighted-squared-error (ITSE) is often employed in control system design because it can be evaluated analytically in the frequency domain [7]. The three integral performance criteria in the frequency domain have their own advantages and disadvantages. For example, a disadvantage of the IAE and ISE criteria is that its minimization can result in a response with relatively small overshoot but a long settling time because the ISE performance criterion weights all errors equally independent of time. Although the ITSE performance criterion can overcome the disadvantage of the ISE criterion, the derivation processes of the analytical formula are complex and time consuming [5].

3-Wavelet Neural Network [1]

In this section a new type of fuzzy wavelet-based model will be proposed, called adaptive fuzzy wavelet networks (AFWN) is presented; the main block diagram of this proposed Fuzzy Wavelet Network FWN is given in Figure (2). This structure introduces a multi input multi output MIMO function approximator model. It consists of four layers namely: the input layer, Fuzzification layer, rule layer and defuzzification layer.

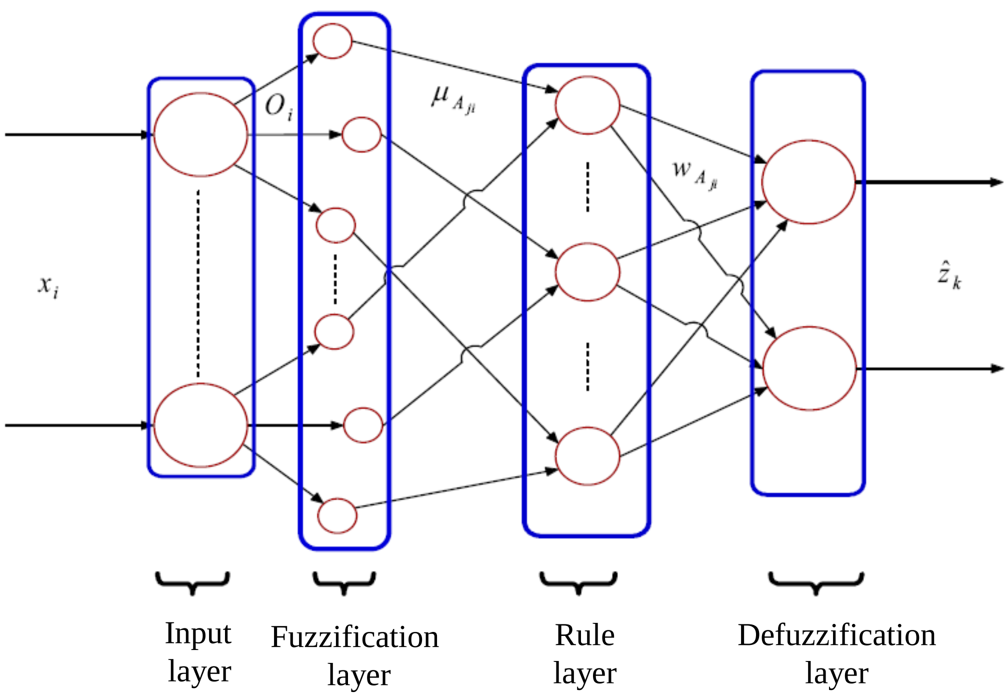

Figure (2): Structure of Fuzzy Wavelet Networks

The computation of the AFWN is illustrated in the following steps:

Step One: The Fuzzification Setup: In this step it is necessary to build the Fuzzification membership through the following procedure.

a) The input to the structure, input layer, is x_i and its outputs o_i will be given to the Fuzzification layer

$$o_i = x_i, \qquad i = 1,2,\dots,N$$

where N is the number of inputs.

b) For each fuzzy term A_{ji} in *jth* rule, associated with *ith* input o_i , the membership μ_{Aji} is

$$\mu_{A_{ji}}(t) = x_i(t).\psi_{a_{ji},b_{ji}}(t)$$

The previous structure of wavelet Network (WN) is extended to be used here as a membership function by translating and dilating the mother wavelet basis function to build up Fuzzification layer. It is shown that a set of 10 to 40 Wavelet basis functions memberships is required for its success [1].

Step Two: Selection of Implicator Rule: This requires setting of the implicators rules that are necessary for convergence of the network. The number of implicators used here is equal to the number of memberships, which use minimum operation implicator.

Step Three: The Defuzzification Setup: The fourth layer in AFWN is the output layer, which realizes using:

$$\hat{z}_k = \sum_{j=1}^{J} w_{jk}\, y_j$$

to produce crisp output value.

Step Four: The Learning Algorithm of the Proposed AFWN: The gradient descent algorithms for tuning the parameters, dilations a_{ji} , translations b_{ji} and weights w_{jk} of the AFWN is used to modify (update) only the gene that activates (or is firing) specific rule. First the following *cost function (E)* for this case was used:

$$E = \frac{1}{2K}\sum_{t=1}^{T}\sum_{k=1}^{K}(\hat{z}_k(t) - z_k(t))^2$$

where $z(t)$ is the k_{th} desired output, $\hat{z}_k(t)$ k is the k_{th} approximated output of FWN, K is the number of output signals and T is the length of the output signal. The training algorithm, which is extended from WN training algorithm is used to update the parameters of FWN, dilations a_{ji} , translations b_{ji} and weights w_{jk} , such as to minimize the cost function *(E)*. Thus the FWN weights can be updated using the following equations:

$$w_{jk}(k+1) = w_{jk}(k) - \eta_1 \frac{\partial E}{\partial w_{jk}},$$

$$a_{ji}(k+1) = a_{ji}(k) - \eta_2 \frac{\partial E}{\partial a_{ji}},$$

$$b_{ji}(k+1) = b_{ji}(k) - \eta_3 \frac{\partial E}{\partial b_{ji}},$$

where:

$$\frac{\partial E}{\partial w_{jk}} = -\sum_{t=1}^{T} e(t)\psi(\tau)o_i(t),$$

$$\frac{\partial E}{\partial b_{ji}} = -\sum_{t=1}^{T} e(t)o_i w_{jk} \frac{\partial \psi(\tau)}{\partial b_{ji}},$$

$$\frac{\partial E}{\partial a_{ji}} = -\sum_{t=1}^{T} e(t)o_i w_{jk} \tau \frac{\partial \psi(\tau)}{\partial b_{ji}} = \tau \frac{\partial E}{\partial b_{ji}},$$

where:

$$\tau = \frac{t - b_{ji}}{a_{ji}}$$

i is the input indicator, *j* is the rule indicator, *k* is the output indicator, μ_A is the membership function which is here considered as the mother wavelet basis function and o_i is the output of the input layer [1].

4- Neural Network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network. [10]

Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. Figure (3) show the basic configuration of ANN

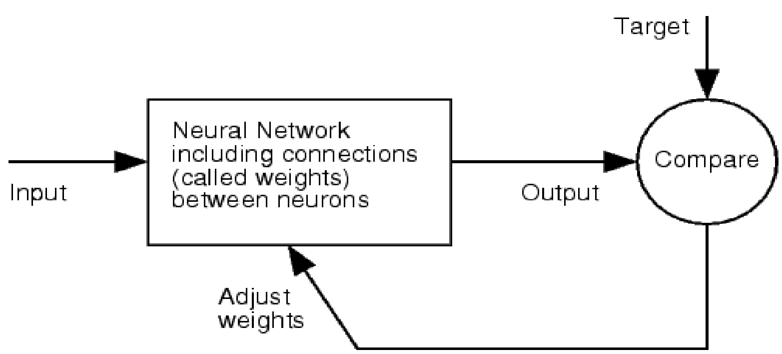

Figure (3) : The basic configuration of ANN

5-Fuzzy Logic Controller [10]

Figure (4) shows the block diagram of a typical fuzzy logic controller (FLC) , and the system plant as it is shown .

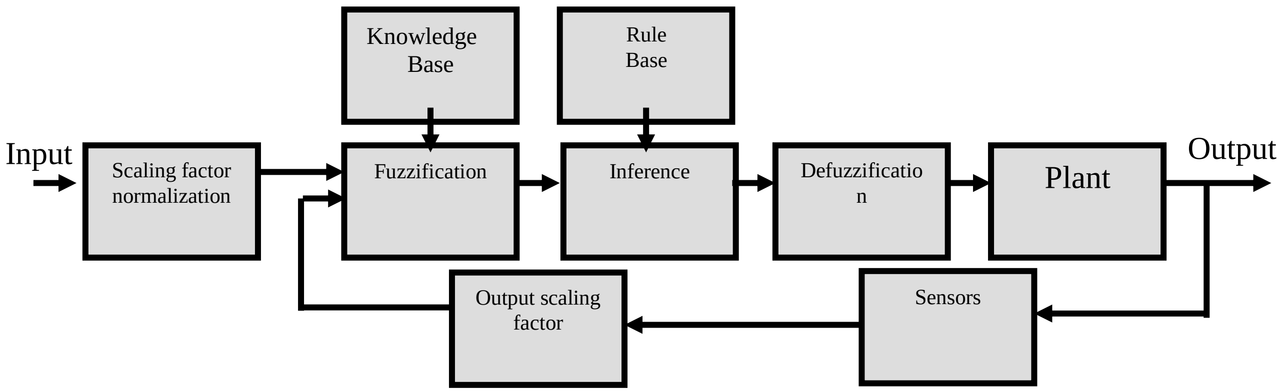

Figure (4) Block diagram of a typical fuzzy logic controller [7]

The fuzzy logic controller consists of:
- Fuzzification (fuzzifier): Change crisp value to linguistic variable .
-Knowledge base: Provides all the necessary definitions for the Fuzzification process .
- Rule base: It is usually obtained from expert knowledge.
- Inference engine: select the firing rules
- Defuzzification: Change linguistic variable to crisp value

6- Simulation Results

In this section, the complete system is tested under different type of controller.The simulation results showed that the intelligent controller provides an improvement in the responses of the system. The effect of the new controller can be realized from decrement of steady state error (e_{ss}), setting time(t_s), rise time (t_r), and integral of squared error (ISE). To verify the efficiency of the AFWN controller, a practical high-order AVR system was tested. The block diagram of the AVR system with a controller is shown in Figure (1). In order to emphasize the advantages of the proposed controller, the comparison with simulation result from [5] with the same parameters of AVR is done . from [5] the Particle Swarm Optimization method is used to tune PID parameters to produce (PSO-PID) controller and the Genetic Algorithms is used also to tune PID parameters to implement (GA-PID) controller are implemented and simulated. Finally the comparison of the characteristics of the three controllers using the same evaluation function and individual definition is shown in table (2)
Figure (5) shows the original terminal voltage step response of the AVR system without a controller.

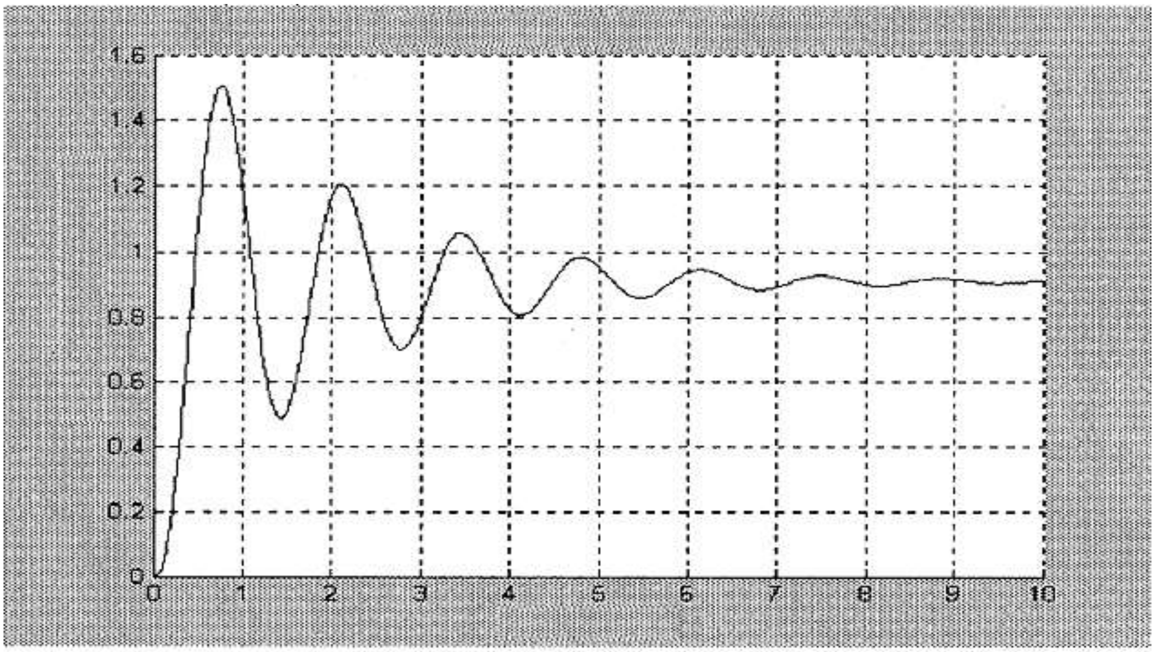

Fig.(5): The original terminal voltage step response of the AVR system without a controller.

Figure (6) show the simulation result for the AVR system with Particle Swarm Optimization. The good enhancement appears when using this controller as shown bellow. Also the Genetic algorithm (GA) is used to tune the PID controller to enhance the output response as shown in figure (7).

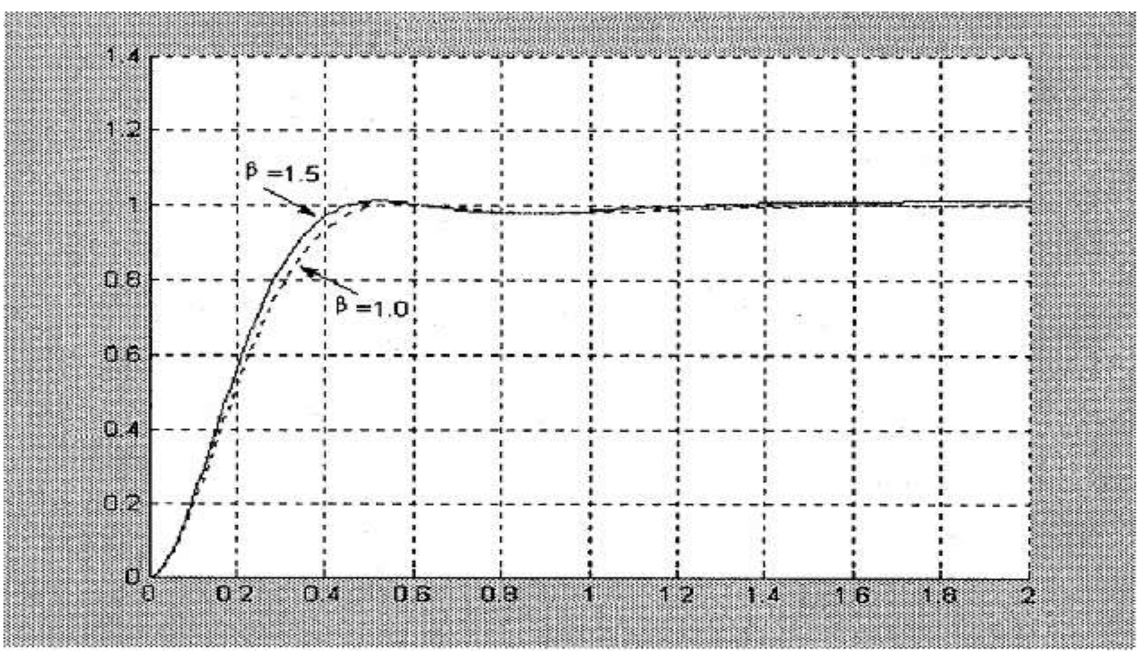

Figure (6):Terminal voltage step response of an AVR with PSO controller for different β[5]

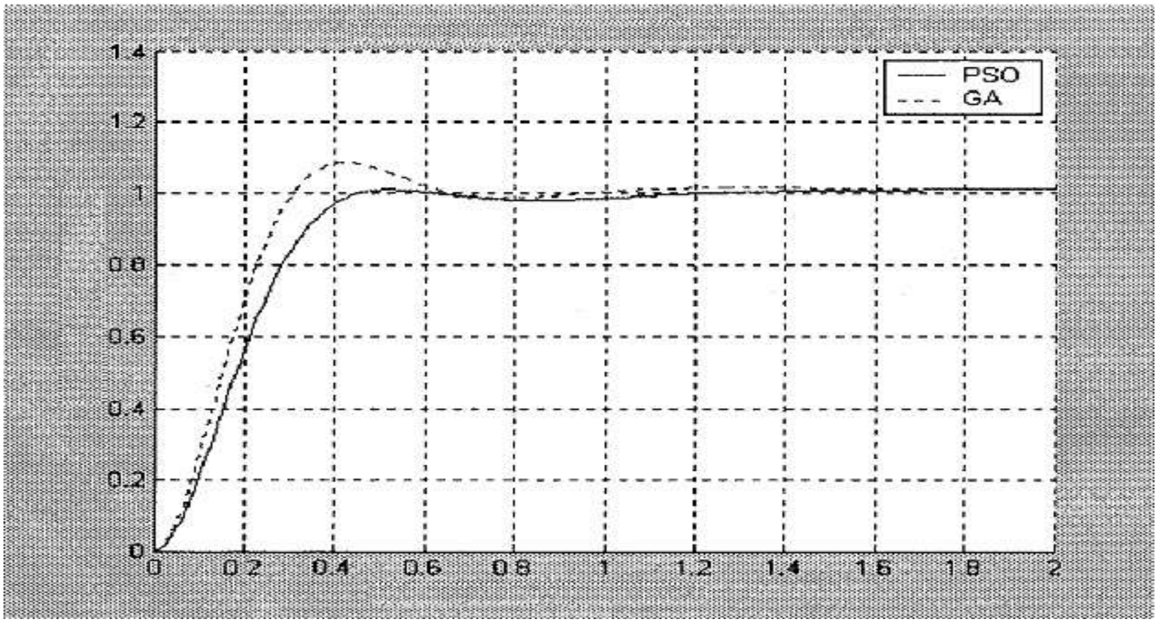

Figure (7):Terminal voltage step response of an AVR with PSO and GA-PID controller.

The PSO method can prompt convergence and obtain good evaluation value. These results show that the PSO-PID controller can search optimal PID controller parameters quickly and efficiently. Now the proposed controller is replaced instead of PSO controller with the same system and the same parameters. Finally the output response shown in figure (8), show that , the new controller is very efficient and the good enhancement appears when using this controller.

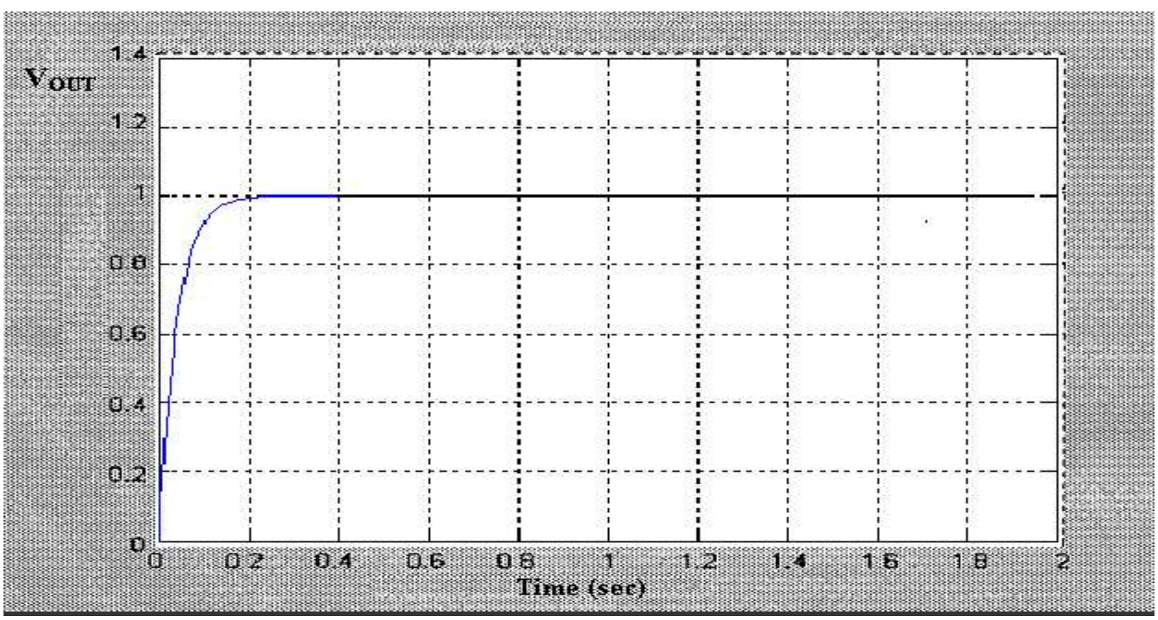

Figure (8): Terminal voltage step response of an AVR with AFWC

Finally, table (1) show the time response parameters for all controllers
Table (1): Time response parameters for all controllers

Controller type	ISE (Integral Squire Error) for Step Input	Time Response Parameters			
		Rise Time	Delay Time	Peak Time	Settling Time
Without Controller	24.2574	0.06	0.05	0.098	8.8901
With PSO-PID	1.2011	0.2019	0.180	0.5102	0.5980
With GA-PID	1.4581	0.2768	0.173	0.5204	0.4027
With AFWC	1.0567	0.0182	0.083	0	0.1867

7-Conclusion

The proposed controller AFWN uses Wavelet Network to realize Fuzzification, fuzzy inference and defuzzification. This controller has many advantages, such as that in it's structure, activation functions in neurons and weights, so it can be easily initialized according to fuzzy linguistic rules.

From the simulation results :

- Integrated several controllers to produce an intelligent controller is really very good method , since the ISE decreased from high value to very small value .

-The proposed approach can perform an efficient three term controller , When two parameters of the controller are tuned, a little better performance at settling time is achieved comparing with one parameter adjustment case. Also The proposed controller really very good controller, since the good responses for two plants with step input are obtained

-More robust stability and good performance characteristic than other controllers such as classical PID or when not use any controller(without controller).

- The rule table for the different plants can be extracted from the output response then modify it to enhance the output ,therefore this method does not depend on any expert for any plant

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