DRUM BOILER LEVEL CONTROL USING NEURAL NETWORK[+]

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Abstract

This paper deals with the control of water level in the drum boilers which are obviously used in electrical power plants. Efficient techniques are applied as a kind of artificial intelligence known as neural networks. Identification networks are trained offline using real process data recorded at *Al-Daura* power plant / unit no.*4*. Drum level is selected as an output of identification network while pressure, feed water flow, steam flow are selected as input. The first step of work was to find network with the least number of hidden neurons and the least value of mean square error. The network is simulated and its output is plotted with the real data. Two types of networks are tested feed forward neural networks and recurrent neural networks. The predicted mean square error is more than 1.0 E-04 for feed forward networks and less than 1.0 E-06 for recurrent networks. The second stage is the prediction of the inverse model. A *MIMO* system network was used for this purpose. Computer programs are implemented using neural network tool box which is available in MATLAB version 6.5.

المستخلص

تناول البحث موضوع السيطرة على مستوى الماء في المراجل البخارية المستخدمة في محطات الطاقة الكهربائية باستخدام احد التقنيات الحديثة وهي تقنية الشبكات العصبية .ان هذه الطريقة هي احد الانواع المعروفة باسم الذكاء الصناعي. تطلب تصميم منظومة السيطرة بناء شبكه عصبية تتدرب على مداخل المنظومة ومخارجها تسمى شبكة التعريف وهي مكافئة لما معروف بالنموذج الرياضي. تم تدريب الشبكات على بيانات تشغيل حقيقيه اخذت من محطة كهرباء الدورة الحرارية / الوحدة الرابعة. اختير المستوى كمخرج لشبكه التعريف بينما اختير ضغط المرجل ومعدل جريان ماء التغديه ومعدل جريان البخار المسحوب كمدخل للشبكه. المرحله الاولى كانت ايجاد الشبكةالتي تحتوي على اقل عدد من العقد المخفية بين مجموعة عقد الادخال وعقد الاخراج التي ينتج منها اقل معدل لمربعات قيمة الخطأ. تم تمثيل الشبكة العصبية ومقارنتها بيانيا" مع القيم الحقيقية. تم اختبار نوعبن من الشبكات التعريفية هما شبكات التغذية الامامية وشبكات التغذية العكسية. وقد كانت نتائج شبكات التغذية الاماميةغير مقبولة من الناحية العمليةلان معامل الاداء الممثل بمعدل مربع الخطا كان اكثر من (1.0 E-04) بينما اظهرت

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طريقة النغذيــة العكســية نتائــج ممتــازه اذ كانــت قيــم معامل الاداء اقل من (1.0E-06). المرحلة الثانيه كانت ايجاد النموذج العكــسي وهــو ممثــل بــشبكة عــصبيــة مــن نــوع التغذيــة العكــسية ولمنظومــة. **SYSTEM** *MIMO* . وقد نفذت البرمجيات في هذا البحث باستخدام الية الشبكات العصبية المتوفرة في لغة البرمجة **MATLAB VERSION 6.5** .

Introduction

Steam drum level control is necessary to add make up water as steam is delivered into the header and to the associated process equipment. The system should control the level at a specific set point while compensating for varying steam demands and drum pressures. For a given volume of steam and blow down leaving steam drum, an equal amount of water should replace that inventory.

Workers expend many efforts on drum boiler, [1] , [2] , [3] made researches on drum boilers using mathematical modelling [4] , [5] , [6] , al used neural identification method. This work is carried out using neural networks as a new method which copes with drum nonlinearities.

Data Collection and Analysis

Before entering inside the work, it is important to analyze the data, the recorded data represents closed loop measurements, the feed water controller is a fast acting flow controller, which uses feed water flow as its process variable and steam flow as its set point, thus for every kg. of steam flow leaving the boiler a kg of feed water is added. This loop has a final control on the feed water control valve. The feed water controller modulates its output to regulate the necessary feed water flow to keep the drum level in a mass/heat balanced and level state.

This work is based on taking the feed water flow and steam flow as the mass balance effective parameters, on the level state and the pressure as it affects the whole system stability; because high pressure in the drum means nonlinear behavior in the level.

Although the problem is treated as a black box modeling, neural network is a type of artificial intelligence, learning and adjustment of the system is based on a logical foundation.

The data used for the development of neural network was recorded by sampling the process variables and the drum level every 2 minutes. 150 data points were used for the identification purpose. The testing data is scaled in the range [-1 +1] using neural control toolbox function premnmx.

Figure (1) shows the scaled feed water flow, figure (2) shows the scaled drum pressure, Figure (3) shows the scaled data for steam flow and level data is shown in Figure (4).

The fluctuation in data is attributed to many factors; all of which lead to the known fact that the system is nonlinear.

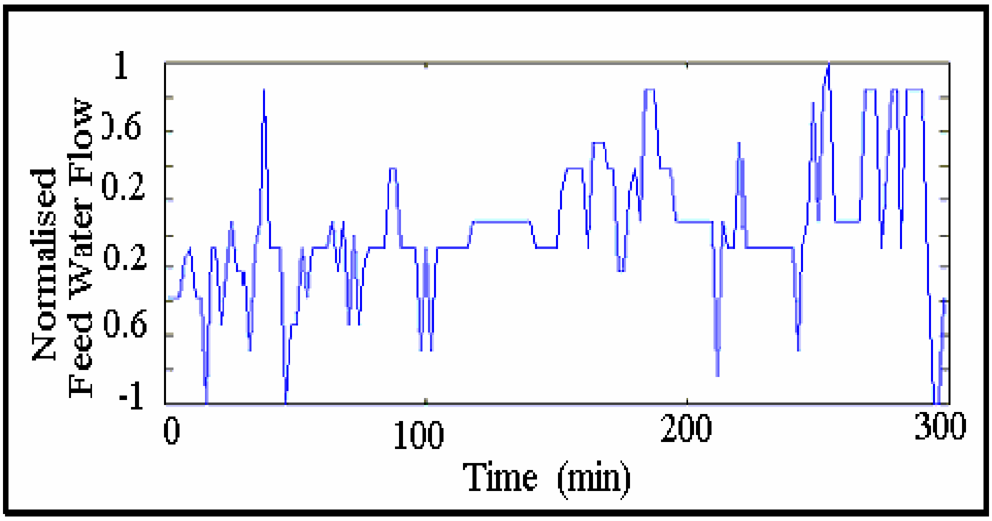

Fig. (1): Normalized Feed Water Flowrate Plot

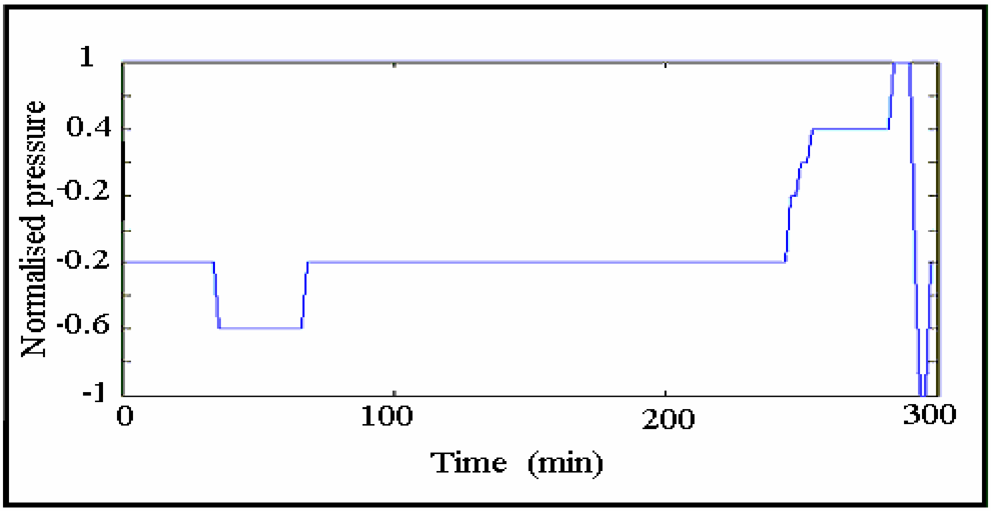

Fig. (2): Normalized Drum Pressure Plot

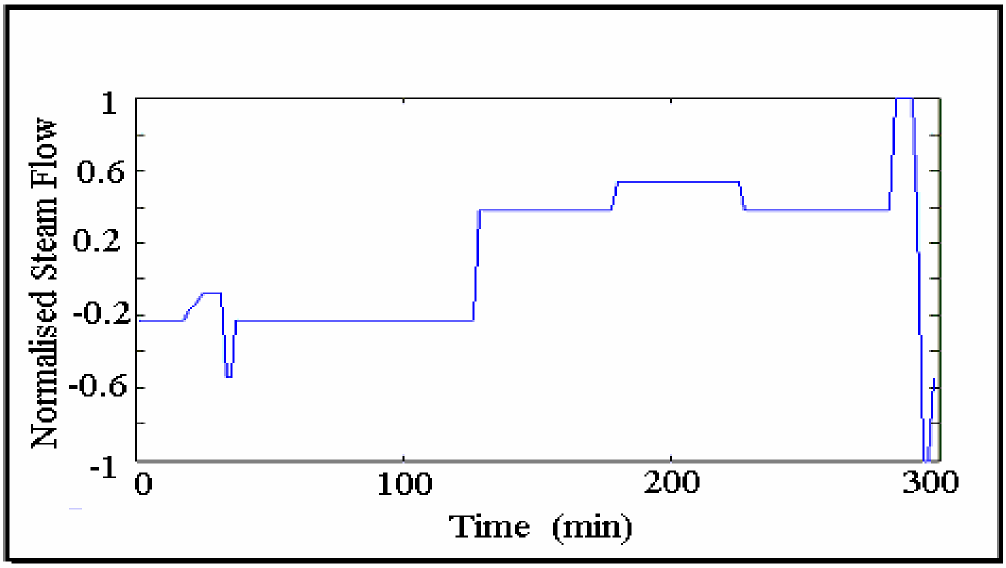

Fig. (3): Normalized Steam Flowrate Plot

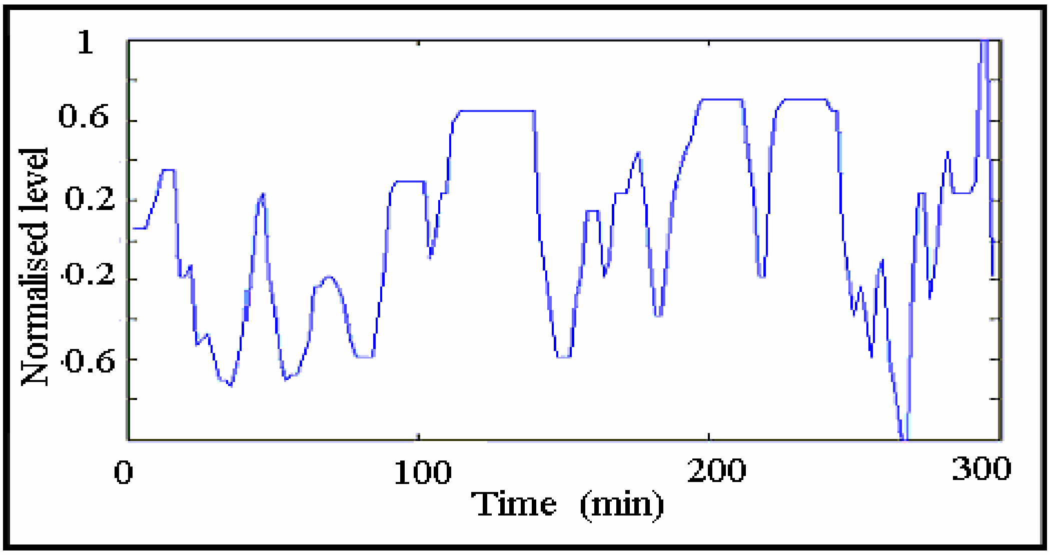

Fig. (4): Normalized Drum Level Plot

<u>Identification</u>

Though there are many statistical methods to correlate the empirical data, there are none that fit the behavior of the input variables on level measurements. For all these reasons, neural network is selected.

First, linear transfer function was used in the identification model, but, bad results of the mean square errors were obtained, they were excluded from the networks. Finally a *tansig* transfer function was chosen in building the network.

The *tansig* “a short for tan-sigmoid” is a squashing function of the form shown in Figure (5) that maps the input to the interval (-1, 1). Level of the considered drum readings is -350 to +350mm.

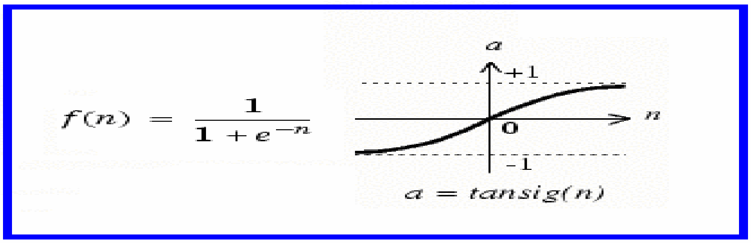

Fig. (5): The tan –sigmoid transfer function

An input output model is used first to identify the system, first trial,we assume the model as shown in the following equation.

$$y_p(k) = f[u(k-1)] \quad \ldots\ldots\ldots\ldots \quad (1)$$

The training set is shown in table (1); many experiments were carried out in order to obtain the optimum structure of the neural network that can fairly approximate the plant dynamics. The work was carried in the graphical user interface, through *Matlab version (6.5)*.

Table (1) Training Set Of Feed Forward Of Boiler Network.

	Pattern form			
Pattern no.	$q_{FW}(k-1)$	$P(k-1)$	$q_S(k-1)$	$q_S(k-1)$
Pattern 1	$q_{FW}(0)$	$P(0)$	$q_S(0)$	$q_S(1)$
Pattern 2	$q_{FW}(1)$	$P(1)$	$q_S(1)$	$q_S(1)$
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---	---	---	---	---
Pattern 149	$q_{FW}(148)$	$P(148)$	$q_S(148)$	$q_S(k-1)$

The optimum number of neurons in the hidden layer is predicted by plotting the number of neurons versus the mean square error. As shown in Figure (6). the increasing number of neurons in the hidden layer above eight does not achieve an observed improvement in the performance of the system.

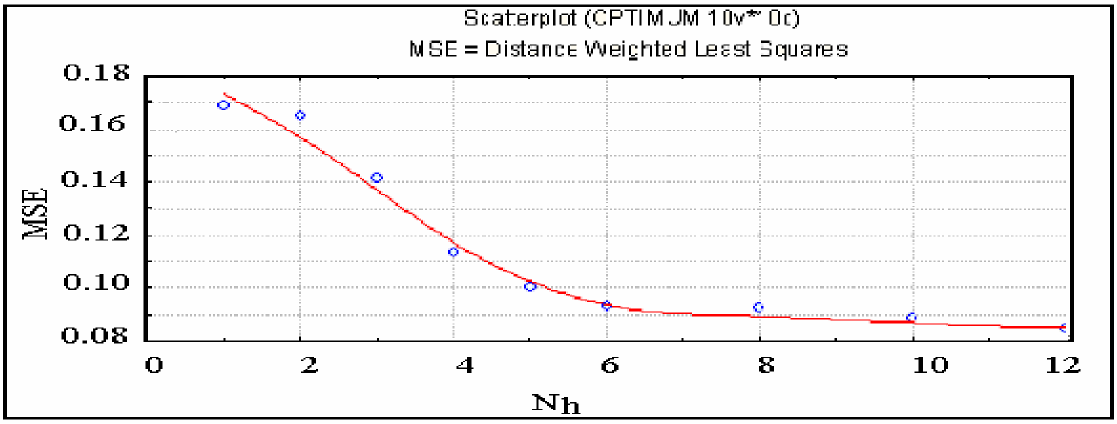

Fig. (6): Optimizing No. of Neurons in the Hidden layer

All the previous figures were estimated at 100 training epoch for 0.001 momentum factor. The best structure was found at ***8*** neurons in the hidden layer. The network is shown in Figure (7). Results of this structure are tabulated in table (2). In this table, W_{ji} is a connection weight from a unit i at the input layer to unit j at the hidden layer. Similarly, W_{kj} is a connection weight from a unit j at the hidden layer to unit k at the output layer. I=1 refers to the normalized feed water flow, i=2 refers to the normalized pressure and i=3 refers to the normalized steam flow. In the output layer k represents the normalized level reading.

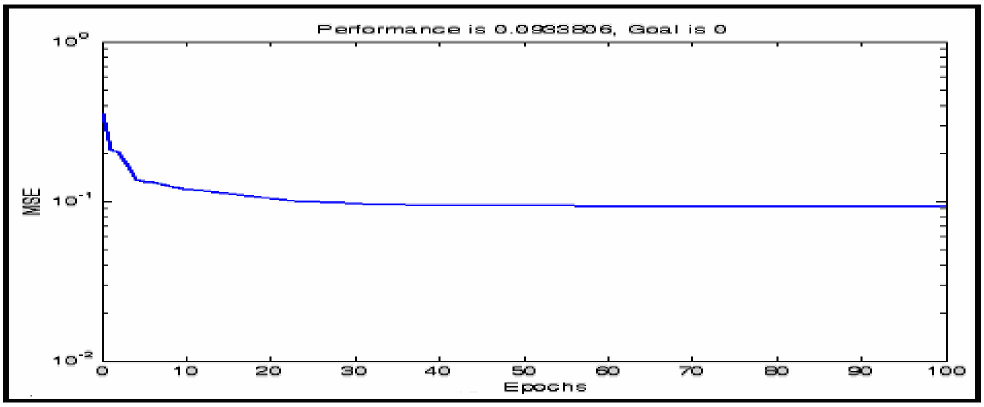

Fig. (7) Training a Network with 8 *tansig* Hidden Neurons.

Table (2) Training Results of Feed Forward Of Boiler Network

Weights ($W_{j,i}$)								
j	1	2	3	4	5	6	7	8
1	1.438	5.268	-6.137	22.260	0.367	-13.141	-0.712	-10.563
2	-1.574	-1.166	2.006	0.331	0.800	4.295	-.0668	3.676
3	70602	-8.022	1.991	4.158	4.195	2.219	3.055	3.676
bj	2.182	-7.603	1.074	-4.140	3.962	1.014	-5.985	1.167
Weights ($W_{k,j}$)								
j	1	2	3	4	5	6	7	8
1	2.316	-0.552	-0.973	-0.619	3.962	1.014	-5.895	1.1672
b_k	-1.069							

After the neural network is fixed, the network is simulated, as shown in Figure (8).

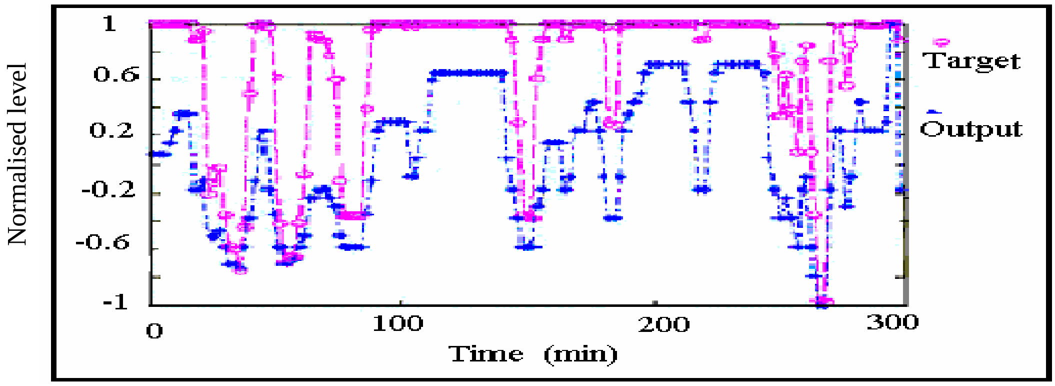

Fig. (8): Simulation Of The feed forward network

Although the training results have the same shape of the model, the model is unsatisfied, there is a time lag which is attributed to the bias values which are not confirmed. Bad simulation results lead to the addition of the feedback to the input as shown in figure (9). This type of network is obviously known as recurrent networks or "*Hopfield networks*". Thus making a new training set represented by equation (2).

$$y_p(k+1) = f[y_p(k), u(k-1)] \quad \ldots\ldots\ldots\ldots \quad (2)$$

In recurrent networks, there are both feedforward and feedback connections along which signals can propagate in opposite directions. Because feed forward network does not have dynamic memory, the tapped delay line method is selected to represent this dynamic system. The adopted method is a fully recurrent type where the feedforward and feedback connections are trainable. The method employs the current inputs and past outputs of the system to be modeled as the inputs to the network. The next output is used as a teaching signal. The tapped delay line method thus turns a temporal modeling problem (learning the dynamic behavior of the system in the time domain) into spatial modeling problem (statistically mapping the delayed inputs to the next output).

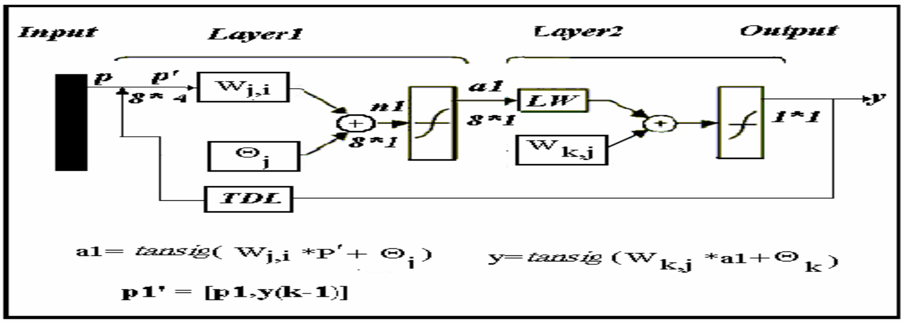

Fig. (9): The Recurrent Neural Network

The new network gives excellent performance, thus the mean square error reaches a value of *4.67 E-7* as shown in Figure (10). The results of this network are tabulated in table (4.3), in this table i=4 represents the current level reading (normalized value) and the simulation result is shown in Figure (11).

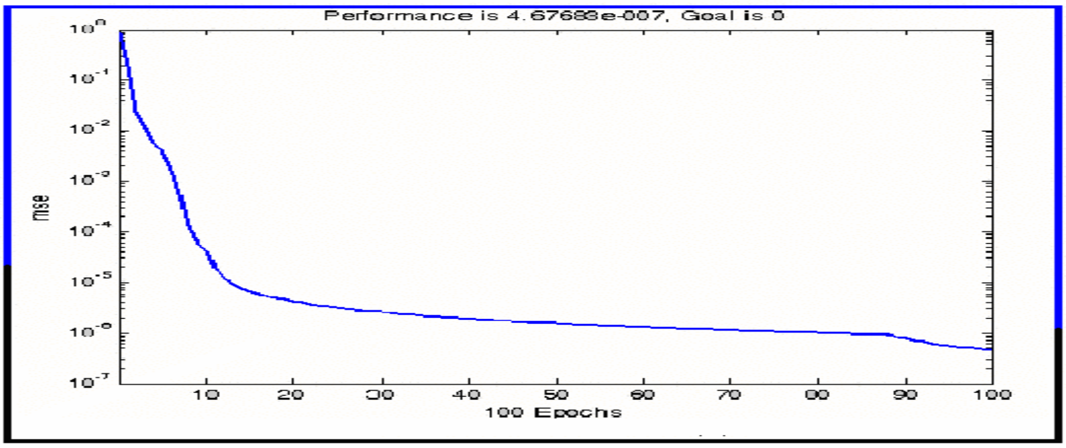

Fig. (10): Training of Recurrent Network

Weights ($W_{j,i}$)								
j	1	2	3	4	5	6	7	8
1	1.179	0.086	1.232	0.610	1.144	-1.270	0.069	-1.242
2	0.992	-0.046	1.224	-0.721	-.083	0.465	-0.055	-2.404

3	1.624	-0.012	2.384	-1.062	2.382	-1.821	-0.062	0.281
4	-0.542	-0.712	-4.313	-5.575	-1.076	-0.135	1.287	0.281
bj	-2.381	0.980	0.485	-5.213	0.195	-1.059	1.349	-2.007
Weights ($W_{k,j}$)								
j	1	2	3	4	5	6	7	8
1	0.047	-2.920	-2.241	-3.294	1.330	0.132	1.018	-0.673

Table (3): Results of Recurrent Neural Network Identification

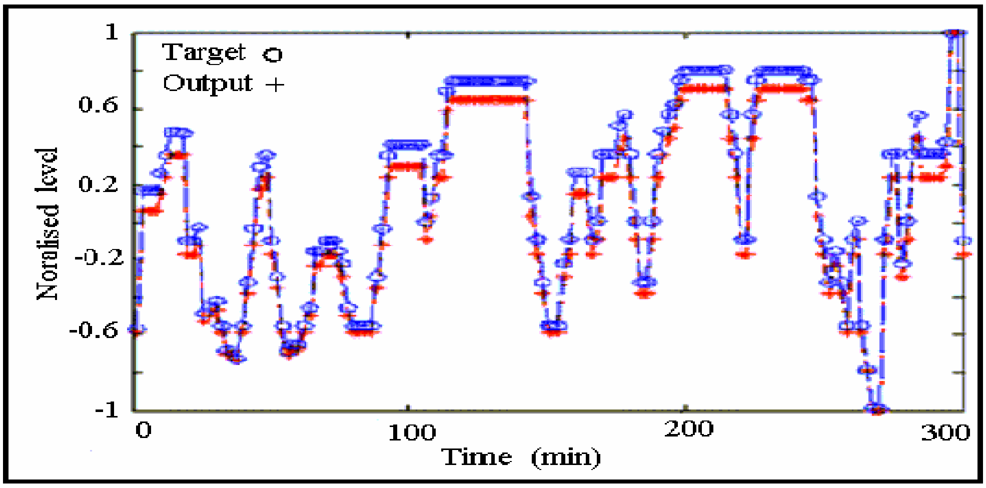

Fig. (11): Simulation of the Recurrent Network

Conclusion

This work focuses on the level control of the drum boilers using artificial neural networks for identification and control of nonlinear dynamic system. The following points outline the most important results that have been obtained in this work.

1. It can be understood that recurrent neural networks give better results than the traditional feed forward networks when trained by backpropagation algorithm. Simulation of identification results is plotted and the MSE reaches 4.5E -08.
2. Recurrent neural network can identify any physical model with a great degree of accuracy.

3. Generalization capabilities of neural networks enable them to map the nonlinear response of the level by choosing the *tansig* transfer functions of each neuron in the hidden layer and output layer, as simulation results showed.

Nomeclature

Symbol	Definition	Units
a1	Hidden layer output	
P	Pressure	kg / cm^2
q_{FW}	Feed Water Flowrate	Ton / hr
q_S	Main Steam Flowrate	Ton / hr
N_h	Number of Neurons in Hidden Layer	
MSE	Mean square error	
u	Manipulated Input	
$W_{j,i}$	Weight Factor, multiplied by the signal going from neuron i in the input layer to neuron j in hidden layer.	
$W_{k,j}$	Weight Factor, multiplied by the signal going from neuron j in the hidden layer to neuron k in the output layer.	
y_p	Plant Output	
Θ	Bia	

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