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System Identification Using Artificial Neural Network

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***Abstract* —System identification is one of the important aspects that needed to be considered before the controller design. The main objective of system identification is to know the model of the system. It is essential to understand the process before handling it. Then we can go for controller design which is apt for the system. A number of methods are existing for system identification. In this paper we propose a method to identify the system model. The proposed method involves use of back propagation neural network to predict the output of the system for a given input from the knowledge of past inputs & outputs. The effectiveness of the model identification is tested using experimental data from pressure process station, level process station, and conical tank process.**

Keywords - system identification, neural network, step response, nonlinear identification, initial condition

I. INTRODUCTION

System identification means identifying the input – output relationship of the system. The order of the system may differ. As the order of the system increases, the analysis part becomes more & more complex. Many methods have been proposed for system identification. There is increasing research interest on Artificial Neural network. We can use ANN for finding nonlinear mappings by learning from given input-output relations and they have been used in control engineering field for identification purpose and the control systems design. The size of neural network depends upon number of units in a single hidden layer. It decides the capability of the neural network to approximately finding out function and size of the neural network for solving a specific problem (In our case system identification).This is a very important issue to be addressed during the design stage. If the starting of training is with a small network, it might not be sufficient to achieve the required learning process. On the other hand, if a large network is used, the learning process will be very slow and it may lead to over-fitting.

If input vector to neural network increases its size, there will be a corresponding increase in the size of neural network. It may lead to oscillations in the output responses. The stability of the system can be improved by adjustment of weights in neural network.

For estimating model of the system Wang and Zhang proposed a method. It was based on step response [11]. Diamesis.Bie et al introduced similar approach for first order models [3],[5],[6]. The problem with these models was that they need a fixed initial condition. It was not possible to introduce transient initial conditions. It has been considered in the integral equation method proposed by S.Ahemed [1],[2].Some new methods were also put forwarded [4],[7],[9].However these were not using step input method. Pulse response method is another method used considering changing initial conditions [8],[10].

In this paper we are going to put forward a new method to identify the system model using neural network similar to the method used in [12]. This identification has two advantages compared to other methods. They are (1) before the input is applied, it is not compulsory to bring the process to steady state and (2) the input need not be constant unlike step input method. This method is an effective method for nonlinear system identification.

Here paper is arranged like this. Section II explains the design of artificial neuron network for system identification. Then in section III the performance of the algorithm is tested using simulation results followed by applying it in real systems in section IV and conclusion in section V.

II. NEURAL NETWORK DESIGN

Artificial neural network (ANN) is based on nervous system. It can be used system identification. It is represented using the neurons that are interconnected as a system. It is capable of learning. Using some learning algorithm we can train the neural network.

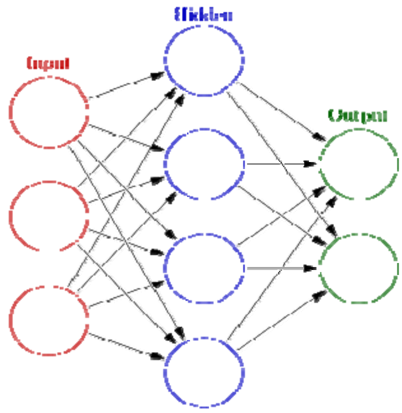

Fig.1.Neural Network

The main advantage of a neural network is its capability to learn from input-output relation. It is a network which is very complex. It is not just complex, it is also adaptive. Neural network changes its values for weights depending on the data given to it. It can be used for various applications. In the above shown diagram, each line between the neurons represents a connection and it shows the map for the flow of data between them. Each connection will be having a weight, A weight is a number which decides what should be the signal between the two neurons. If the output given by the network is accurate, the values for weights need not be varied. But if it gives value which does not resemble the required output, then we have to consider error, which is the difference between required output and the obtained output using neural network. Then we have to use capability of adaptation of the neural network. It helps to improve the next results.

Consider model representation in fig2. It represents a perceptron. It is the simplest neural network which we can consider for analysis. Fig.2 shows model of a single neuron. It consists of a single output &multiple inputs.

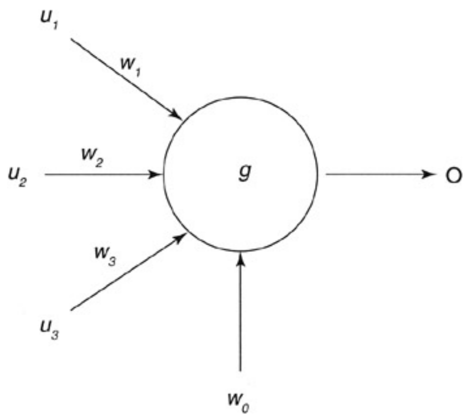

Fig.2.Perceptron model.

A perceptron can be represented using a model shown above. Here different inputs are applied to the neuron, and the neuron generates an output after processing these inputs. As shown in fig.2 inputs are applied on the left side and output is taken from right side.

The Perceptron Algorithm:

1. Multiply input with corresponding weight for each input, 2. Results obtained from step 1 is added (ie, for different inputs).3. Calculate the output depending upon the overall added sum applied to the function which is used for activation.

Let us define the activation function as the sign of the sum obtained. Otherwise, if the sum is a positive number, the output is given as 1; if it is negative, the output is -1.If both the inputs are zero, sum of its weighted inputs is also zero. To avoid this dilemma, the perceptron will require a third input, typically referred as a bias input. A bias input always has the value of 1 and is also weighted. There is known answer for each inputs given to neural network. The network compares the known answer with its output & by this method network can determine whether guess made by it is correct or not. If the guess is wrong, the network can learn from the mistake it made. It can vary its weights. The process is explained below:

1. Give different inputs to the perceptron. It should be having expected answers for that.
2. Guess the value.
3. Calculate the error which is the difference between expected value and the value got.
4. Depending on the error adjust weight given to perceptron.
5. Go to Step 1 and repeat.

The error is defined as the difference between the expected answer and actual answer. Error = Expected output - Actual output. It can be said that the error is the critical factor which determines how the weights of perceptron should be varied. What should be the change in weight while considering a single weight. We are looking forward to calculate this change in weight. It is called Δweight.

The back-propagation Algorithm - a mathematical approach:

The steps in back-propagation algorithm:

1. Calculate the rate at which the error is changing. It is called error derivative (EA).It is usually represented as difference between original activity and required activity.

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \text{..................(1)}$$

$$y_j = \frac{1}{1+e^{-x_j}} \text{...............................(2)}$$

$$x_j = \sum_i y_i w_{ij} \text{...............................(3)}$$

Where,
Y_j-j^{th} unit activity level and d_j- j^{th} unit output

2. Calculate the rate at which error is changing with respect to total input when the output unit is changed.

$$EI_j = \frac{\partial E}{\partial x_j} = EA_j y_j (1-y_j) \text{.........(4)}$$

3. When an output unit is changed calculate the rate at which error is changing comparing with weight in the connection. This quantity is called *Ew*. It can be given as the product of step 2 output and the activity level of the connected unit.

$$Ew_{ij} = \frac{\partial E}{w_{ij}} = EI_j y_i \text{......................(5)}$$

4. Calculate the fastness of the changes in error with the activity of different units in its previous layers. This critical step helps for applying algorithm for multilayered networks. When something happens in the activation of a unit in a layer which comes previous to the given layer, it directly influences the activities of all output units connected to this layer. Therefore in order to calculate the resultant effect of them on the error, all these effects are added on the output units. We can calculate these values separately. As we can see this is the product of step 2 result and the weight corresponding to the connected output unit as shown below.

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_j EI_j w_{ij} \text{..................(6)}$$

III. SIMULATION AND RESULTS

In the above section we discussed about designing of neural network for different applications. Through this section discussion is made about how system identification can be done. We applied a step input to a first order system and the obtained output along with the input applied is used for training ANN. After training it we can predict the system output for various inputs from the neural network.

To check the performance of the algorithm, we have chosen a first order system .It's actual output is compared with identified model output and is plotted in a graph.
The output of the chosen first order system for a step input is given by the equation.

$$y(t) = 50 * (1 - e^{-t}) \ldots\ldots\ldots \ldots\ldots\ldots\ldots \ldots(7)$$

We applied step input to the system and random noise was also introduced. The obtained input and output data are given to the algorithm. The comparison between the actual output &identified model output is shown in the fig.4.The identified output follows the actual output. Hence we can use the developed algorithm to find out the output of the system for any given input.

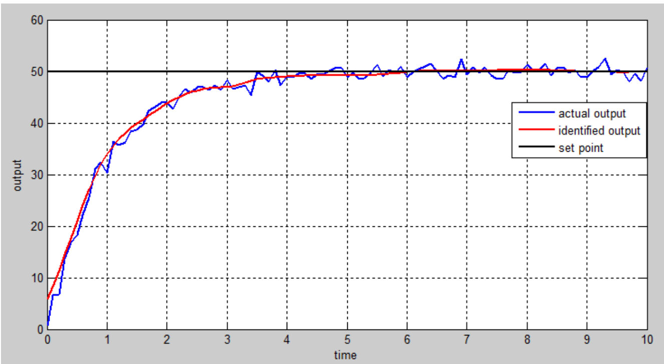

Fig.3.Comparison between step response of actual & estimated model for first order system.

IV. PRACTICAL DEMONSTRATION

The proposed algorithm was tested using the experimental data obtained from pressure process, level process and conical tank process.

A. Pressure Process Identification

A series of step inputs are applied to pressure process and a table having input and process variable values is imported. The fig.5 shows the complete setup of a pressure process station. The imported notepad file is given to the algorithm and the algorithm identifies system. The actual system output is compared with the identified model output as shown in fig.6. The identified output follows the actual output. Hence we can use the developed algorithm to find out the output of the system for any given input.

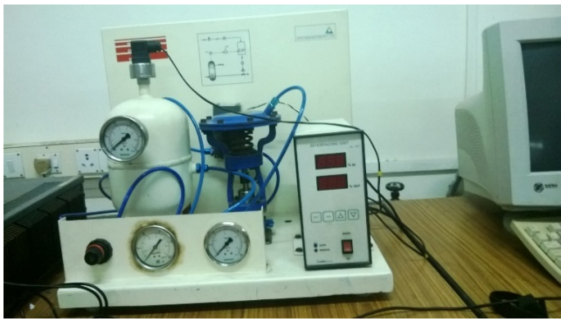

Fig.4.Pressure process station.

B. Level Process Identification

A series of inputs are applied to the water level process and level value for each input is noted down. Level process is subjected to same procedure as pressure process.Fig.7 shows the considered level process station. Using the algorithm model was identified and actual process output was compared with its output and it is shown in fig. 8. The identified output follows the actual output. Hence we can use the developed algorithm to find out the output of the system for any given input.

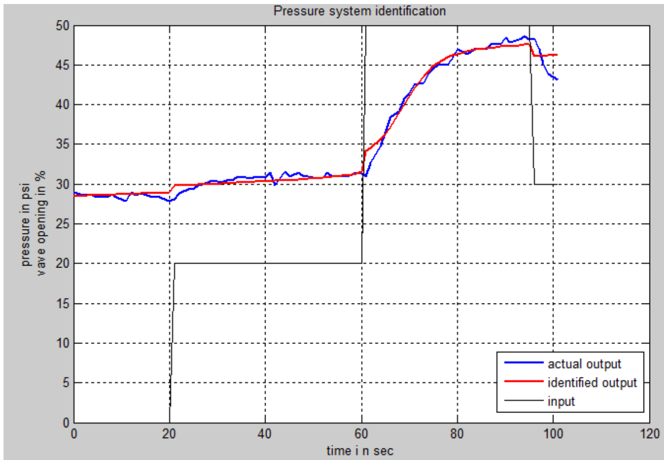

Fig.5.Comparison of step response of actual and estimated model of pressure process.

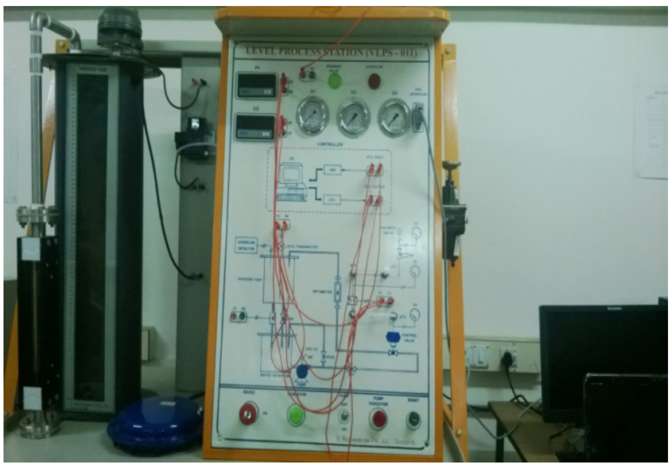

Fig6.Level process station.

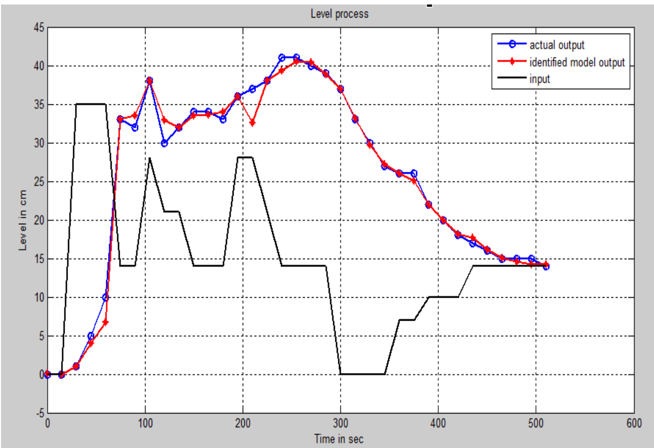

Fig.7.Comparison of actual and estimated response of level process.

C. Conical Tank Level Process Identification

Similar to the first two processes, all the procedures are done. Both applied input & the corresponding level values are fed to the algorithm and model is identified.Fig.9and Fig.10 shows the set up and performance comparison respectively. The identified output follows the actual output. Hence we can use the developed algorithm to find out the output of the system for any given input.

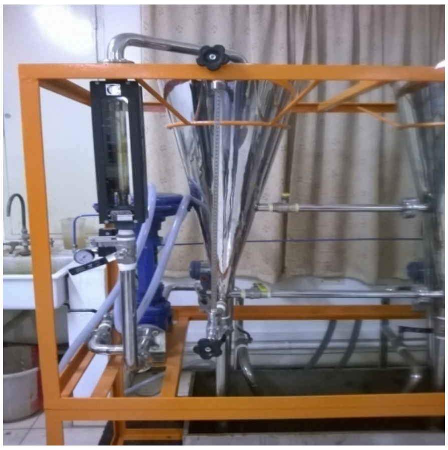

Fig.8.Conical Tank Level Process Station.

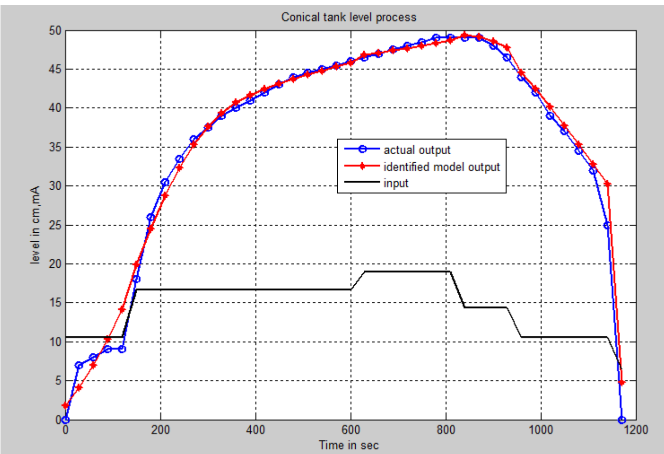

Fig.9.Comparison of actual and estimated response of conical tank level process.

V. CONCLUSION

A new method was proposed for system identification using neural network back propagation approach. This algorithm was tested using an empirical model developed. The actual system output and identified model output were compared and verified. Also the algorithm was tested using real time data from three different process stations. From the responses we concluded that neural network is a good method for model identification of nonlinear systems.

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