Application of Back Propagation Neural Network to Drum Level Control in Thermal Power Plants

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Abstract

The paper describes the development and testing of a neural network based drum level controller for sub-critical thermal power plant boilers. Experimental data obtained from an operational coal fired power plant (500MW Thermal Power Station, Korba, India) is used to train the neural network. This model proposes a simple training algorithm for a class of nonlinear systems, which enables the neural network to be trained with the output errors of the controlled plant. The only a priori knowledge of the controlled plant is the direction of its output response. Due to its simple structure and algorithm, and good performance, the proposed controller has high potential for handling difficult problems in process-control systems. The Artificial neural networks (ANN) modeling can significantly reduce the frequency of deviations and the degree of deviation of the water level in the drum. The ANN model to be applied for the boiler feed system in the power plant will not only increase the efficiency of the system but also shall considerably reduce the tripping of the power plant.

Keywords: Artificial neural network, Power plant, Boiler model, Boiler drum.

1. Introduction

The power generating industry is currently undergoing an unprecedented reform. Artificial intelligence techniques offer one of the most potentially profitable usages in recent developments. Artificial neural networks (ANNs) have been used in a broad range of applications including: pattern classification, pattern recognition, optimization, prediction and automatic control. In ordinary water tube boiler system the foremost difficulty is the fluctuation of water level in the Boiler drum.

The boiler needs very precise control and measurement for its efficient operation. The following designed and working parameters are taken into consideration while taking experimental data (table 1).

Table 1: Power plant parameters

Parameter	Value
1.Load	503 MW
2.Main steam flow	1485 t/h
3. Drum operating pressure	189 bar
4. Superheated steam temperature	545 C
5. Reheater steam temperature	545 C
6. Superheater, Reheater spray	35 t/h
7. Feed water flow	1480 t/h
8. Feed water temperature	259 C
9. Water wall Total projected surface area of Tubes	2580 m^2
10. Water wall tube diameter	53 mm
11. Number of the water wall tube	869
12. Drum internal diameter	1778 mm
13. Overall Length of Drum	22.07 m
14. Normal water level of drum	0.755m

A sudden decrease in the water level may uncover boiler tubes, allowing them to become overheated resulting into Boiler tube failures and unexpected shut down of power plants. On the other hand, increase in this level may interfere with the process of separating moisture from steam within the Boiler drum, thus reducing boiler efficiency and carrying moisture into the process or turbine. The tripping logics are provided to save the unit from any abnormal condition in the boiler/turbine or generator. This tripping of the power plant leads to great loss of production of power and money, at the cost of saving the equipment life. The 24% of the tripping of the

Boiler is due to the high fluctuation of water level in the drum of the Boiler. The practice of tripping the generator breakers immediately would follow a boiler turbine tripping. Therefore, it would be an ideal condition if before hand the opening of the pneumatic valves at scoop and at the feed control station can be predicted and transfer this signal to the controller of the valves. This will supply precise feed water according to the requirement of a unit of thermal power plant. The model in this paper reduces the tripping of a unit of thermal power plant due to fluctuation of the water level in the drum of the Boiler.

To predict the behavior of boilers, there are number of dynamic models, which can be used. These models are used for controller synthesis and real-time evaluation of controller performance. Conventional proportional integral (CPI) controller is used to control the pneumatic valve. However, even after the use of CPI controller, desired precision of drum level control is not achieved. H. Ying in 1990 proposed a practically efficient and mathematically rigorous fuzzy proportional integral (Fuzzy PI) controller. The fuzzy controller can control the time delay process model and nonlinear process model significantly better than the non-fuzzy linear PI controller. In 1994, L.Fausett [4] and S. N. Sivnandan et. al. [11] inspired the better stability in fuzzy proportional derivative (PD) controller. D. Misir et. al. [5] in 1995 enhanced the self tuning capability of the system with the help of fuzzy Proportional Derivative (PD) controller. The fuzzy proportional integral with derivative (Fuzzy PID) controller proposed by Om Prakash et.al. [10] in 2007 and Sweeka Meshram et.al. [15] in 2011 kept on improving the results.

1.1 Need of Work

The desired Drum level is difficult to control using conventional Proportional Integral Derivative (PID) type controllers, mainly due to a long system response time, random disturbances resulting from the variation of feed water flow from Boiler feed pump to Boiler. Several related schemes have been proposed to design a controller using neural networks. References such as [6], [8], [10], [12] and [13] are such examples. B. Perunicic et.al. [6] tried to identify disturbance in power supply to industrial equipments and quality is improved using wavelets and ANN. H.M. Yao et.al. [8] predicted hydrogen content of coal that is important to know before combustion in thermal power plant. A. N. Seghir et.al. [12] proposed approach for speed control of motors using ANN. The use of fuzzy proportional integral and derivative (Fuzzy PID) controller is inspired by the work of B. Kosko [3] for the better performance of ANN model. However, most of the work mentioned above is in the form of indirect adaptive control or suffer from problems of complex training methods and system structures. Contemporary industrial process control systems dominantly rely on PID-type controllers, though the hardware to implement control algorithms has been improved significantly in recent years. In addition to the difficulty in achieving high control quality, the fine-tuning of the controller's parameters is a tedious task, requiring experts with knowledge both in control theory and process dynamics. The reliability of such a system is also very important for operational security and efficiency. All these factors generate need for the development of new controllers. The goal of this paper is to develop such a new controller using artificial neural networks. Particularly, the focus is on dealing with the nonlinearity, the negative effects of long response delays and process noises.

The proposed BPNN (Back propagation neural network) controller is trained by using the system's output errors directly, with little a priori knowledge of the controlled plant. In Section 2, the variation of parameters related to drum level is described with block diagram of drum level control by BPNN. The basic structure of the proposed ANN-controller is developed in Section 3 and its implementation. Section 4 summarizes the simulation results. The controlled system is characterized by the properties of long response delay, nonlinearity of drum level and process noise. The performance of the ANN-controller is also compared with a PI controller. Finally, the paper concludes with Section 5.

2. Artificial Neural Network

Artificial neural networks are powerful tool that have the ability to identify underlying highly complex relationships from input–output data only. Over the last 15 years, ANNs have been extensively studied to present process models, and their use in industry has been rapidly growing. The main advantage of ANN is the ability to model a problem by the use of data associated with process, rather than analysis of process by some standard numerical methods. In this model the system's output error is propagated back through the plant using its partial derivatives at an operating point. In a set of actual system, outputs are selected as training data and provided as input to the ANN during its training period. By comparing the output of the ANN with the desired system output, the network's output error is computed, which is then used to train the neural network. After the neural network is well trained, its input is switched to the desired system output. Then, the ANN acts as the inverse of the plant and its output will drive the system to reach the desired value.

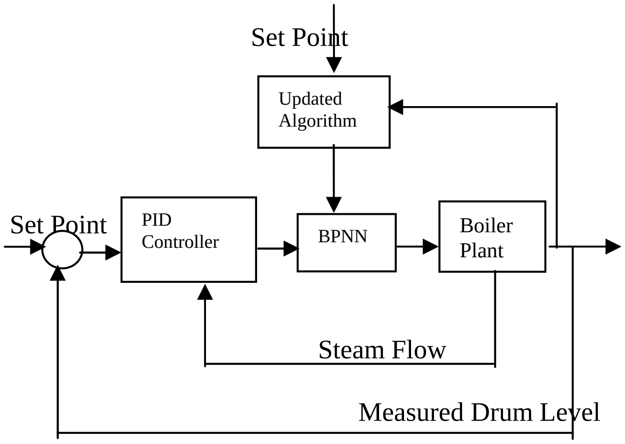

Fig. 1 Block diagram for Boiler with BPNN

The block diagram of the proposed ANN model as shown in fig. 1 predicts the degree of opening of the pneumatic valves. To control the water level in the drum, one has to control the two pneumatic valves. One valve is located in the feed control station and another one is in the scoop. This scoop is the hydraulic coupling to control the Boiler feed pump. In this coupling, the transmission of power from driving shaft of the motor to driven shaft of the Boiler feed pump takes place with the help of oil. It consists of a radial pump impeller mounted on a driving shaft and a radial flow reaction turbine mounted on the driven shaft. When the driving shaft is rotated, the oil starts moving from the inner radius to the outer radius of the pump impeller. This oil of increased energy enters the runner of the reaction turbine at the outer radius of the turbine runner and flows inwardly to the inner radius of the turbine runner. The oil, while flowing through the runner, transfers its energy to the blade of the runner and makes the runner rotate. The oil from the runner then flows back into the pump impeller, resulting in continuous circulation. A pneumatic valve controls the quantity of flow of oil inside the scoop. In this manner, control of boiler feed pump happens. To predict the valve opening of the feed control station, neural network take three inputs: steam flow from Boiler to the Turbine, feed water flow from Boiler feed pump to Boiler and water level in the drum of boiler in previous state. By observing all the inputs, ANN model predicts the valve opening of feed control station as shown in fig. 6. To control the feed water, scoop is used. This scoop is hydraulic coupling between Induction motor and Boiler feed pump.

2.1 Drum Level Control

The objective of this control system is to maintain the drum level to the normal water level of the drum at all loads. The variation of drum level and steam flow of 500MW thermal power plant is shown in fig. 2 and fig. 3 respectively. The reasons for variation may be change in frequency, requirement of spray in super heater and reheater, emergency in parallel running units etc. At lower loads less than 30%, the start up feed control valve will be used as final control element whereas at higher loads, speed control of Boiler Feed water Pumps (BFPs) will be used.

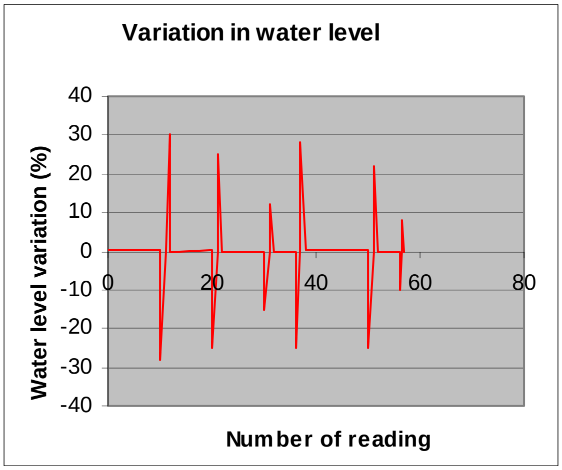

Fig. 2 Variation in drum level

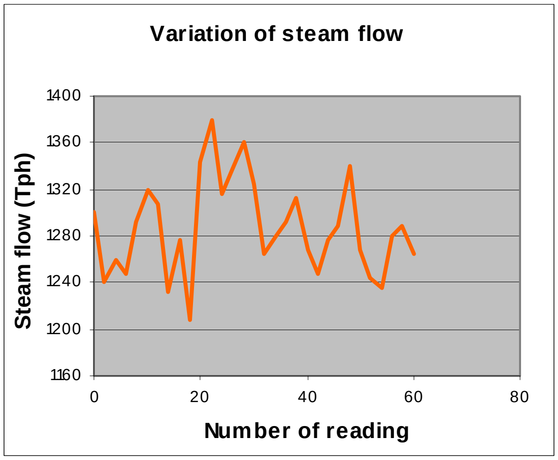

Fig. 3 Variation in steam flow

Low load: The drum level measured signal is compared with the drum level set point. The error signal will have a proportional, integral and differential action in the single element controller. This controller output will be the position demand signal for the start up feed control valve. Auto/manual station is provided for auto/manual selection and operation. Position indicator is provided for the start up feed control valve.

High load: At higher loads the start up control valve shall be closed. The steam flow shall be measured. In order to prevent sudden response due to drum swell and shrink on load change, a time lag unit shall be included in the steam flow signal. The temperature compensated feed water flow signal is computed by adding feedwater flow at economiser inlet and superheater spray water flow. The error signal produced between drum level measured signal and drum level set point shall have proportional, integral and differential action in the three-element drum level controller. This will be added with steam flow signal, which is the feed water flow demand signal (set point for feed water flow). This will be compared with the feed water flow in the feed water controller. Deviation if any will have a proportional and integral action in the feed water controller. This controller output will be the desired speed signal for the individual Boiler Feedwater Pump (BFP) speed control system.

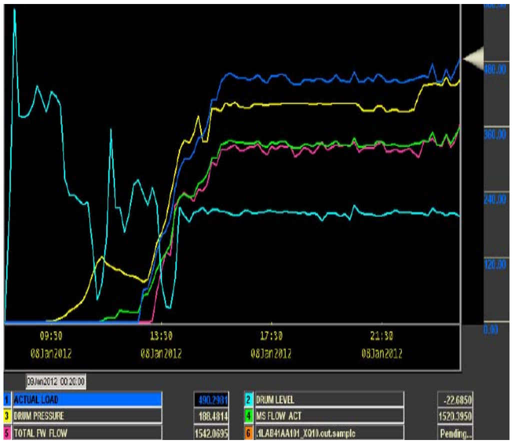

Fig. 4 Variation in power plant parameters

The real-time fluctuation of drum level with load, feed water flow, steam flow and drum pressure are shown in fig. 4 for 500MW thermal power plant during emergency.

3. Proposed Neural Network Model

There are many ANN architectures for which the choice depends on the type of problem and may require experimentation of different algorithms. One of the most popular architecture is a multilayer perceptron with the back propagation (BP) algorithm. BPNN (Back propagation neural network) is applied for the prediction of water level in boiler drum. It is proved that a four-layer (with two hidden layers) perceptron can be used to approximate any continuous function with the desired accuracy. BP has been used successfully for pattern classification, though its original development placed more stress on control applications. A controller is usually connected serially to the controlled plant under consideration. For a multilayer perceptron, the weights of the network need to be updated using the network's output error. For an ANN-controller, the output is the control command to the system. However, when the ANN is serially connected to a controlled plant, the network's output error is unknown, since the desired control action is unknown. This implies that BP cannot be applied to control problems directly. Thus, one of the key problems in designing a neural network controller is to develop an efficient training algorithm. Fig. 5 shows the ANN architecture for the feed control station of the power plant. This is used to control the feed water of the Boiler.

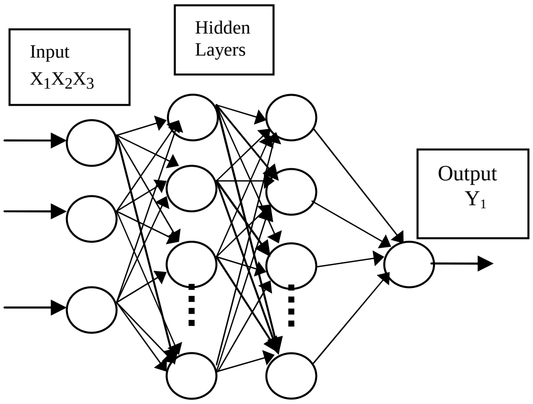

Fig. 5 ANN architecture for the feed control station

In this model, there are three inputs: steam flow from Boiler to the Turbine, feed water flow from feed pump to Boiler and existing water level in the drum and one output: degree of opening of the pneumatic valve in the feed control station. The valve regulates the excess water in the feed water system. Trials are performed using two hidden layers with the number of neurons one hundred in each of hidden layer, two neurons in the input layer and one in the output layer. Training the ANN is an important step for developing a useful network.

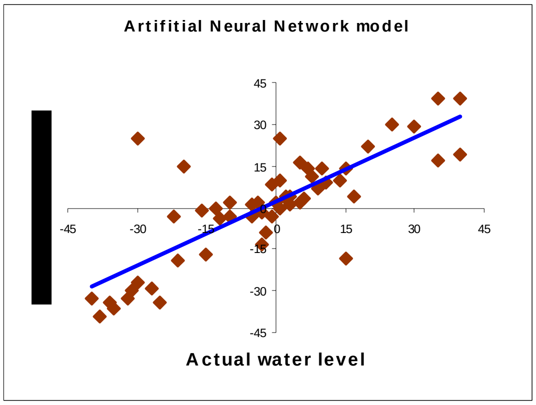

Fig. 6 Feed control station ANN

The experimental data from an operational coal fired power plant (500MW Thermal Power Station, Korba, India) is used as the learning samples to train the ANN. The power plant boiler is sub-critical, pulverized coal fired, balance draught. The numbers of reading are taken at regular interval in stable and unstable conditions for training. Each time a pattern is presented to the network, the weights leading to an output node are modified slightly during learning in the direction required to produce a smaller error the next time the same pattern is presented.

If the learning rate is high, weight changes may vary a lot and learning never completes and even if it converges the solution obtained is not the optimum. The learning rate is 0.85. Smoothing effect without oscillation is achieved by make the weight change a function of the previous weight change. The momentum factor determines the proportion of the last weight change that is added into the new weight change. This is taken as 0.76. As neurons pass values from one layer of the network to the next layer in back propagation networks, the values are modified by a weight value in the link that represents connection strengths between the neurons. Here weight is 0.76. The training will stop when correlation coefficient for model of feed control station 0.885 is achieved. The excitatory effect of the weight factors is straightforward which makes the transfer function quite advantageous. Therefore the sigmoid transfer function is chosen for the neurons in the all layers.

Three input parameters given to the program result in one output parameter. This output parameter (predicted valve opening) is passed to the valve controller resulting in precise valve opening. This leads to optimum control of the water level in the drum of the boiler because of which, tripping due to abnormal water level in the drum can be avoided. Fig. 6 shows predicted water level in millimeter. Even an avoid of single power plant tripping can significantly reduce scarcity of power, saving lot of fuel, reducing operation and maintenance cost, increasing equipments life.

4. Results and Discussion

The water level in the drum of the Boiler is one of the most sensitive parameter involved in all Thermal Power Plants. This parameter is directly related to the control of the scoop and the control of the feed control station. Fig. 6 clearly shows the relationship between actual water level and predicted water level of the boiler. A careful study was done on the existing PI controller system in the Power plant and compared with the designed ANN model. The unstable condition of boiler is considered to observe the effect of neural network to control Drum level. The results obtained with the proposed neural network of the boiler plant shows that back propagation can converge the neural network to improve performance. The drum level with the converged neural network is shown in fig. 7. It shows comparison of neural network results with desired drum level and percentage of deviation of drum level without neural network. It has been clearly proved that the ANN model is more accurate and efficient making the system robust and reliable as compared to the former.

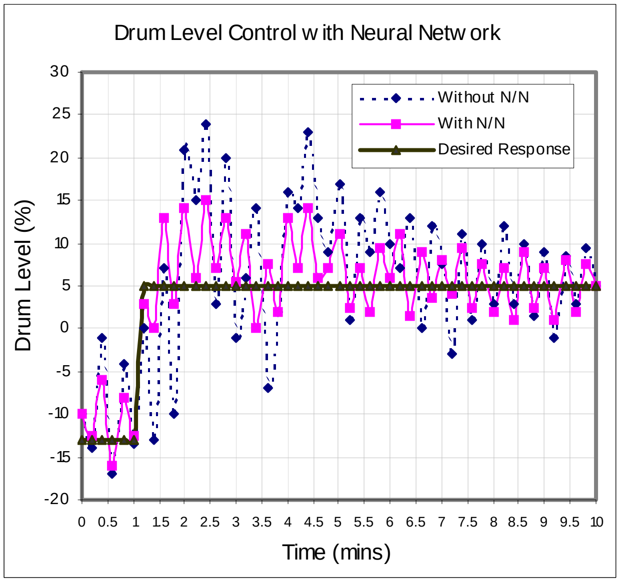

Fig. 7 Results of Back propagation Neural Network

The drum level of the plant with the neural network optimizes with less time and lowers degree of deviation taking into consideration time delay in the process. The summed squared error (SSE) between the desired drum level and the actual drum level for the case without the neural network was 812, and for the case with the converged neural network with two-foot step input, was 217, which is almost a four-fold decrease in SSE. The back propagation greatly reduced the summed squared error of the drum level with increase in foot step inputs and increased the performance of the boiler plant. The results of ANN are very sensitive to number of neurons. Increasing the number of neurons in hidden layer will decrease the number of calculation steps with subsequent decrease in summed squared error. The proposed ANN controller can replace a conventional controller, and is shown to overcome most of the problems mentioned above. A training algorithm is derived based on BP, enabling the neural network to be trained with system-output errors, rather than the network-output errors. In the BP algorithm, weights need to be modified by using the network-output error that is not known when a multilayer perceptron is applied directly to the controlled plant. Therefore, the proposed algorithm enhances the NN's ability to handle control applications. The only a priori knowledge about the controlled plant is the direction of its response, which is usually easy to determine. The proposed ANN controller has been applied to the drum level control in a thermal power plant and extensive simulations conducted show promising results.

5. Conclusions

The proposed back propagation neural network proves to be an efficient modeling system for calculation and optimization of the water level in the Boiler drums. It significantly reduces the frequency of deviations and the degree of deviation of the water level in the drum that can reduce the tripping of the boiler during load fluctuations. Focusing on process control systems, a new direct adaptive controller using neural networks has been designed and tested for the drum level control in a thermal power plant. For such a control system, the negative effects of a long system response delay and nonlinear elements are the main obstacles in designing a high performance controller and fine-tuning its parameters. Good performance, a simple structure and algorithm, and the potential for fault tolerance make the proposed ANN controller attractive for process-control applications.

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