Modeling of the Steam Pressure in Separator of a Once-through Unit Based on the ANN

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Abstract. It is challenging and interesting to establish a precise steam pressure in separator dynamic model of a once-through power plant unit in order to meet large scale load demands from the power grid and the needs of the engineering research. Steam pressure reveals the energy balance of boiler and turbine. This study proposes to establish such a steam pressure in separator mathematical model of a once-through boiler-turbine unit under dry operating conditions. Then the BP neural network model and the RBF neural network model were used to predict the steam pressure in separator, combined with running data. Moreover, in order to improve the performance of the network, the exhaustive method is used to optimize the parameters of the RBF network. After this, to further enhance model performance, the dynamic mathematical model was extended to be the one with different sets of parameters under different load ranges. More importantly, the dynamic model captures the essential dynamic characteristics of the unit. Therefore, the model can be feasible and applicable for simulation analysis and testing control algorithms.

1. Introduction
At present, the supercritical and ultra supercritical once-through boiler unit, which is characterized by high capacity, high temperature and high pressure, has been widely used. So the accurate and efficient dynamic mathematic model is critical. With increasing number of supercritical boiler units, many studies have been performed for modeling [1]. Many of the artificial neural network models of energy systems have been studied by many researchers [2-4]. The use of soft computing techniques for simulation of thermodynamic systems is presented by Mohammad Hossein Moradi [5]. Several authors have reported the capability of ANN to replicate an established correspondence between points of an input domain and points of an output domain to interpret the behavior of phenomena involved in energy conversion plants [6-8]. The simplified model of the direct current boiler was established by He Fan, which verified the feasibility of the model under the open loop and closed loop mode [9]. In this paper, ANN was trained with the real-life data; the objective of the model was to predict the steam pressure in separator. Developed model was also checked with real operational data not presented to the ANN during training for validation of the model for real-life applications.

2. Description of the Object

The schematic diagram of the boiler side model is shown in Figure 1. The coal-pulverized system is a combination of devices and connected tubes, including coal feeder, coal mill, and primary air pipe. The system can transform the raw coal into the pulverized coal, and then deliver it to a furnace for suspension combustion. The boiler side equipment includes economizer, water wall, separator and other auxiliary devices. It is simplified as a three inputs and single output system to study the relationship between input and output. The inputs of the model are feed water flow, mass flow rate of fuel in the furnace and turbine valve opening as well as primary air press and second air flow. The output of the system is steam pressure in separator.
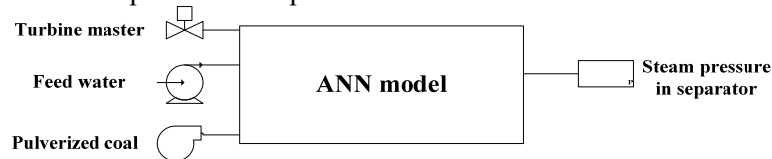

Figure 1. The schematic diagram of the boiler side model.

During the training process, the data is randomly divided into different groups: the training data set, the cross validation data set and the test data set. In order to ensure no overtraining, cross validation sets are used. In all models, when the error of the cross validation set starts to increase, the training is stopped.

3. Data Preprocessing

In order to improve the quality of data, data preprocessing technology is produced. Data processing is completed by filling out missing values, smoothing noise data, identifying or deleting outliers and solving inconsistencies. Usually large amount of plant data is captured continuously by the on-line plant data acquisition system. In the process of practical production, parameters include those related to coal mills, air and water flows to the boiler, valve openings, fan speeds, coal conveyor speeds, etc. However, for ANN modeling only some of them are sufficient to develop the equivalent model as the rest are interrelated and thus redundant. Before using data from the plant for the training of the ANN, some preprocessing is required. This is necessary as there will always be some erroneous data in a large data set. As the accuracy of prediction by a trained ANN can never be better than that of the training data, a critical scrutiny of obtained real data is required to identify and remove these erroneous data. Moreover, any data for the off-nominal operation of the plant must be removed from the training data set as it may confuse the ANN. Thus any data during the rapid changes should also be excluded from the training data set as the conditions during these periods are completely different from the normal operation and sufficient data are usually not available to train the ANN for such highly transient situations. This process of identification of outliers for all the relevant parameters was carried out rigorously and achieved good results. Therefore, before the system identification, preprocessing of data is needed. This process mainly includes the outlier detection and correction, data filtering and zero mean treatment processing.

3.1. Outlier Detection and Correction
In the actual industrial environment, there will inevitably be a temporary failure of sensors or measuring devices, resulting in serious historical data deviating from the actual value stored in the database. These jump data are called outliers. If you don't eliminate the outliers, it will affect the statistical properties of variables and lead to inaccurate identification result. In this paper, the k-means clustering method is used to remove data outliers.

3.2. Data Filtering Processing
The system identification of statistical characteristics of data samples is independent of the statistical time starting point, that is, the input and output data of the system are stationary, normal and zero

mean. Data drift, slow trend change and high frequency interference noise appeared in the industrial can have a significant impact on parameter estimation results. Therefore the samples data filter is needed. A low-pass filter can eliminate the high frequency noise, and smooth the "burr" phenomena of curve of data sample. The result of data filter was showed as Figure 2.
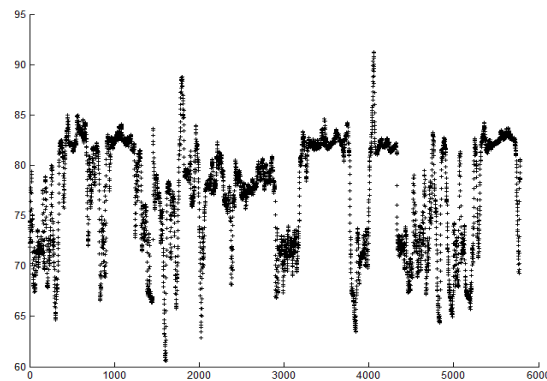

Figure 2. The data of opening of the valve after filter processing.

3.3. Zero Mean Processing
In the same way, zero mean processing is necessary before the data sample is identified. On the one hand, the DC component of the system can be eliminated and the accuracy of the recognition results can be improved. On the other hand, it is necessary to meet the characteristics of the model. The results of zero mean processing of some parameters of training data were showed as Figure 3.
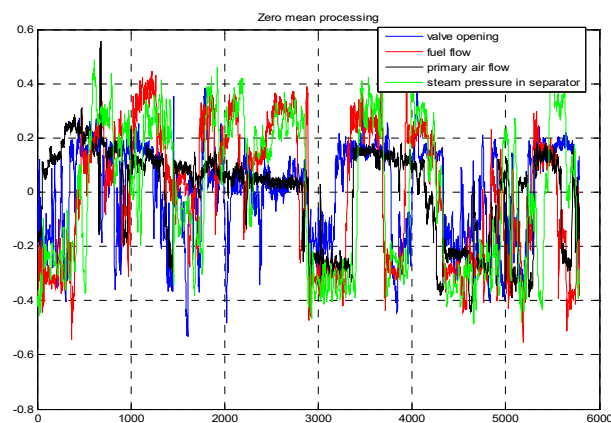

Figure 3. Zero means processing for training data.

4. Modeling Training and Verification
The learning of artificial neural networks is divided into three steps: training, verification and testing. In the training process, once the inputs are presented to the networks they are multiplied by their adjustable weights and then they are summed and transferred in the processing elements in order to produce an output. On the basis of input data, an ANN sets the weights on the connections to be compared to the threshold of a neuron. Setting of weights on the next layer depends on the decision of individual neurons on the previous layer. This process leads to the final decision at the exit, where the result obtained is compared to the anticipated result from the learning model. If the solution is within the tolerance, the network will store the distribution of weights and thresholds as appropriate, or else the procedure is repeated.

4.1. BP Network and RBF Network

The training of the BP neural networks and RBF neural networks was carried out with 6000 historical data processed and the corresponding test experiment was done. For input layer, the input variables were selected by how much influence each assumed input parameter has on the output parameters and thereby to remove unnecessary inputs. Eventually, the input were identified as fuel flow, steam turbine inlet valve opening, feed water flow, primary air press and second air flow. The output is steam pressure in separator. For hidden layer, the number of neurons was determined by the empirical formula.
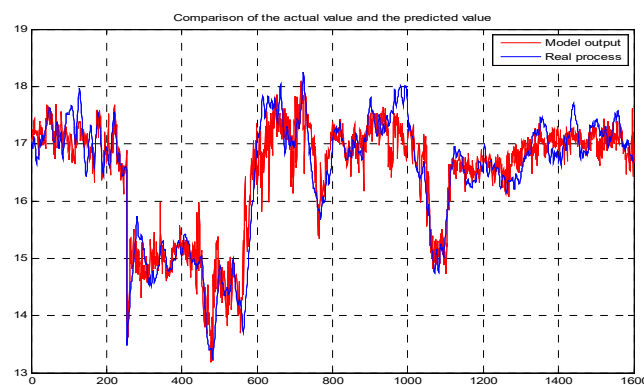

Figure 4. The output of BP model and the pressure of real process.

Figure 4 shows the BP neural network model output and real process data. Although the training process has good convergence, the generalization ability of BP network is poor because of its own characteristics. So the result of the test is not so ideal, that is, there is a big error.

Due to the fixed learning rate of BP neural network so that network learning speed is slow. In addition, the weights of BP algorithm can make the convergence to a certain value but does not guarantee for the minimum of the error plane. From the above, we can also see that the BP neural network prediction result is not ideal from the curve. Therefore, we use RBF neural network which conversion function is the Gaussian function with local response. It can reach the optimal value more quickly and accurately. Figure 5 shows the RBF neural network model output and real process.
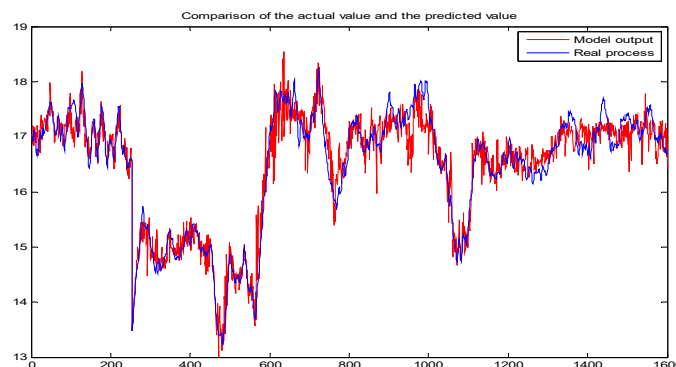

Figure 5. The output of RBF model and the pressure of real process.

4.2. RBF Network Based on Parameter Optimization

Compared with the BP neural network, the prediction effect of RBF neural network has been greatly improved. But on the other hand, we can see from the absolute error that the prediction results can not achieve satisfactory results, because the maximum deviation of the separator pressure is about 1.5MPa,

which is not acceptable at the actual production site. The main parameters of the RBF neural network include the weight, the location of the center point and the response width of the hidden layer to the input vector. These three key parameters determine the performance of the network to a great extent. From the diagram we can clearly see the impact of this parameter on the network. Therefore, for the low prediction accuracy of the RBF neural network, we take the mean square root error as the objective function to use the exhaustive method to optimize the parameters. This is mainly for response width. The results showed that the selection of appropriate network parameters can greatly improve the predictive performance of the network. Figure 6 shows the RBF neural network model output and real process after parameter optimization. Figure 7 shows the testing error. Table 1 more clearly shows the superiority of RBF neural network after parameter optimization from the root mean square error and maximum error. From this, we can clearly see the effect of parameter adjustment on network performance and precision. The greater the response width is, the greater the response ranges of the hidden layer neurons to the input vector, and the better the smoothness of the neurons.
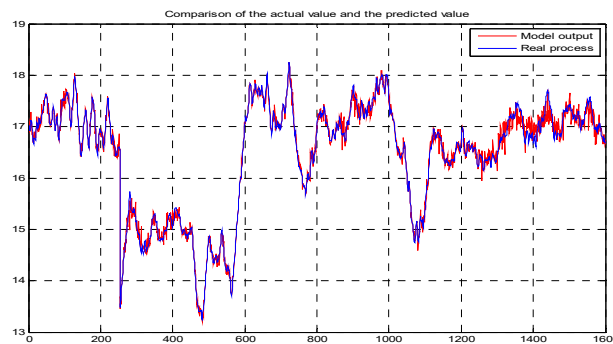

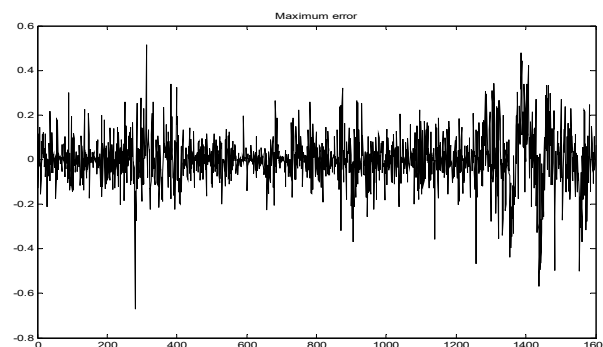Figure 6. Output of RBF model after parameter optimization.

Figure 7. Testing error of RBF after parameter optimization.

Table 1. Comparison of RBF and BP.

	BP	RBF	Optimized RBF
RMSE (Root mean square error)	0.4078	0.3	0.0191
Maximum error	2.3	1.5	0.7

5. Paper Submission

Steam pressure reveals the energy balance of boiler and turbine, so it's a quite important parameter to control. Development of accurate physical models for pressure of coal-fired boilers can be difficult due to complexity of the system. On the other hand, ANN models can be developed by training data which needs smaller number of input parameters. In addition, ANN has fast response and therefore useful for on-line applications. In this paper, development of ANN model for a once-through coal-fired boiler of a DaTong plant was discussed. We selected six variables closely affecting the separator pressure as the input of the model and achieved ideal results. By the test data and the model of the output, the model precision can completely satisfy the requirements of industrial field. What's more, we use the BP neural network and RBF neural network separately; the results show that the RBF neural network has better precision and speed after parameter optimization. Due to the RBF neural network local corresponding, there is no local optimum, so it can faster converge in training and has high generalization ability.

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