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The Dynamic Neural Network Model of a Ultra Super-critical Steam Boiler Unit

Xiangjie Liu, Xuewei Tu, Guolian Hou and Jihong Wang

Abstract—**Thermal power unit is an energy conversion system consisting of the boiler, the turbine and their auxiliary machines respectively. It is a complicated multivariable system with strong nonlinearity, uncertainty and multivariable coupling. These characters will be more evident with the unit tending to large-capacity and high-parameter. It is expensive to build the model of the unit using conventional method. The paper presents modeling of a 1000MW ultra supercritical once-through boiler unit. Based on these field data, two different neural networks are used to model the thermal power unit. The simulation results validate the efficiency of the neural networks in modelling the ultra supercritical unit.**

I. Introduction

ULTRA super-critical (USC) coal fired plant technology is one of the leading options in today's power generation industry, with improved efficiency and hence reduced CO_2 emissions per unit of electrical energy generated. In addition to higher energy efficiency, lower emission levels for supercritical plants are achieved by better conversion of fuel and using well-proven emission control technologies. In China, there has been near twenty 1000 MW-steam-boiler generation units in operation, ever since the first operation of 1000MW steam boiler generation in Yuhuan Power Plant in December 2006.

Accurate power plant modelling is most important in the assessment and prediction of performance, and in constituting advanced control strategies. Power plant modelling approaches are mainly composed of two groups, e.g., the experimental modelling and the first-principal-based modelling. The experimental modeling approach [1-2] reflects the major nonlinear dynamics and is frequently used for control strategy design. The modelling based on first-principals [3-7] can represent the relationship among the physics links and true plant parameters, which is more fitful for control algorithm evaluation.

Generally speaking, the basic tool for derivation and validation of plant models is by system identification, commonly using recursive least squares (RLS) method. The linear RLS performs well around the plant operating point, where the plant can be approximated by a linear model. However, as the USCs are highly nonlinear, nonminimum, and subject to various types of uncertainties and load disturbances, the performance of the RLS may deteriorate, and suitable nonlinear modeling techniques need to be used.

Neural networks offer a framework for nonlinear modelling and control based on their ability to learn complex nonlinear functional mappings. Consequently, they are useful tools for modelling large-scale power plant steam-boiler system. Irwin originally designed neural network model for a 200MW boiler system [8]. Later on, the authors developed modelling and control technique using neuro-fuzzy networks [9]. Recently, the group of Kwang presented several research progresses concerning modelling and control of USC [10], mainly using neural networks.

This paper presents two types of neural network modelling techniques on a 1000 MW ultra super-critical coal fired boiler-turbo generator unit. Based on the on-site measured data, neural networks with different structures are used. The simulation results demonstrated the efficiency and the advantage of the neural network modeling approach over the linear models.

II. The Ultra Super-critical Coal Fired Boiler-Turbo Generator Unit

The power plant considered in this paper is a pulverized coal firing, once-through type, steam-boiler generation unit rated at 1000 MW. The maximum steam consumption of the power plant is 2980 T/h at a superheated steam pressure and temperature of 26.15 MPa and 605 °C, respectively.

Compared with the ordinary subcritical boiler power plants, the ultra super-critical coal fired plant is more complicated in the following aspects:

1) Strong coupling effect. In drum boilers, the total system is usually decoupled into three simplified subsystems, e.g., the fuel system, the feedwater system and the steam temperature system. In USC, situations are quite different. The fuel system and the feedwater system directly decide steam temperature, resulting in the strong coupling effect among boiler parameters.

2) Strong nonlinearity. Load-cycling operation of the ultra super-critical generation leads to the change of operating point right across the whole operating range, with steam-pressure mostly ranging between 10-25Mpa. As a

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Xiangjie Liu and Guolian Hou are with the Department of Automation, North China Electric Power University, Beijing, 102206, P.R. China (corresponding author. Tel: 86-10-61772103; e-mail: liuxj@ncepu.edu.cn).

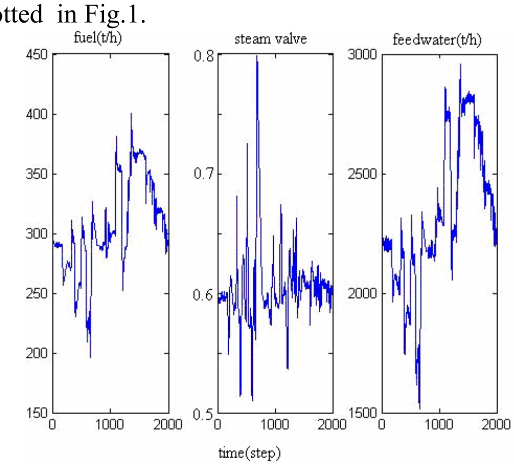
Xuewei Tu is with the Electrical and I&C Department, State Nuclear Electric Power Planning Design and Research Institute, Beijing, 100094, P.R. China.(e-mail: tuxuewei@snpdri.com).

Jihong Wang is with the School of Engineering, the University of Warwick, Coventry CV4 7AL, UK (e-mail: jihong.wang@warwick.ac.uk).

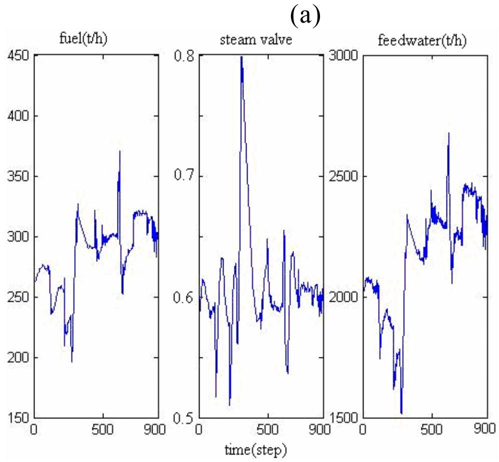
result, the nonlinearity of the plant variables becomes more serious. Moreover, the USC runs under the two modes: the super-critical mode and the sub-critical mode. The super-critical contains three phase: the heating, the evaporation and the super-hearting. In the super-critical, the density of the water and steam is equal. Water changes to steam instantly.

Under the once through operation of USC, the feed-water will directly affect the main steam parameters. Consequently, keeping the fuel\water ratio at a desired value is a major task. In this way, the coordinated system can be modeled as a three-input-three-output system, with the three outputs to be the electric power, the steam pressure and the separator outlet steam temperature, and the three input variables to be the fuel flow, the governor valve input and the feedwater flow, respectively.

For identification purpose, it is necessary to collect the data resulting from scheduled changes of operating points, to ensure that the data is representative of the dynamic behavior of the steam-boiler generation unit. In this way, 2000 sets of input data were selected for testing. Another 900 sets of input data were chosen for validating. These data were used to establish the linear and neural network models. The data are plotted in Fig.1.



(a)



(b)

Fig.1 The data pattern selected for testing.(a) and validating(b)

III. IDENTIFICATION OF ARMAX MODELS USING RLS

In order to utilize the RLS method for identification purpose, the system structure needs to be defined first. A third-order, three-input three-output, ARMAX model of the form

$$\begin{aligned} Y(k) + A_1Y(k-1) + A_2Y(k-2) + A_3Y(k-3) \\ = B_0U(k) + B_1U(k-1) + B_2U(k-2) \end{aligned} \tag{1}$$

was identified from the I/O data, where $Y(k) = [y_1(k), y_2(k), y_3(k)]^T$, $U(k) = [u_1(k), u_2(k), u_3(k)]^T$, A_1 A_2 , B_0 , B_1 and B_2 are all 3×3 dimensional polynomial matrices in the backward shift operator,

$$A_i = \begin{bmatrix} a_{1i1} & \cdots & a_{1i3} \\ \vdots & \ddots & \vdots \\ a_{3i1} & \cdots & a_{3i3} \end{bmatrix}, B_i = \begin{bmatrix} b_{1i1} & \cdots & b_{1i3} \\ \vdots & \ddots & \vdots \\ b_{3i1} & \cdots & b_{3i3} \end{bmatrix}, i = 0,1,2$$

In using RLS, persistency of excitation conditions should be satisfied in order to guarantee the exponential convergence of the parameter estimation process. In real-time power plant situation, this persistency excitation may be difficult to realize for security purpose. Since the dynamics of the plant is well understood by the operators, sufficiently reliable estimate of the parameters of the plant model can be obtained if the collected data covers sufficient dynamic behaviors of the steam-boiler generation unit. With the testing data shown above, the resulting identified model is as follows:

$$\begin{aligned} Y(k) + &\begin{bmatrix} 0.71342 & -0.70787 & -0.17607 \\ -0.17408 & 0.70713 & -0.25851 \\ 0.31156 & -0.18739 & -0.62445 \end{bmatrix} Y(k-1) \\ + &\begin{bmatrix} -0.1965 & 0.60755 & 0.12676 \\ -0.2593 & 0.57673 & -0.30503 \\ -0.048988 & 0.4584 & -0.97332 \end{bmatrix} Y(k-2) \\ + &\begin{bmatrix} -0.24339 & -1.1433 & 0.23733 \\ -0.67618 & -0.61539 & 0.11612 \\ -0.044767 & -0.43905 & 0.65192 \end{bmatrix} Y(k-3) \\ = &\begin{bmatrix} -0.24183 & -0.094649 & 0.42274 \\ 0.41525 & -0.45735 & -0.30785 \\ 0.028714 & 0.46121 & 0.048596 \end{bmatrix} U(k) \\ + &\begin{bmatrix} 0.66004 & 0.048006 & -0.82958 \\ -0.80194 & 0.39523 & 0.073095 \\ -0.33973 & -0.41338 & -0.38357 \end{bmatrix} U(k-1) \\ + &\begin{bmatrix} -0.3764 & 0.35845 & 0.571 \\ 0.85246 & -0.24037 & -0.079496 \\ 0.41829 & -0.048467 & 0.33457 \end{bmatrix} U(k-2) \end{aligned} \tag{2}$$

Figs. 2 show the resulting model output and the plant output over the test. It can be seen that the linear model matches the plant quite closely around this range.

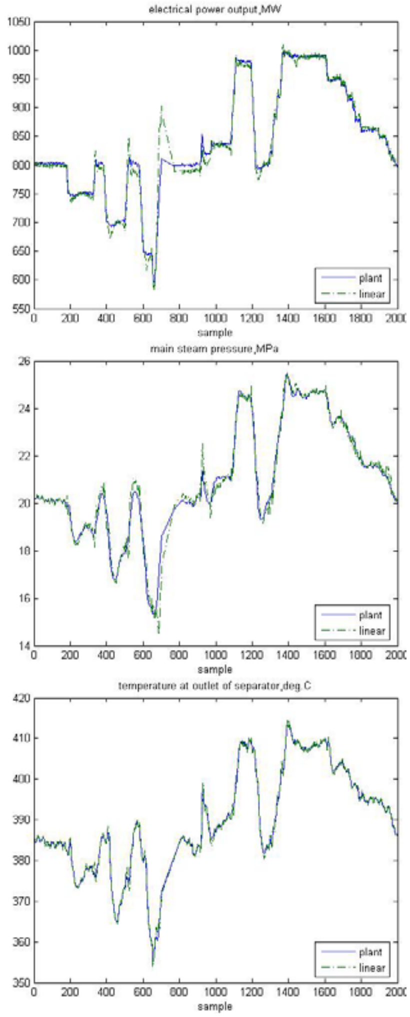


Fig .2 Comparison of boiler system and linear model(test)

Fig. 3 shows the resulting model output and the plant output over the validating using another 900 sets of data. The poorer responses are obtained. When using a different operating data, the dynamics of the plant will change and the original linear model is no longer able to represent the whole process working at different operating conditions, which indicates that the plant is quite nonlinear. This motivated the authors to investigate other nonlinear modeling techniques.

IV. NEURAL NETWORK MODELLING

The neural network shown in Fig.4 is called the radial basis function (RBF) network, if the activation function $g(\bullet)$ is choosen to be Gaussian function. The mapping is described by

$$y_l = \sum_{m=1}^{M} w_{lm} G\left(\left\| X - X^m \right\|\right) \qquad (3)$$

where M is the number of hidden unit, $X^m \in R^n$ is the center of the m*th* hidden unit and can be regarded as a weight vector from the input layer to the m*th* hidden unit, G is the m*th* radial basis function or response function, and w_{lm} is the weight from the mth hidden unit to the lth output unit.

The Gaussian type functions, given by, $G(X) = \exp(-\frac{\left\| X - X^m \right\|^2}{2\sigma^2})$ offers a desirable property making the hidden units to be locally tuned, where the locality of the $G(X)$ is controlled by σ.

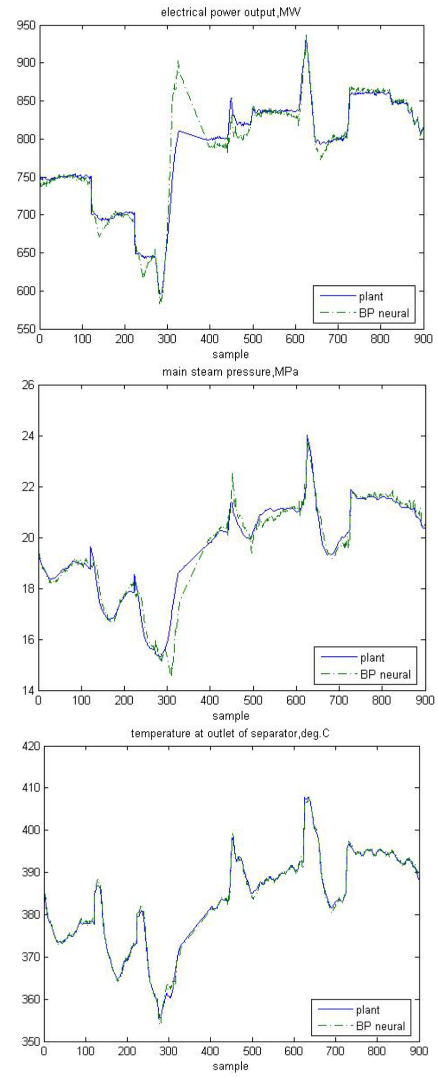


Fig .3 Comparison of boiler system and linear model(validating)

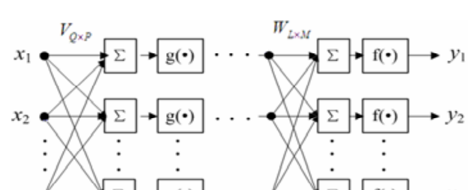


Fig.4. Multi layer perceptron(MLP) network

A three-input three-output third-order dynamic nonlinear model was simulated using a 18-30-3 RBF as shown in Fig.5, under the same I/O data as used with the RLS method, to make a fair comparison.

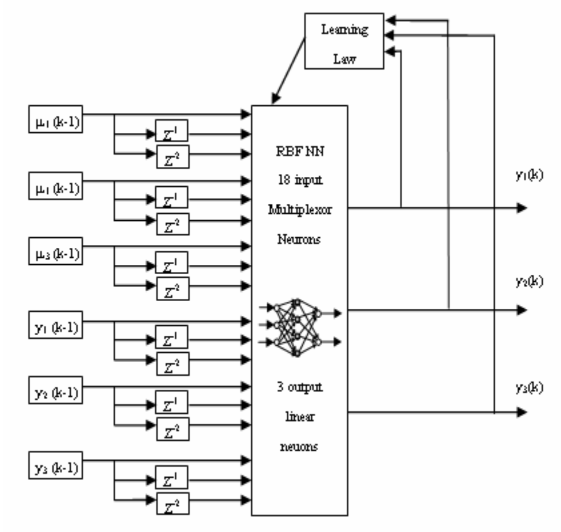


Fig.5. Neural network dynamic model structure

The initial network weights were chosen to be a random in [-1, 1], let σ=1. Fig.6 shows the resulting model output and the plant output over the test.

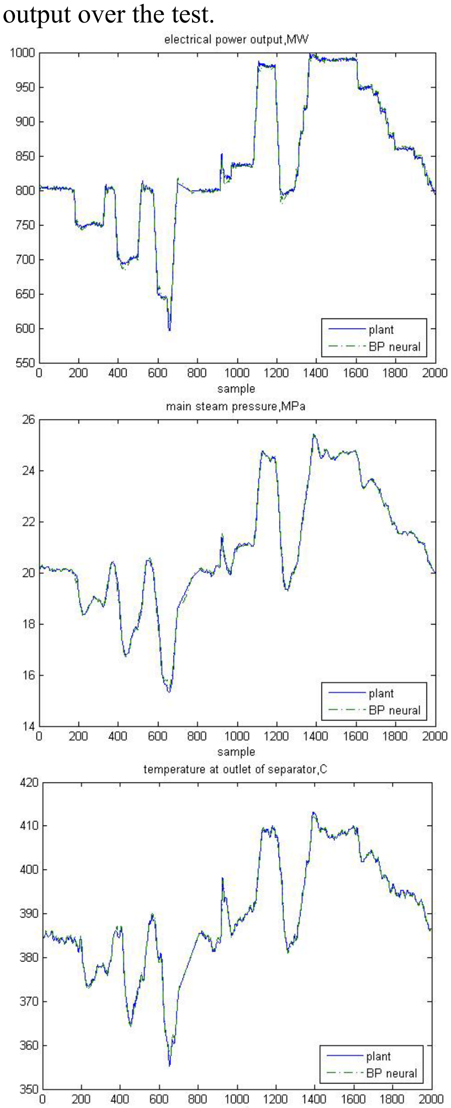


Fig .6 Comparison of boiler system and RBF network model(test)

Fig.7 shows the resulting model output and the plant output over the validating. The better responses are obtained. When moving to a different set of operating data, the neural network can still well represent the plant dynamics.

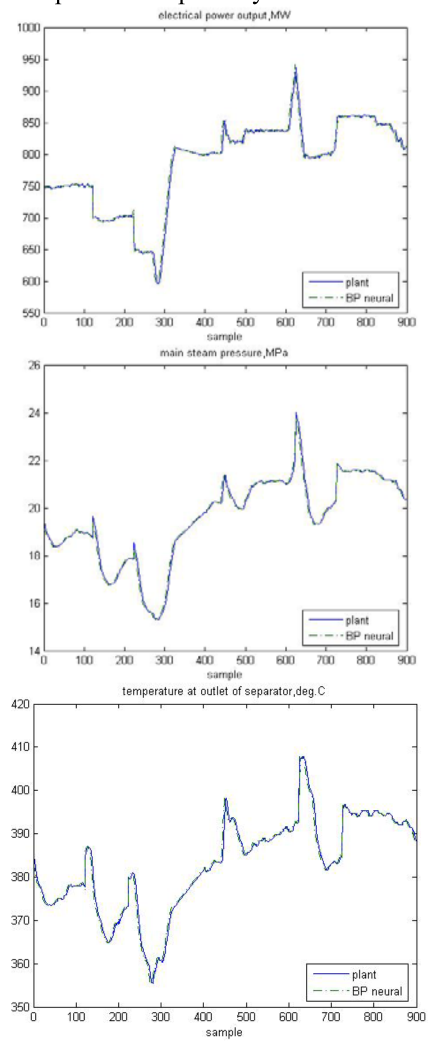


Fig .7 Comparison of boiler system and BP network model(validating)

V. Identification of Neural Fuzzy Network Models

A typical schematic diagram of the fuzzy neural network (FNN) structure is shown in Fig. 8, which consists of five layers.

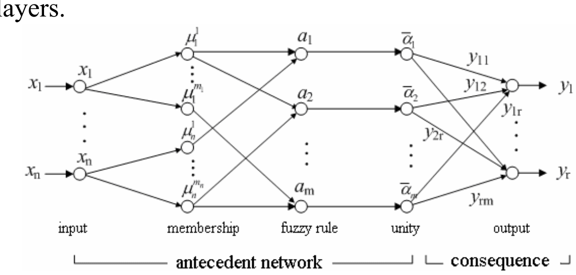


Fig. 8 The schematic diagram of the fuzzy neural network (FNN) structure

A. Reasoning method

For an n-input-r-output system, let x_i be the ith input linguistic variable and define α_j as the firing strength of rule j, which is obtained from the product of the grades of the membership functions μ_i^j in the antecedent. The proposed fuzzy neural network realizes the inference as follows[11]

$\mathbf{R}^j$: if x_1 is R_1^j ,…, and x_n is R_n^j , then

$$y_{ij} = p_{1j}^i x_1 + p_{2j}^i x_2 + \cdots + p_{nj}^i x_n = \sum_{k=1}^{n} p_{kj}^i x_k$$

$$j = 1,2,\cdots,m; i = 1,2,\cdots,r \qquad (4)$$

In the second layer, each node performs a membership function. The Gaussian function is adopted here as a membership function.

$$\mu_i^j = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \qquad (5)$$

where c_{ij} and σ_{ij} are, respectively, the mean (or center) and the variance (or width) of the Gaussian function in the jth term of the ith input linguistic variable. The number of nodes in this layer is $N_2 = \prod_{i=1}^{n} m_i$.

Each node in the third layer represents a product of the grades of the membership functions of the fuzzy rule:

$$\alpha_j = \min\{\mu_1^{i_1}, \mu_2^{i_2}, \cdots, \mu_n^{i_n}\} \text{ or } \alpha_j = \mu_1^{i_1}\mu_2^{i_2}\cdots\mu_n^{i_n} \qquad (6)$$

where, $i_1 \in \{1,2,\cdots,m_1\}$, $i_2 \in \{1,2,\cdots,m_2\}$, $\cdots$, $i_n \in \{1,2,\cdots,m_n\}$, $j = 1,2,\cdots,m$, m is the total number of the rules. $m \le \prod_{i=1}^{n} m_i$. The number of nodes in this layer is $N_3=m$. The fourth layer realizes the unitary function:

$$\bar{\alpha}_j = \frac{\alpha_j}{\sum_{j=1}^{m} \alpha_j} \qquad (7)$$

In the consequence links, the output of the model is:

$$y_i = \sum_{j=1}^{m} \bar{\alpha}_j y_{ij} \quad i = 1,2,\cdots,r \qquad (8)$$

B. Test results

Models were formed using the same I/O structure and training data as that used in RBF network. The membership functions, after training, are shown in Fig.9.

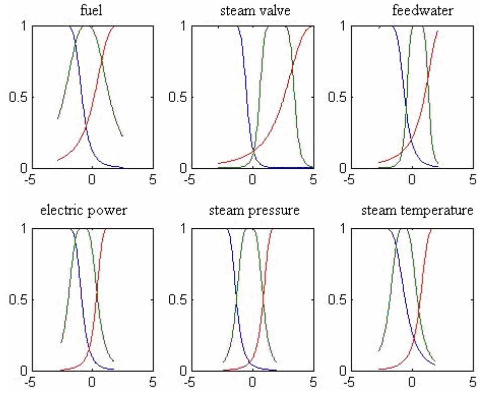


Fig. 9. Final membership functions

The resulting fuzzy rules are expressed as:

R1: if $\boldsymbol{u_1}$ is R_1^1 and $\boldsymbol{u_2}$ is R_2^1 and $\boldsymbol{u_3}$ is R_3^1 and $\boldsymbol{y_1}$ is R_4^1 and $\boldsymbol{y_2}$ is R_5^1 and $\boldsymbol{y_3}$ is R_6^1 , then

$$\begin{aligned}
y_1(k)=&-0.24183u_1(k\text{-}1)-0.094649u_2(k\text{-}1)+0.42274u_3(k\text{-}1)\\
&+0.66004u_1(k\text{-}2)+0.048006u_2(k\text{-}2)-0.82958u_3(k\text{-}2)\\
&-0.3764u_1(k\text{-}3)+0.35845u_2(k\text{-}3)+0.571u_3(k\text{-}3)\\
&-0.71342y_1(k\text{-}1)+0.70787y_2(k\text{-}1)+0.17607y_3(k\text{-}1)\\
&+0.1965y_1(k\text{-}2)-0.60755y_2(k\text{-}2)-0.12676y_3(k\text{-}2)\\
&+0.24339y_1(k\text{-}3)+1.1433y_2(k\text{-}3)-0.23733y_3(k\text{-}3)
\end{aligned}$$

$$\begin{aligned}
y_2(k)=&0.41525u_1(k\text{-}1)-0.45735u_2(k\text{-}1)-0.30785u_3(k\text{-}1)\\
&-0.80194u_1(k\text{-}2)+0.39523u_2(k\text{-}2)+0.073095u_3(k\text{-}2)\\
&+0.85246u_1(k\text{-}3)-0.24037u_2(k\text{-}3)-0.079496u_3(k\text{-}3)\\
&+0.17408y_1(k\text{-}1)-0.70713y_2(k\text{-}1)+0.25851y_3(k\text{-}1)\\
&+0.2593y_1(k\text{-}2)-0.57673y_2(k\text{-}2)+0.30503y_3(k\text{-}2)\\
&+0.67618y_1(k\text{-}3)+0.61539y_2(k\text{-}3)-0.11612y_3(k\text{-}3)
\end{aligned}$$

$$\begin{aligned}
y_3(k)=&0.028714u_1(k\text{-}1)+0.46121u_2(k\text{-}1)+0.048596u_3(k\text{-}1)\\
&-0.33973u_1(k\text{-}2)-0.41338u_2(k\text{-}2)-0.38357u_3(k\text{-}2)\\
&+0.41829u_1(k\text{-}3)-0.048467u_2(k\text{-}3)+0.33457u_3(k\text{-}3)\\
&-0.31156y_1(k\text{-}1)+0.18739y_2(k\text{-}1)+0.62445y_3(k\text{-}1)\\
&+0.048988y_1(k\text{-}2)-0.4584y_2(k\text{-}2)+0.97332y_3(k\text{-}2)\\
&+0.044767y_1(k\text{-}3)+0.43905y_2(k\text{-}3)-0.65192y_3(k\text{-}3)
\end{aligned}$$

R2: if $\boldsymbol{u_1}$ is R_1^2 and $\boldsymbol{u_2}$ is R_2^2 and $\boldsymbol{u_3}$ is R_3^2 and $\boldsymbol{y_1}$ is R_4^2 and $\boldsymbol{y_2}$ is R_5^2 and $\boldsymbol{y_3}$ is R_6^2 , then

$$\begin{aligned}
y_1(k)=&0.050561u_1(k\text{-}1)-0.016772u_2(k\text{-}1)-0.6142u_3(k\text{-}1)\\
&+0.44067u_1(k\text{-}2)+0.1171u_2(k\text{-}2)+0.77706u_3(k\text{-}2)\\
&-0.3973u_1(k\text{-}3)-0.15174u_2(k\text{-}3)-0.17433u_3(k\text{-}3)\\
&+0.92962y_1(k\text{-}1)-0.52748y_2(k\text{-}1)-0.27394y_3(k\text{-}1)\\
&-0.072739y_1(k\text{-}2)-0.60357y_2(k\text{-}2)+0.80486y_3(k\text{-}2)\\
&+0.35157y_1(k\text{-}3)+0.85186y_2(k\text{-}3)-0.53729y_3(k\text{-}3)
\end{aligned}$$

$$\begin{aligned}
y_2(k)=&-0.15159u_1(k\text{-}1)-0.39286u_2(k\text{-}1)-0.046314u_3(k\text{-}1)\\
&+0.44532u_1(k\text{-}2)+0.34132u_2(k\text{-}2)+0.55281u_3(k\text{-}2)\\
&-0.36892u_1(k\text{-}3)+0.23627u_2(k\text{-}3)-0.58238u_3(k\text{-}3)\\
&-0.56719y_1(k\text{-}1)-0.61907y_2(k\text{-}1)+0.23047y_3(k\text{-}1)\\
&-0.36337y_1(k\text{-}2)+0.73598y_2(k\text{-}2)+0.089885y_3(k\text{-}2)\\
&-0.63593y_1(k\text{-}3)+0.37216y_2(k\text{-}3)-0.018879y_3(k\text{-}3)
\end{aligned}$$

$$\begin{aligned}
y_3(k)=&0.3152u_1(k\text{-}1)+0.29253u_2(k\text{-}1)-0.23407u_3(k\text{-}1)\\
&-0.3864u_1(k\text{-}2)-0.53482u_2(k\text{-}2)+0.18486u_3(k\text{-}2)\\
&+0.049695u_1(k\text{-}3)+0.33026u_2(k\text{-}3)-0.032981u_3(k\text{-}3)\\
&+0.41128y_1(k\text{-}1)+0.02565y_2(k\text{-}1)+0.001924y_3(k\text{-}1)\\
&+0.30104y_1(k\text{-}2)+0.27294y_2(k\text{-}2)-0.087338y_3(k\text{-}2)\\
&-0.97075y_1(k\text{-}3)+0.29885y_2(k\text{-}3)+0.84204y_3(k\text{-}3)
\end{aligned}$$

R3: if $\boldsymbol{u_1}$ is R_1^3 and $\boldsymbol{u_2}$ is R_2^3 and $\boldsymbol{u_3}$ is R_3^3 and $\boldsymbol{y_1}$ is R_4^3 and $\boldsymbol{y_2}$ is R_5^3 and $\boldsymbol{y_3}$ is R_6^3 , then

$$y_1(k)=0.03967u_1(k\text{-}1)\text{-}0.10969u_2(k\text{-}1)+0.18505u_3(k\text{-}1)$$
$$\text{-}0.046311u_1(k\text{-}2)+0.20497u_2(k\text{-}2)\text{-}0.20821u_3(k\text{-}2)$$
$$+0.058611u_1(k\text{-}3)\text{-}0.08526u_2(k\text{-}3)+0.030352u_3(k\text{-}3)$$
$$+0.69863y_1(k\text{-}1)\text{-}0.3476y_2(k\text{-}1)+0.053512y_3(k\text{-}1)$$
$$+0.51744y_1(k\text{-}2)+0.16003y_2(k\text{-}2)+0.071529y_3(k\text{-}2)$$
$$\text{-}0.28024y_1(k\text{-}3)+0.20373y_2(k\text{-}3)\text{-}0.13474y_3(k\text{-}3)$$
$$y_2(k)=\text{-}0.044165u_1(k\text{-}1)+0.0523u_2(k\text{-}1)+0.00084u_3(k\text{-}1)$$
$$+0.09663u_1(k\text{-}2)\text{-}0.14928u_2(k\text{-}2)+0.0014758u_3(k\text{-}2)$$
$$\text{-}0.010149u_1(k\text{-}3)+0.062767u_2(k\text{-}3)+0.019042u_3(k\text{-}3)$$
$$\text{-}0.25615y_1(k\text{-}1)+0.82349y_2(k\text{-}1)+0.2154y_3(k\text{-}1)$$
$$+0.35284y_1(k\text{-}2)\text{-}0.090736y_2(k\text{-}2)\text{-}0.24819y_3(k\text{-}2)$$
$$+0.000885y_1(k\text{-}3)+0.1208y_2(k\text{-}3)+0.020325y_3(k\text{-}3)$$
$$y_3(k)=0.04766u_1(k\text{-}1)+0.068072u_2(k\text{-}1)\text{-}0.10261u_3(k\text{-}1)$$
$$\text{-}0.072139u_1(k\text{-}2)\text{-}0.12163u_2(k\text{-}2)+0.28645u_3(k\text{-}2)$$
$$+0.024555u_1(k\text{-}3)+0.083279u_2(k-3)\text{-}0.22937u_3(k\text{-}3)$$
$$\text{-}0.33874y_1(k\text{-}1)+0.8068y_2(k-1)+0.71583y_3(k-1)$$
$$+0.33206y_1(k\text{-}2)\text{-}0.095012y_2(k\text{-}2)+0.62572y_3(k\text{-}2)$$
$$\text{-}0.083247y_1(k\text{-}3)\text{-}0.56376y_2(k\text{-}3)\text{-}0.35532y_3(k\text{-}3)$$

The neural fuzzy model was also tested and validated using the same data as that in the RBF network. Define the Root-Mean-Square-Errors (RMSE) to evaluate the modelling effect:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{K}(y_k^* - y_k)^2}{K}} \tag{9}$$

where y_k^* is the model output and y_k is the plant output, k is the number of the data. Table 1 list the RMSE for these three methods.

TABLE I
THE ROOT-MEAN-SQUARE-ERRORS(RMSE)

		power	pressure	temperature
linear	test	0.061	0.083	0.0398
	validate	0.2191	0.1952	0.0596
neural network	test	0.0114	0.0068	0.0128
	validate	0.0806	0.0370	0.0083
neural fuzzy	test	2.8e-005	3.3e-005	3.1e-005
	validate	3.1e-005	3.6e-005	3.7e-005

VI. CONCLUSION

The application of neural network techniques to model a 1000MW, ultra super-critical coal fired boiler turbogenerator unit has been proposed in this paper. Real-time on-site measurement data, for testing and validating purpose, resulting from scheduled changes of operating point, were used to establish the linear and neural network models.

Identification of multivariable linear models using RLS showed good predictive capabilities at the respective operating points, but, as expected, the performance deteriorated when the models were used to represent the real plant at different operating conditions. The results illustrate clearly the limitations of linear models for representing a highly nonlinear plant. RBF network was then trained and tested using the same sets of data under the same operating conditions. The results has improved dramatically for model fidelity, which demonstrated the advantage of the neural network modeling technique on such type of complex nonlinear power plants. The result was further improved by using the neural fuzzy network approach, with local support functions. The modelling effectiveness was evaluated by comparing the calculated RMSE. The overall simulation results show that the neural network can well be applied for analyzing the dynamic characteristics of the ultra super-critical boiler turbogenerator unit.

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