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NEURO-FUZZY BASED APPROACH TO ESTIMATE TURBINE-GENERATOR OUTPUT IN NUCLEAR POWER PLANTS

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Abstract. *This paper presents a hybrid soft-computing modeling technique used to develop a turbine cycle model for the Maanshan Nuclear Power Plant (NPP) in Taiwan. The technique utilizes a neuro-fuzzy based approach to estimate turbine-generator output. First, operating data above the 95% load level from the plant's past three fuel cycles were collected and validated to serve as a baseline performance data set. Signal errors in new operating data were then detected and compared with the allowable range determined from the baseline data set. Finally, the variables most strongly influence turbine-generator output were selected as inputs for the neuro-fuzzy based turbine cycle model. After training and validation of key parameters, including main steam pressure, condenser backpressure, feedwater flow rate, and final feedwater temperature, the proposed model was used to estimate turbine-generator output. The effectiveness of the proposed neuro-fuzzy based turbine cycle model was demonstrated using plant operating data obtained from Manansan NPP. In addition, to assess the performance of the neuro-fuzzy based turbine cycle model, this study adopted a widely used commercial software program, PEPSE, for developing the thermodynamic turbine cycle of Maanshan NPP. Results show that the neuro-fuzzy based turbine cycle model is more reliable than the PEPSE turbine cycle model with the good estimation and the trend. Furthermore, the results of this study provide an alternative approach to evaluate thermal performance in nuclear power plants.*

Keywords: Adaptive neural-fuzzy inference system, Turbine cycle model, Turbine-generator, Nuclear power plant

1. **Introduction.** Confronted with climate change, countries need to reduce carbon dioxide (CO_2) output, and existing nuclear power plants must respond by improving their operating efficiency. It is therefore important for nuclear power plant operators to evaluate the performance of plants. As competition increases in the power industry, power utilities may be forced to reevaluate their operating status and optimize thermal performance to reduce costs. In this regard, the Electric Power Research Institute (EPRI) has already issued guidelines by which utilities can set up performance monitoring programs [1,2].

Nuclear power plants consist of very complex sets of component systems and interrelated thermodynamic processes, making it very difficult to accurately estimate turbine-generator output. Fundamental steady-state mass and energy balance equations have been used to develop turbine cycle models. Recently, several solutions have been proposed to model the turbine cycle and evaluate plant performance. PEPSE® is a commercial software application developed by Scientech Inc., widely used to develop turbine cycle models for power plants under normal operation conditions, yielding performance analysis of the major components [3]. Using PEPSE®, the evaluation of system modeling and performance proceeds in a step by step process to construct a turbine cycle model based on a thermal kit provided by the turbine vendor. Heo et al. [4] developed a need-oriented turbine cycle simulation toolbox, and Kim and Choi [5] developed a performance upgrade system to aid on-line turbine cycle performance analysis for nuclear power plants in Korea. In addition, an on-line thermal efficiency monitoring and analysis system was developed for Kuosheng NPP in Taiwan to calculate turbine-generator output, heat rate, and component operating conditions [6]. NaKao et al. [7] developed a general-purpose software application to analyze the static thermal characteristics of power generation systems.

In developing the turbine cycle model, a number of researchers have used fundamental steady-state mass and energy balance equations, while others have adopted commercial tools to model the turbine cycle and analyze performance. However, these approaches all have the same drawback. They depend on system models that may deviate from ideal conditions, often involving empirical relationships, approximations of actual processes, and linearization of nonlinear phenomena. Moreover, conventional models usually include a large number of parameters supplied by turbine vendors for modeling the turbine cycle.

A practical alternative to overcome these problems is soft computing, which can be used to solve computationally complex and mathematically intractable problems. The main components of soft computing, fuzzy logic and neural networks, have shown the ability to solve complex problems of identification in nonlinear systems [8]. These methods are the basis of artificial intelligence, which has been widely applied in most fields involving computational studies. The main features of these two methods are the ability to self-learn and self-predict particular desired outputs.

An adaptive neuro-fuzzy inference system (ANFIS) combines these two methods, utilizing the advantages of both [9,10]. Since Jang first proposed ANFIS [9], it has been applied in numerous fields, including engineering, management, health, biology, and even the social sciences. Specifically, the literature contains several articles on ANFIS applications in automatic control, robotics, nonlinear regression, nonlinear system identification, adaptive signal processing, decision making, quality control, power systems, and pattern recognition [11-13]. Many claim that ANFIS is a universal approximator capable of representing highly nonlinear functions more effectively than conventional statistical methods [14]. Guo and Uhrig [15] proposed a 3-layer hybrid neural network approach to study the heat rate and thermal performance of nuclear power plants. This hybrid neural network, combining self-organization and back-propagation neural networks, analyzes plant data and extracts some useful information to operate the plant more efficiently.

This study uses ANFIS to develop a turbine cycle model for Maanshan NPP in Taiwan to estimate turbine-generator output using key parameters. The objective of the ANFIS based turbine cycle model is to estimate turbine-generator output without any prior system knowledge of the exact structure of the mathematical model. To assess the performance of the neuro-fuzzy based turbine cycle model, we adopted a commercial software program, PEPSE, for developing the thermodynamic turbine cycle of Maanshan NPP.

Measurement data for the model were obtained from the operating data of Maanshan NPP Units 1 and 2 above the 95% load level during the past three fuel cycles. Since these data need to be validated and verified, a linear regression model was adopted as a reference to detect sensor failure or degradation. Signal errors in the new operating data were then detected and compared with the allowable range determined by the baseline data set.

2. The Maanshan Nuclear Power Plant.

The Maanshan NPP in Taiwan is a two-unit pressurized water reactor (PWR) nuclear power plant owned by the Taiwan Power Company (TPC). Each unit was provided with a three-loop nuclear steam supply system (NSSS) from Westinghouse. Unit 1 began commercial operations in July 1984, and Unit 2 began commercial operations in May 1985. Both units were licensed with an original thermal power rating (OLTP) of 2775 MWt. After employing the measurement uncertainty recapture power uprate (MUR PU) program, the core thermal power of each unit was uprated to 2822 MWt (101.69% OLTP) in December 2008 and July 2009, respectively. MUR PU was achieved using state-of-the-art feedwater flow measurement devices, i.e., ultrasonic flow meters (UFMs), to reduce the degree of uncertainty associated with feedwater flow measurement and in turn, accurately calculate core thermal power. Increases in turbine-generator output for Maanshan Unit 1 and Unit 2 due to the MUR PU are approximately 11.9 MWe and 12.4 MWe, respectively [16].

Figure 1 shows a simplified schematic of the overall PWR NPP. The turbine-generator is the primary component converting thermal energy produced by the reactor and primary system into electrical power. The turbine-generator and its auxiliaries were provided by General Electric, and the low pressure turbines were replaced by Asea Brown-Boveri (ABB) in 1992 and 1991 in Units 1 and 2, respectively. The turbine for each Maanshan unit consists of three sections; a double-flow high pressure (HP) section and two double-flow low pressure (LP) sections. The generator is a directly driven, three-phase, 60 Hz, 25 KV, 1800 rpm, hydrogen and water inner cooled, synchronous generator. The generator is rated at 1057 MVA for both units [17].

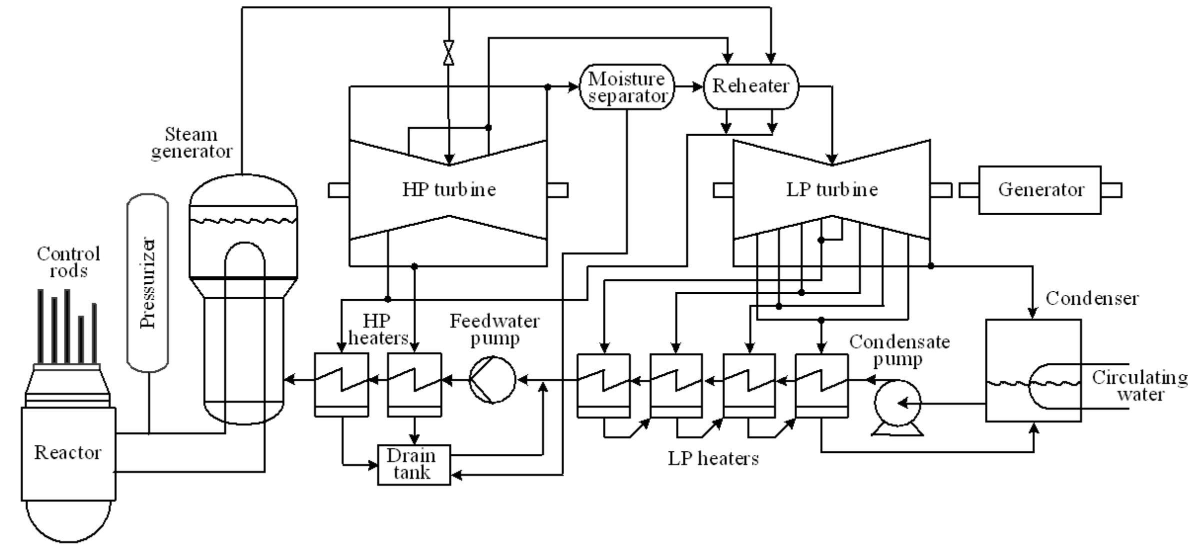


FIGURE 1. Simplified schematic of the overall PWR nuclear power plant

3. **Operating Data Acquisition and Processing System.** The system used to acquire and process operating data was designed to collect the signal data under actual operating conditions for display and prediction purpose. 240 signal data were selected from the plant Emergency Response Facility (ERF) computer. Normally, daily data is acquired with 40 minutes in the morning and then treated on average to one data set and stored as plant historical databases. Figure 2 shows the overall structure of the acquisition and processing of the plant's operating data.

The baseline performance of the turbine cycle is established according to specific key parameters, adjusting for the seasonal effects of circulating water temperature at condenser inlet using the past three fuel cycles. Statistical analysis was performed where signals lying outside the confidence interval were excluded (a 95% confidential level was adopted, but this could be altered depending on other key parameters). Signal errors

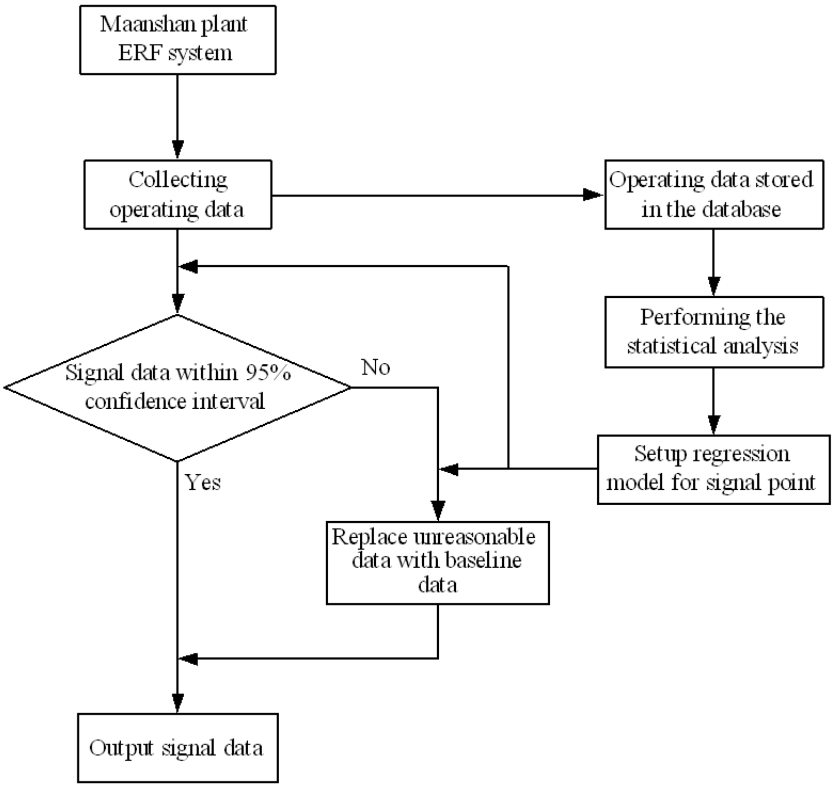


Figure 2. Overall system structure for acquiring and processing plant operating data

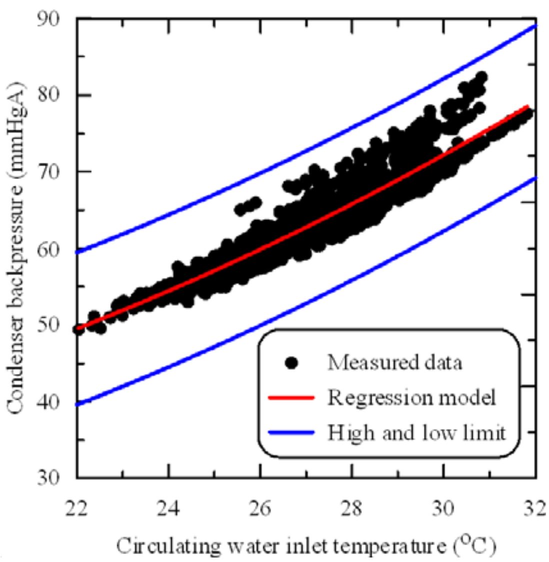


Figure 3. Regression model of condenser backpressure versus circulating water inlet temperature

were then detected by comparing them with the allowable range determined by the reference baseline data. Signal data deviating from the allowable range were designated as sensor failures and replaced by reference baseline data. In addition, all daily or monthly processed signal data were documented and stored for user reference.

After signal preprocessing, the signals not designated as failures were accepted and the signal estimation step was performed. This procedure is quite useful to users and designers wishing to develop performance analysis tools.

Linear regression was adopted due to its easy of use, clearly derived process, and effectiveness in estimating important signals such as main steam pressure, condenser backpressure pressure, or feedwater flow rate. The solid curve (red color) shown in Figure 3 displays the curve fitting regression model representing condenser backpressure as a function of circulating water inlet temperature for the operating data (95% confidence interval). The operating data of the plant in the turbine cycle required validation and verification to create the data used to calculate the turbine-generator electrical output.

4. Adaptive Neuro-Fuzzy Inference System (ANFIS).

Neural network models are based on data, whereas fuzzy logic models are based on expert knowledge. In situations in which both data and knowledge of the underlying system are available, a neuro-fuzzy approach can exploit both sources of information. This study employs an adaptive neuro-fuzzy system (ANFIS). The system is an adaptive network, functionally equivalent to a first-order Sugeno fuzzy inference system [18]. The ANFIS uses a hybrid learning rule combining backpropagation, gradient-descent, and a least-squares algorithm to identify and optimize the parameters of the Sugeno system.

For simplicity, we assume that the fuzzy inference system under considerations has two inputs, x and y, and one output, f. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is as follows [10]:

Rule 1: IF x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule 2: IF x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

Figure 4(a) illustrates the reasoning mechanism for this Sugeno model. The corresponding ANFIS architecture is shown in Figure 4(b). The model has five layers and every node in a given layer has a similar function. In the fuzzy if-then rule set, the outputs are linear combinations of their inputs.

Layer 1 consists of adaptive nodes that generate linguistic-label membership grades based on premise parameters, using any appropriate parameterized membership function, such as the generalized bell function:

$$O_{1,i} = \mu_{Ai}(x) = \frac{1}{1 + \left| \dfrac{x - c_i}{a_i} \right|^{2b_i}} \tag{1}$$

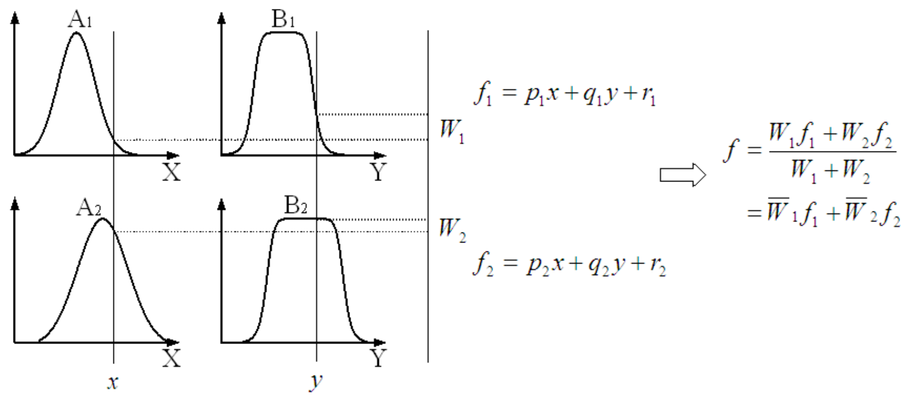
where $O_{1,i}$ is the output of the ith node in the first layer, x is the input to node i, A_i is a linguistic label (such as small or large) from the fuzzy set $A = \{A_1, A_2, B_1, B_2\}$ associated with the node, and $\{a_i, b_i, c_i\}$ is the premise parameter set used to adjust the shape of the membership function.

The nodes in layer 2 are fixed nodes labeled Π, which represent the firing strength of each rule. The output of each node is the fuzzy AND (product or MIN) of all the input signals:

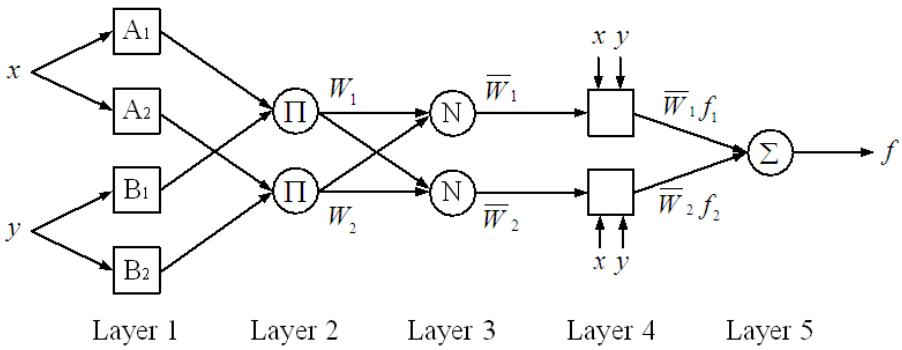
$$O_{2,i} = W_i = \mu_{Ai}(x)\,\mu_{Bi}(y), \quad i = 1, 2. \tag{2}$$

The outputs of layer 3 are the normalized firing strengths. Each node is a fixed rule labeled N. The output of the ith node is the ratio of the ith rule's firing strength to the sum of all the rule's firing strengths:

$$O_{3,i} = \overline{W}_i = \frac{W_i}{W_1 + W_2}, \quad i = 1, 2. \tag{3}$$



(a)



(b)

FIGURE 4. (a) A two-input first-order Sugeno fuzzy model with two rules; (b) equivalent ANFIS architecture [10]

The adaptive nodes in layer 4 calculate the rule outputs based upon consequent parameters using the following function:

$$O_{4,i} = \overline{W}_i f_i = \overline{W}_i(p_i x + q_i y + r_i) \tag{4}$$

where $\overline{W}_i$ is a normalized firing strength from layer 3, and $\{p_i, q_i, r_i\}$ is the consequent parameter set of the node.

The single node in layer 5, labeled $\sum$, calculates the overall ANFIS output from the sum of the node inputs, as follows:

$$O_{5,i} = \sum_i \overline{W}_i f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \tag{5}$$

Training the ANFIS is a two-pass process over a number of epochs. During each epoch, node outputs are calculated up to layer 4. At layer 5, the consequent parameters are calculated using a least-squares regression method. The ANFIS output is calculated and the errors are propagated back through the layers in order to determine the premise parameter (layer 1) updates.

The MATLAB software package and its associated Fuzzy Logic Toolbox were used to develop the ANFIS based turbine cycle model. MATLAB supports first order Sugeno systems that have a single output and unity weights for each rule.

5. System Development.

5.1. Determining the input and output variables.

The operating limit of a nuclear power plant is directly related to its core thermal power production. The energy balance equation can be expressed as [19]:

$$P_t = W_{fw}(h_s - h_{fw}) \pm P_{loss} \tag{6}$$

where P_t is core thermal power, W_{fw} is feedwater flow rate, h_s and h_{fw} are enthalpies of main steam and feedwater, respectively, and P_{loss} is system losses. The enthalpies, h_s and h_{fw} are influenced by the main steam pressure and final feedwater temperature, respectively. In addition, the circulating water system of Manshan NPP takes water from sea and the sea water temperature directly influences condenser backpressure. When the circulating water inlet temperatures increase, condenser backpressure increases, which in turn reduces generator output.

On this basis, the variables that most strongly influence turbine-generator output are the input variables, including main steam pressure, condenser backpressure, feedwater flow rate, and final feedwater temperature. The output variable is the turbine-generator electrical output.

The operating data used in this study were obtained from Units 1 and 2 of the Maanshan NPP and the method stated in Section 3 was applied to verify the data. The main steam pressure, condenser backpressure, feedwater flow rate, final feedwater temperature, and turbine-generator output data were collected for three fuel cycles between June 2006 and March 2011 for Unit 1 and between May 2005 and March 2011 for Unit 2. As shown in Table 1, 13 signal points were selected from each unit and their average values were used in this study. The trends of selected operating parameters for both units are also shown in Figure 5.

The results show that turbine-generator output is influenced mainly by condenser backpressure under normal operating conditions. The relationships among turbine-generator output, feedwater flow rate, and condenser backpressure are shown in Figure 6. The turbine-generator outputs are proportional to feedwater flow rate, and inversely proportional to condenser backpressure.

TABLE 1. Selected operating parameters for each unit

ANFIS	Computer point	Unit	Plant ID	Signal description
Input 1	ACP 014	kg/cm^{2}G	PT-28	Main steam pressure
Input 2	ADP 001 ADP 002	mmHgA	PT-73 PT-86	Condenser A backpressure Condenser B backpressure
Input 3	AEF 013 AEF 016 AEF 014 AEF 017 AEF 015 AEF 018	Mkg/hr	FT-476 FT-477 FT-486 FT-487 FT-496 FT-497	Feedwater flow rate for the 3 loops (each loop equipped with 2 sensors)
Input 4	AET 001 AET 002 AET 003	°C	TE-60A TE-66A TE-72A	Final feedwater temperature for the 3 loops (each loop equipped with 1 sensor)
Output	BBQ 001	MWe	MAQ-001	Generator electrical output

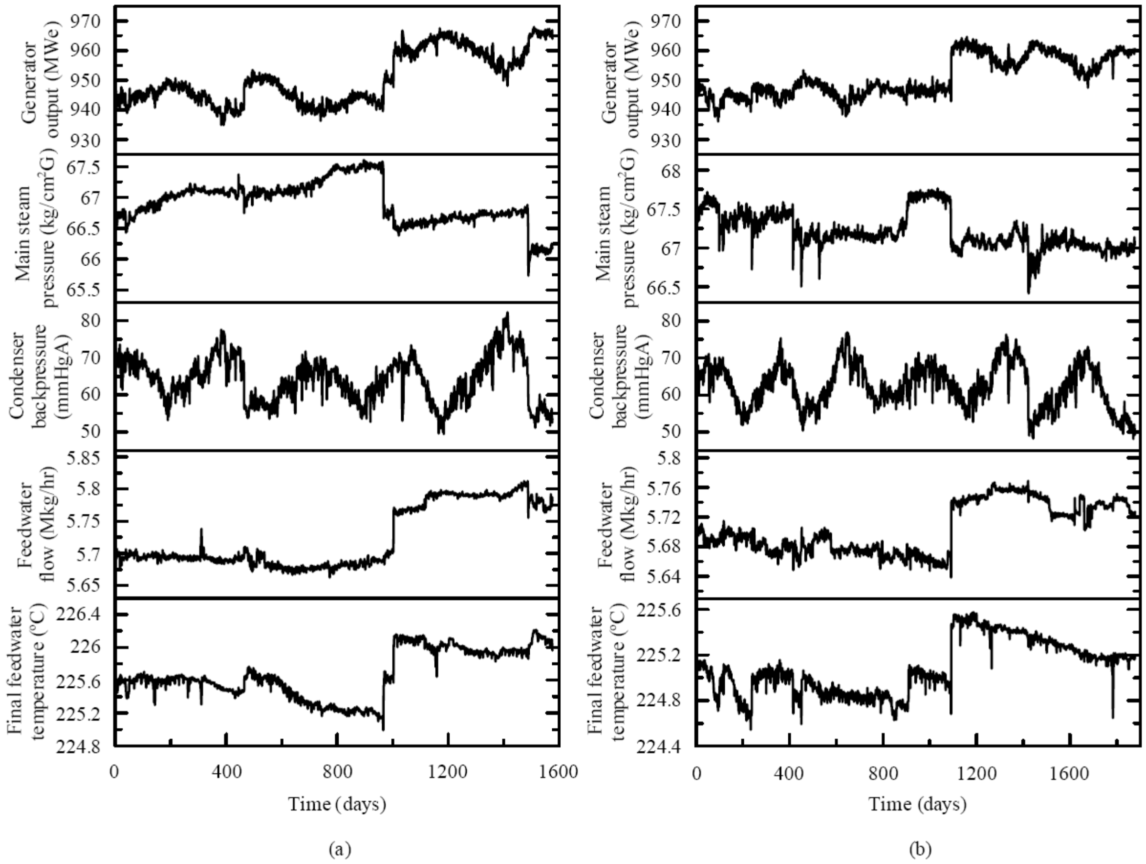


Figure 5. Trending data for generator output, main steam pressure, condenser backpressure, feedwater flow rate, and final feedwater temperature: (a) unit 1; (b) unit 2

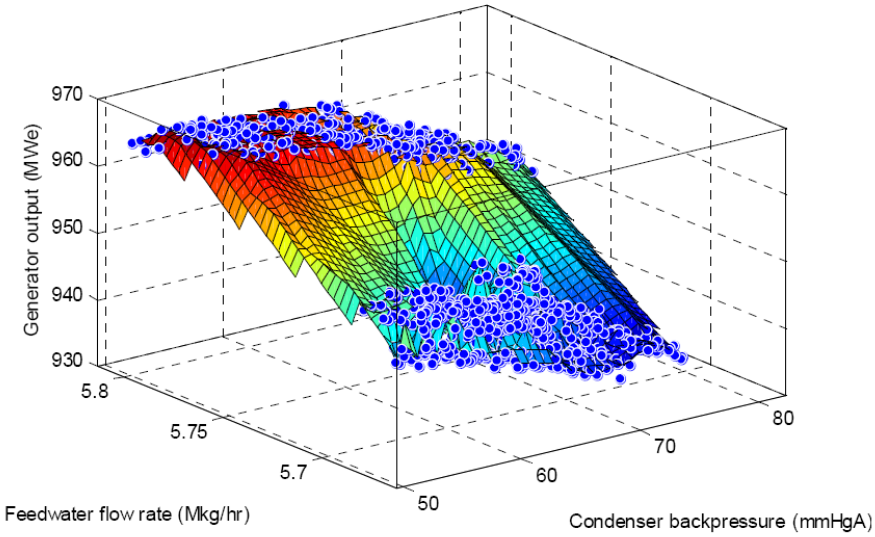
5.2. **ANFIS structure.** To simulate the nonlinear relationship between input and output variables, we use four inputs and three membership functions for each input, resulting in $3^\wedge 4 = 81$ rules.

Linguistic values may be viewed as the labels of fuzzy sets. In this paper, three linguistic variables, low, medium, and high, were used for each input variables. The membership functions of all input variables were designated as Gaussian to provide smoothness and conciseness. The structure of the ANFIS model developed in this study consists of 4 inputs and 81 rules, as shown in Figure 7. We used the Fuzzy logic Toolbox of MATLAB to develop the ANFIS based turbine cycle model in this study [20].

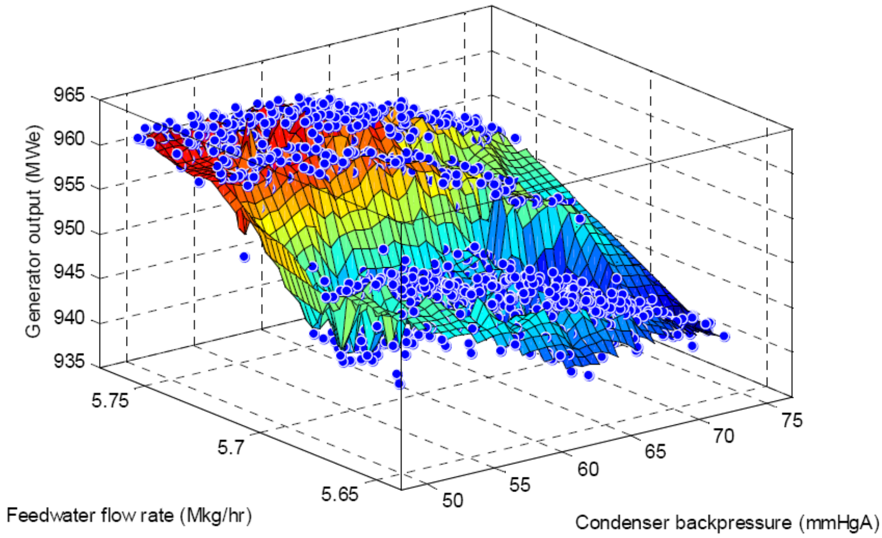
5.3. **Training, validation, and testing data.** The operating data used in this study were obtained from Maanshan NPP. Plant operating data comprising the 5 parameters (including the 13 signal points) listed in Table 1 were obtained between June 2006 and March 2011 for Unit 1, and between May 2005 and March 2011 for Unit 2, as shown in Figure 5.

The 1,576 (1,879) available input patterns for Unit 1 (Unit 2) were subdivided into three sets: a training set of 1,074 (1,296) patterns, a validation set of 444 (504) patterns, and a test set of 58 (79) patterns. Each pattern contained values of main steam pressure, condenser backpressure, feedwater flow rate, feedwater temperature, and the target value (turbine-generator electrical output).

Training and validation sets were used to construct the ANFIS model. Validation set was used to prevent overtraining and overfitting problems on the training set, and then,



(a)



(b)

Figure 6. Relationship of generator output to feedwater flow rate and condenser backpressure: (a) unit 1; (b) unit 2

the generated model was applied to the test set. Figure 8 shows the final membership functions of the ANFIS model for Unit 1.

6. **Results.** The following results were obtained by modeling the turbine cycle on the ANFIS based approach. Figure 9 shows the training results, which demonstrate that the ANFIS based turbine model performed well and the mismatch between the measured turbine-generator output and the ANFIS model output is small. The ANFIS based turbine cycle model for the nuclear power plant was then validated with measured data not included in the training procedure.

Figure 10 shows the results of validation between the measured and estimated output of the ANFIS model, demonstrating that the output of the ANFIS model accurately matches the measured turbine-generator output. After the ANFIS model was trained and validated, it was used to estimate turbine-generator output. In addition, to compare the performance of the ANFIS based turbine cycle model, a widely used commercial software

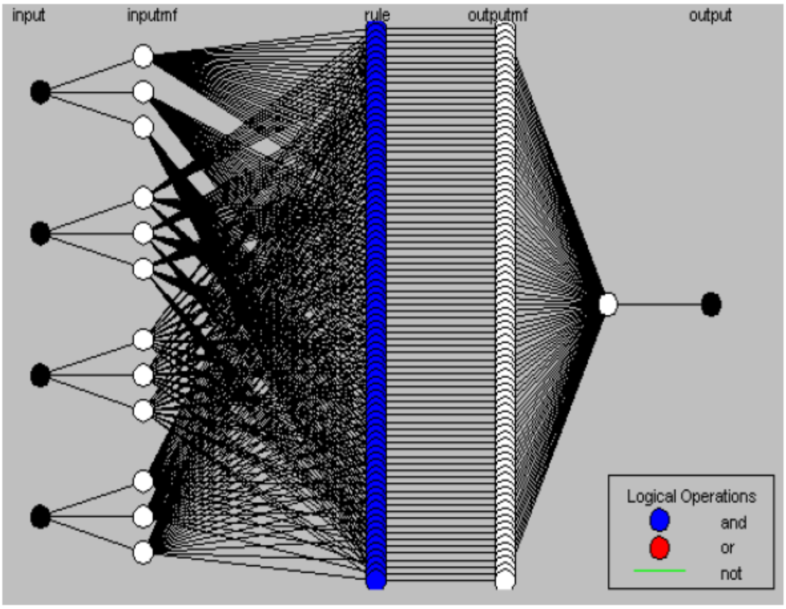


FIGURE 7. Structure of the ANFIS model with four inputs and 81 rules

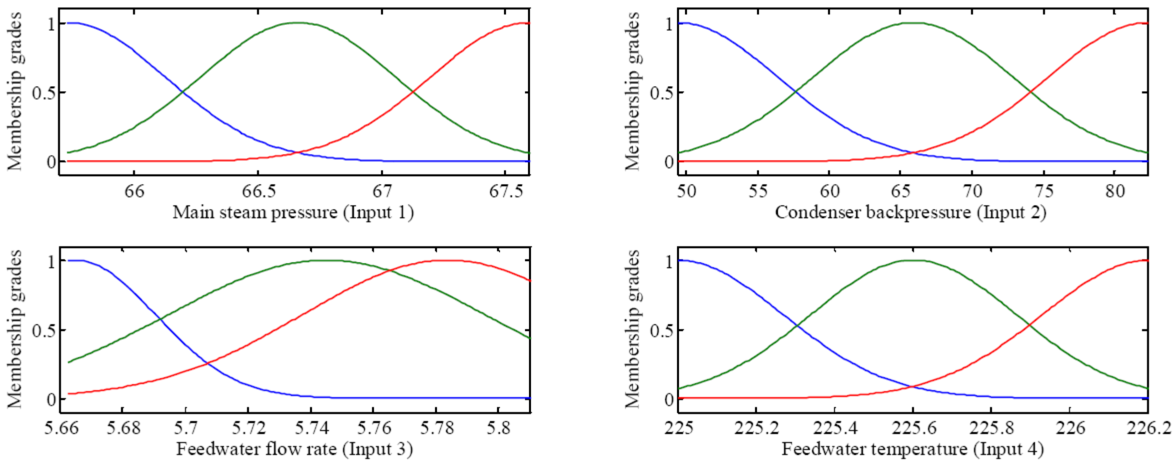


FIGURE 8. Final membership functions for the ANFIS based turbine cycle model for unit 1

program, PEPSE, was adopted for developing the thermodynamic turbine cycle of Maanshan NPP. A comparison between the measured values of the turbine-generator output and the data estimated using the ANFIS and PEPSE based models is shown in Figure 11. The results show that the ANFIS based turbine cycle model can be used to accurately estimate the turbine-generator output. Furthermore, the results also demonstrate that the neuro-fuzzy based turbine cycle model is more reliable than the PEPSE turbine cycle model with the good estimation and the trend.

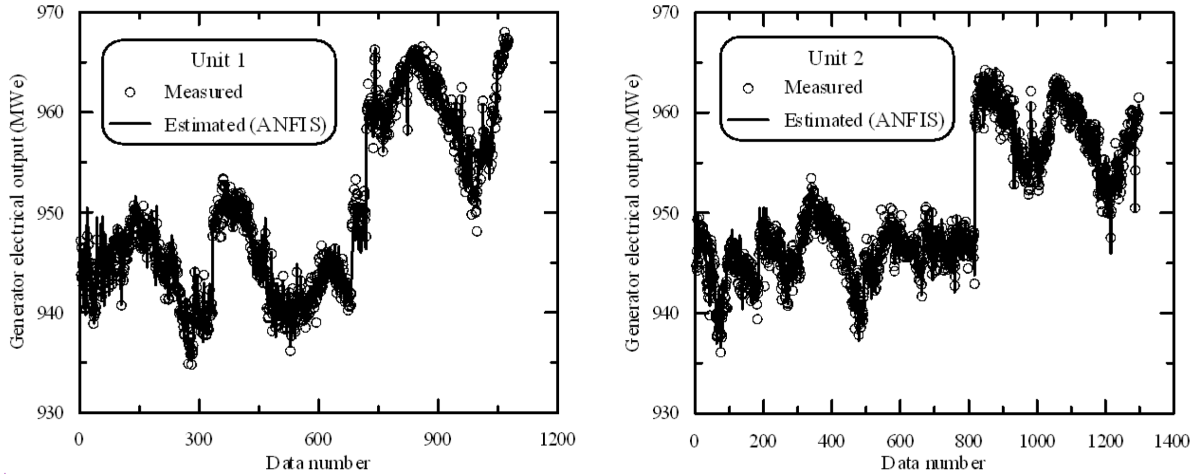


Figure 9. Training results for units 1 and 2 from the ANFIS based turbine cycle model

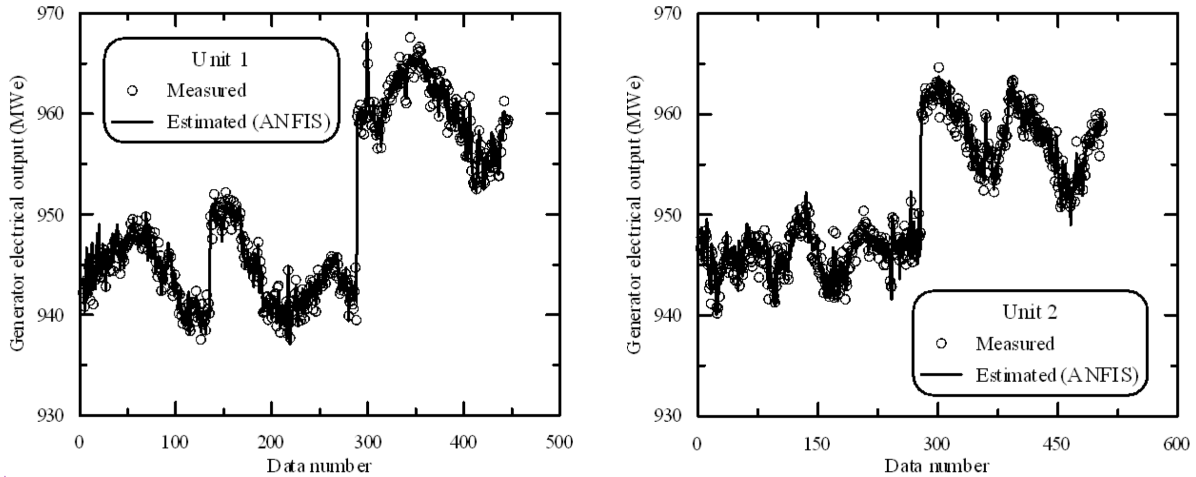


Figure 10. Comparison of measured and validated results

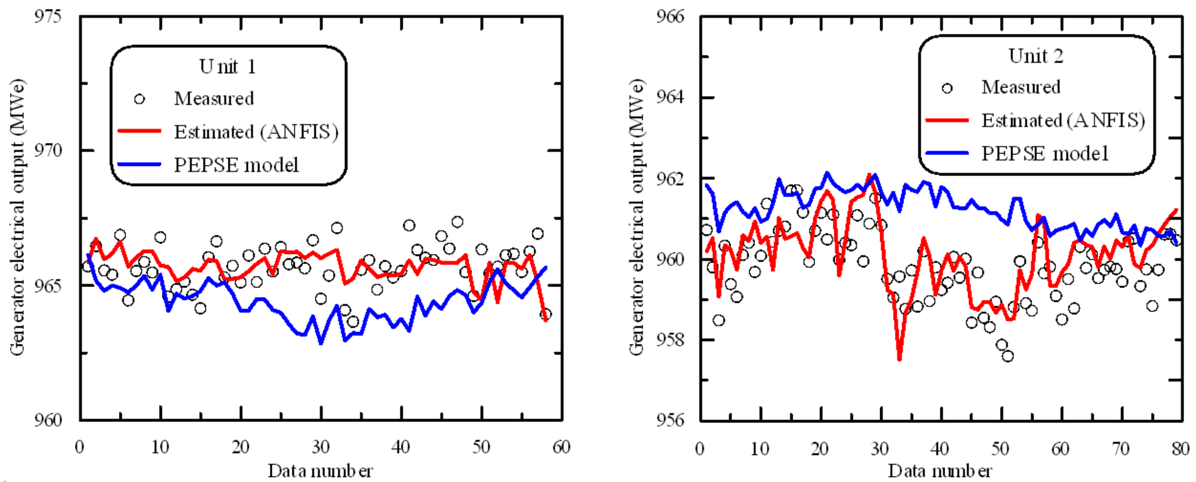


Figure 11. Comparison of measured and estimated turbine-generator output using ANFIS and PEPSE model

Table 2. Statistical parameters of the ANFIS based turbine cycle model

Parameters	Unit 1	Unit 2
MAE (%)		
Training set	0.076	0.069
Validation set	0.067	0.072
Testing set	0.062	0.063
RMSE (MWe)		
Training set	0.94	0.88
Validation set	0.82	0.86
Testing set	0.77	0.73

In this study, model performance was measured by using the mean relative error (MRE) and root mean square error (RMSE) and is defined as [21]

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^*}{y_i}\right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2} \tag{8}$$

where y_i and y_i^* represent the measured and the estimated values of the turbine-generator output, respectively, and n is the number of values provided. The calculated results of MRE and RMSE for both Units of Maanshan NPP are summarized in Table 2, showing that the proposed ANFIS based turbine cycle model is capable of estimating turbine-generator output very accurately.

In using PEPSE software to estimate the turbine-generator output of Maanshan NPP, the calculated MREs for both Units are 0.143 and 0.147%, respectively, and the calculated RMSEs for both Units are 1.618 and 1.642 MWe, respectively. Compared with the MRE and RMSE calculated using the ANFIS and PEPSE models, it can be concluded that the ANFIS based turbine cycle model resulted in more accurate estimates.

Nuclear power plants are almost always operated at full load to supply the demanded load and to operate economically. Under this condition, we are unable to obtain partial load data, i.e., below the 95% load level. Therefore, the present ANFIS based turbine cycle model was used to estimate the turbine-generator output above the 95% load level with higher accuracy. Fossil-fired, combined cycle, or power generation plants of other types may continually operate at partial load conditions. We anticipate that the ANFIS based turbine cycle model can also be used in those power plants to predict the turbine-generator output.

7. **Conclusion.** This study successfully developed an ANFIS based turbine cycle model for the Maanshan NPP to estimate turbine-generator output using the operating data of the plant. Operating data was verified using a linear regression model with a corresponding 95% confidence interval. The variables most strongly influence turbine-generator output were selected as the input variables of the ANFIS model, which was then used to estimate the turbine-generator output above the 95% load level under normal operating conditions.

A comparison of measured data with estimated results shows that the ANFIS based turbine cycle model is reliable and effective. In addition, to assess the performance of the ANFIS based turbine cycle model, a widely used commercial software program, PEPSE, was adopted for developing the thermodynamic turbine cycle of Maanshan NPP. The results show that the ANFIS based turbine cycle model is more reliable than the PEPSE turbine cycle model with the good estimation and the trend. The main advantage of the proposed neuro-fuzzy based turbine cycle model is the requirement that only key parameters be used as inputs, which enable the rapid development of a turbine cycle model. Thus, the ANFIS based turbine cycle model is an appropriate model for the development of turbine cycle models for nuclear power plants. Furthermore, this study provides an alternative approach to evaluate the thermal performance of nuclear power plants. We anticipate that the ANFIS based turbine cycle model may also be used in fossil-fired and combined cycle power plants.

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