Progress Of Electrical And Electronic Engineering
2023 Volume 1, Issue 1
ISSN: 2630-4643

Modeling of Boiler Steam System in a Thermal Power Plant Based on Generalized Regression Neural Network

Soon-Young Lee[1], Jung-Hoon Lee[2]*

[1]Department of Electrical Engineering, Gyeongsang National University, Jinju, Gyeongsangnam, Republic of Korea

[2]Department of Control & Instrument Engineering, Gyeongsang National University, Jinju, Gyeongsangnam, Republic of Korea

***Corresponding author:** Jung-Hoon Lee, leejh@gnu.ac.kr

Abstract

In thermal power plants, boiler models have been used widely in evaluating logic configurations, performing system tuning, applying control theory, etc. Furthermore, proper plant models are needed to design accurate controllers. Sometimes, mathematical models can not exactly describe a power plant due to time-varying, nonlinearity, uncertainties, and complexity of the thermal power plants. In this case, a neural network can be a useful method to estimate such systems. In this paper, the models of boiler steam systems in a thermal power plant are developed by using a generalized regression neural network (GRNN). The models of the superheater, reheater, attemperator, and drum are designed by using GRNN, the models are trained and validated with the real data obtained in a 540 MW power plant. The validation results showed that the proposed models agree with the actual outputs of the drum boiler well.

Keyword

Generalized regression neural network (GRNN)
Modeling
Validation
Drum
Superheater
Reheater
Attemperator

1. Introduction

A boiler is a device that generates steam at rated pressure and temperature using energy produced by combusting fuel and air. It consists of components such as a drum, superheater, reheater, and other heat exchange devices. Such boilers are closely related to the efficiency and stability of power generation facilities, and their control is crucial for the normal operation of thermal power plants. Precise modeling of the system is required to achieve accurate control of the boiler.

There are various methods for modeling a boiler, including analyzing the physical phenomena of the boiler to derive mathematical models and using neural network algorithms for modeling. To develop a mathematical model, it is necessary to have an accurate physical representation and analysis of the boiler. However, due to the high nonlinear nature of the system with significant coupling between variables, there are limitations in obtaining an accurate model [1,2]. In addition, mathematical models are constrained by parameters with time-varying characteristics and may lose accuracy with changes in the operating environment. In such cases, modeling using neural networks can yield good results [3,4].

Modeling based on neural networks involves training neural network algorithms using input-output data from the system to generate patterns and construct the model. With sufficient training data, this approach can yield highly accurate models for various environments and operating conditions. Due to these advantages, neural network-based modeling is widely used in various fields today and is also applied to boiler system modeling.

In this paper, a type of neural network algorithm called generalized regression neural network (GRNN) was used to model the steam generation system of a boiler. The model was trained and validated using data obtained from a 540 MW thermal power plant for components such as superheaters, reheaters, desuperheaters, and drums. The data required for modeling and validation were collected from sensors in the boiler, considering data representativeness, and selecting 23,500 data points at 30-second intervals. Among these, 20,000 data points were used for training, and the remaining 3,500 were used for validation. The validation results confirmed a good match between the proposed model's output and the actual output of the drum boiler.

2. GRNN

The GRNN algorithm is a suitable feedforward neural network for system modeling and prediction, with a structure similar to the Radial Basis Function (RBF) neural network [5]. The architecture of GRNN is shown in **Figure 1**.

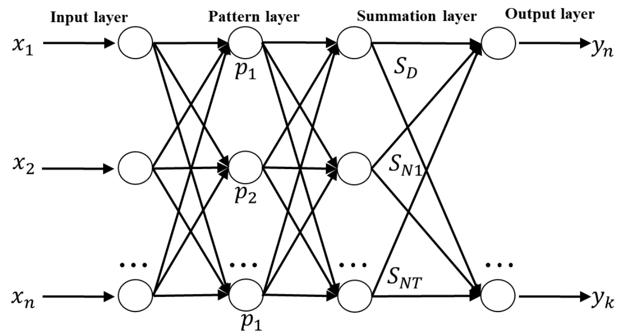

Figure 1. Network structure of GRNN

The input of the neural network is denoted as $x = [x_1x_2\ldots x_n]$ and the output is $y = [y_1y_2\ldots y_n]$. The first layer is the input layer, with the number of neurons equal to the order n of the input vector x. The second layer is the pattern layer, with one neuron for each input pattern. This layer is composed of RBF neurons that use the Gaussian function as their transfer function. The third layer is the linear operation layer, consisting of two types of neurons to addition: simple addition neurons and weighted addition neurons. Weighted addition neurons compute the sum of the weighted outputs from the pattern layer, while simple addition neurons compute the sum of the unweighted outputs from the pattern neurons. The equations for simple additive neurons and weighted additive neurons are as follows:

$$S_D(x) = \sum_{i=1}^{n} P_i(x) \tag{1}$$

$$S_{Nj}(x) = \sum_{i=1}^{n} w_{ij}P_i(x)\,, j = 1,2,\cdots k \tag{2}$$

Here, $S_D(x)$ represents the output of simple addition neurons, $S_{Nj}(x)$ represents the output of weighted addition neurons, and w_{ij} represents the weight vector.

Finally, the fourth layer is the output layer. In the output layer, the normalized output is obtained by dividing the output of weighted addition neurons by the output of simple addition neurons, resulting in the final output.

$$y_j = \frac{S_{Nj}}{S_D}, j = 1,2,\cdots k \tag{3}$$

GRNN training involves storing each input pattern in the pattern layer and calculating weights in the addition layer. If there is insufficient information about the system to be learned, a large training dataset is required to ensure its representativeness. This can lead to the need for significant memory capacity and slightly longer processing times due to the use of many pattern neurons. However, when GRNN is trained with representative training data, it becomes an excellent algorithm in terms of the optimal number of pattern neurons and accuracy.

3. Modeling

3.1. Modeling of superheaters and reheaters

The steam generated in the boiler drum contains some moisture, making it saturated steam. Superheaters are devices that evaporate this moisture and further raise the temperature to produce superheated steam. Superheated steam reduces the size of turbines, reduces friction losses in steam piping and turbines, and mitigates turbine corrosion caused by moisture content.

On the other hand, with the increase in steam pressure due to the large-scale expansion of steam in a steam turbine power plant, there is a risk of increased humidity at the turbine outline, leading to increased friction losses and a higher risk of turbine blade corrosion. To prevent this, reheat devices, known as reheaters, are used to increase dryness and achieve the desired superheat temperature by extracting and reheating the steam expanded within the high-pressure turbine in the boiler.

Superheaters and reheaters play a role in increasing the temperature of the steam as it passes through tubes within the boiler, as shown in **Figure 2**.

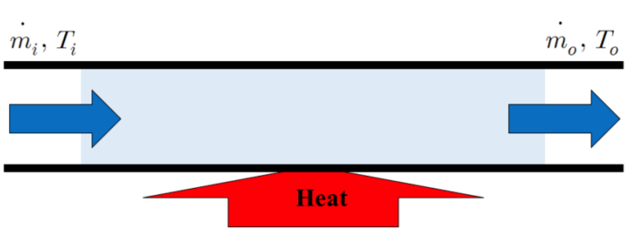

Figure 2. Superheater and reheater model

The inputs for modeling superheaters and reheaters include the feedwater flow rate ($\dot{m}_i$), coal quantity, and input temperature (*Ti*), with the output being the output steam temperature (*To*).

Figure 3 represents the verification results for the steam temperature model of the superheater, while **Figure 4** shows the verification results for the steam temperature model of the reheater. The mean absolute errors for the superheater and reheater models are 4.7°C and 5.2°C, respectively, indicating an error of less than 1%.

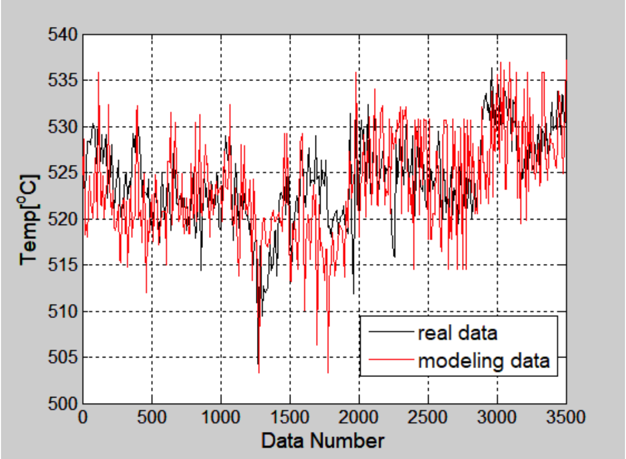

Figure 3. Validation of superheater model

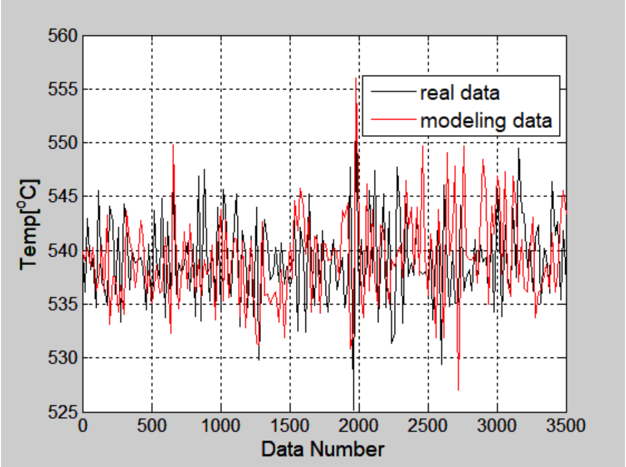

Figure 4. Validation of reheater model

3.2. Modeling of attemperators

Maintaining the rated temperature of steam is closely related to power plant efficiency. If the temperature exceeds the design specifications, efficiency increases, but it can lead to the boiler's reduced lifespan and damage due to increased thermal stress in the superheater and turbine. Conversely, operating at temperatures below the rated value for extended periods can result in issues such as turbine erosion and water ingress due to a decrease in steam quality. Attemperators, as shown in **Figure 5**, are used to control steam temperature by utilizing water (spray) to regulate the temperatures of superheaters and reheaters.

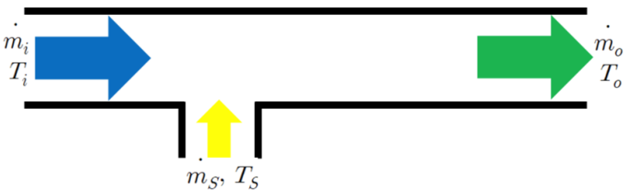

Figure 5. Attemperator model

Attemperators are installed in both superheaters and reheaters. The inputs for modeling attemperators include the spray flow rate ($\dot{m}_s$), feedwater quantity ($\dot{m}_i$), steam temperature (T_i), and spray temperature (T_s), with the output being steam temperature (T_o).

Figure 6 shows the modeling results of the attemperator installed in the superheater, while **Figure 7** shows the modeling results of the attemperator in the reheater. The mean absolute error of the attemperator model is 0.57°C for the superheater and 0.76°C for the reheater.

3.3. Modeling of drums

The drum is a crucial component in a boiler, serving as the device responsible for steam generation, making it one of the most important equipment in a thermal power plant. Proper control of the drum's steam pressure and water level is essential to maintain the stability of the boiler-turbine system. If the water level in the drum becomes too high, it can result in water overflowing into the steam passages, potentially damaging turbine blades. Conversely, if the water level is too low, it can lead to overheating of the boiler vessel [6,7]. The structure of the drum is depicted in **Figure 8**.

The drum is connected to evaporation pipes (risers) and precipitation pipes (downcomers). A mixture of water and steam is supplied to the steam drum through the risers, where the water and steam are separated. The

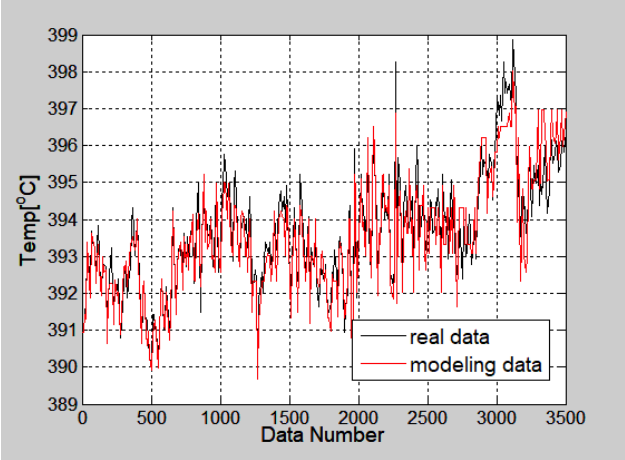

Figure 6. Validation of attemperator model-superheater

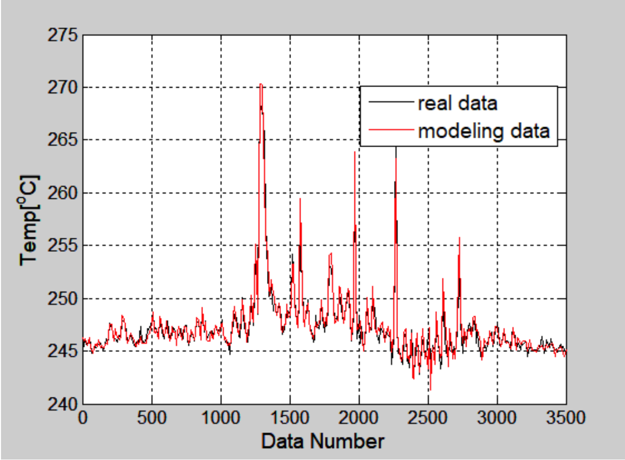

Figure 7. Validation of attemperator model-reheater

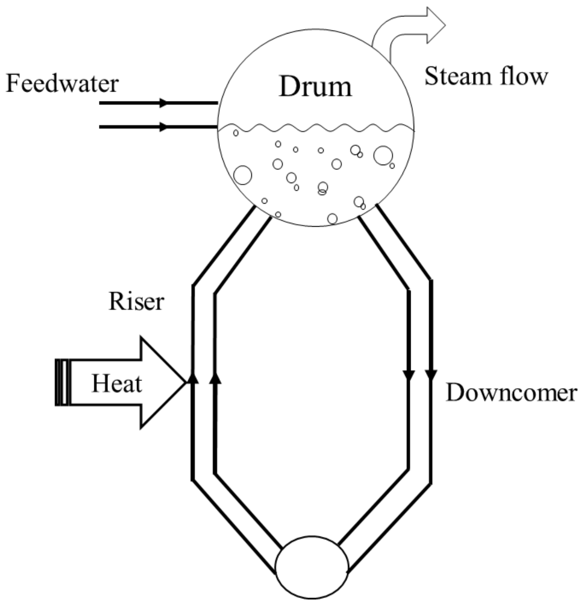

Figure 8. Boiler drum schematic

separated steam is supplied to the superheater, while the water flows down through the downcomers, gets heated in the boiler, and returns to the steam drum.

Data related to the drum's water level, pressure, and steam flow are associated with factors such as coal flow into the boiler and feedwater flow into the drum. **Figure 9** represents the verification results for drum pressure, with an average error of approximately 0.8 kg/cm^2.

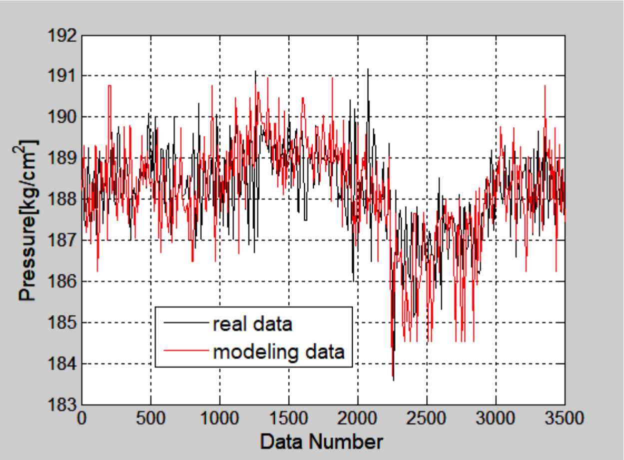

Figure 9. Validation of drum pressure model

Figure 10 shows the verification results for drum water level, while **Figure 11** shows the verification results for steam generation. For drum water level, the average absolute value error is approximately 2.17 mm, and for steam generation, it is approximately 16.6 km/s.

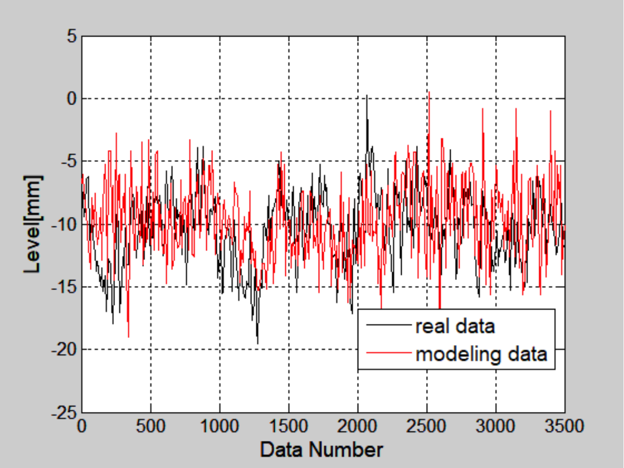

Figure 10. Validation of drum water level model

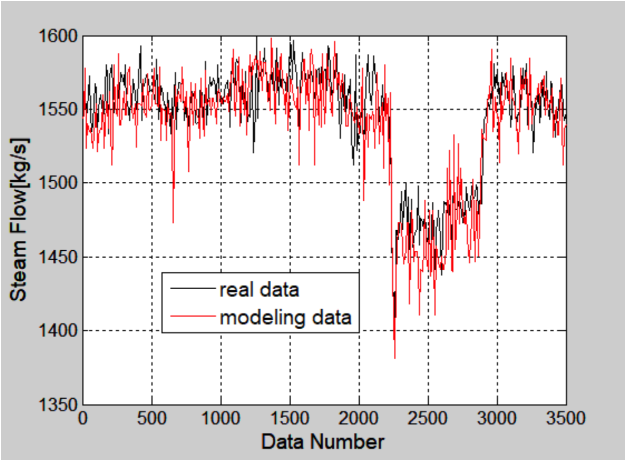

Figure 11. Validation of steam flow model

These verification results confirm a good match between the model's output and the actual system output, indicating the quality of the modeling results.

4. Conclusion

Boiler modeling finds applications in various fields within thermal power plants, including tuning, control, and logic design. Particularly, accurate control and tuning require appropriate modeling. Mathematical modeling faces limitations due to the complexity, time-variance, and nonlinearity of the systems. In such cases, modeling using neural networks can serve as a valuable alternative. In this paper, a type of neural network called GRNN was utilized to model the steam system of a thermal power plant boiler. Modeling for superheaters, reheaters, and attemperators, as well as modeling for drum water level, pressure, and steam generation were conducted. The models were trained using data obtained from a 540 MW thermal power plant. Through verification by comparing the mode's output with the actual system's output, it was confirmed that the developed models closely match the real system.

Disclosure statement

The authors declare no conflict of interest.

Acknowledgment

This work was supported by the Korea South-East Power Co.

References

[1] Halauca C, and Lazar C. 2009 European Control Conference (ECC), August 23–26, 2009: Dynamic Simulation Model for a Steam Drum Boiler System. 2009, Computer and Automation Research Institute of the Hungarian Academy of Science, Budapest, 3480–3485. https://doi.org/10.23919/ECC.2009.7074938

[2] Smrekar J, Pandit D, Fast M, et al., 2010, Prediction of Power Output of a Coal-Fired Power Plant by Artificial Neural Network. Neural Computing and Applications, 19: 725–740. https://doi.org/10.1007/s00521-009-0331-6

[3] Oko E, Wang M, Zhang J, 2015, Neural Network Approach for Predicting Drum Pressure and Level in Coal-Fired Subcritical Power Plant. Fuel, 151: 139–145. https://doi.org/10.1016/j.fuel.2015.01.091

[4] Selvi BST, Kalpana D, Thyagarajan T. 2017 Trends in Industrial Measurement and Automation (TIMA), January 6–8, 2017: Modeling and Prediction of Boiler Drum in a Thermal Power Plant. 2017, Chennai, 1–6. https://doi.org/10.1109/TIMA.2017.8064820

[5] Li Y, Tian Y, Chen W. 2011 International Conference on Electronics, Communications and Control (ICECC), September 9–11, 2011: sEMG Pattern Recognition Based on GRNN and Adaboost. 2011, Ningbo, 1661–1664. https://doi.org/10.1109/ICECC.2011.6066678

[6] Iacob M, Andreescu G-D. 2011 3rd International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), October 5–7, 2011: Drum-Boiler Control System Employing Shrink and Swell Effect Remission in Thermal Power Plants. 2011, Budapest, 1–8.

[7] Chakraborty SK, Manna N, Dey S, 2014, Importance of Three-Elements Boiler Drum Level Control and Its Installation in Power Plant. International Journal of Instrumentation and Control System, 4(2): 1–12. https://doi.org/10.5121/ijics.2014.4201