Sangram Bhagwanrao Savargave* and Madhukar Jagannath Lengare

Modeling and Optimizing Boiler Design using Neural Network and Firefly Algorithm

DOI 10.1515/jisys-2016-0113
Received July 17, 2016; previously published online May 11, 2017.

Abstract: The significance of researches in modeling of boiler design and its optimization is high for saving energy and minimizing emissions. Modeling the boiler plant with all demands is rather challenging. A lot of techniques are reported in the literature for enhancing the boiler efficiency. The neural network scheme has been proved for the boiler design, and it provides a framework for the non-linear system models. In this paper, a hybrid of artificial neural network and firefly algorithm is proposed. The proposed modeling technique is simulated in MATLAB, and the experimentation is carried out extensively. The performance of the proposed modeling technique is demonstrated using type I and II error functions, followed by performing higher statistical measures such as error deviation and correlation analysis. Comparative analysis is made to substantiate the superiority of the proposed modeling technique.

Keywords: Boiler, design, optimization, ANN, firefly.

1 Introduction

Recently, boiler plants have been involved in finding the applications of energy-saving technology and management for power saving and reduction of emissions. Thus, the circulated fluidized bed (CFB) boiler emerged as a new boiler combustion technology that has the capacity of low nitrogen oxide emission and increased desulfurization. The development of CFB boiler technology involves the need for increased energy saving with high capacity and parameters. To meet the demands for the development of CFB boiler technology, optimization and parameter management are necessary, which will enhance optimizing the working parameters, in turn leading to energy saving and emission reduction in boiler plants.

The advanced boiler plant modeling strategy includes experimental-based modeling [2, 16] and first-principle-based modeling [12, 35]. Experimental modeling is utilized for control designing and reflecting the major non-linear dynamics. First-principle-based modeling shows the relationship between engineering principles and physics and true plant parameters, and it can control the algorithm evaluation. For better boiler efficiency, innovative methods have to be developed with advanced optimization approaches. The optimization of boiler operation parameters can be achieved by two broad methodologies, namely (a) traditional method and (b) intelligent method. In the traditional method, the design value, experimental value, historically optimum value, and actual data are used to optimize the boiler operational parameters. The method has advantages such as real-time updating at good probability, while it has disadvantages such as difficulty in handling multiparameters, high investment of manpower and resource, survey and installation errors, equipment aging issues, and limitations in mining strategies. The intelligent method is based on data mining technology and intelligent technologies. The data mining technologies include correlation analysis, clustering, prediction, and deviation inspection. Intelligent technology includes neural network [4, 6, 28], fuzzy

***Corresponding author: Sangram Bhagwanrao Savargave,** Pacific Academy of Higher Education and Research University, Udaipur, India, e-mail: sangrambhagwanrao@gmail.com
Madhukar Jagannath Lengare: Konkan Gyanpeeth College of Engineering, Karjat (MH), Maharashtra 410201, India

logic [17, 22], pattern recognition, and genetic algorithm. The advantages include strong maneuverability, real-time updating, and solving complex modeling. The disadvantages include longer running time for correlation. Thus, considering its drawbacks, new advanced boiler power plant modeling strategies are introduced for better optimization.

1.1 Motivation and Contributions

Based on the description of the works related with modeling and controlling of the boiler design process, it can be asserted that the role of artificial intelligence is greater. The primary intelligent methodologies such as artificial neural network (ANN) and fuzzy inference system have been adopted in Refs. [5, 15, 19]. The second category of artificial intelligence, such as particle swarm optimization (PSO) and genetic algorithm, has been adopted in Refs. [13, 29, 30].

As the need of exploiting the intelligence concept is essential in accomplishing precise boiler modeling, we intended to work on it. However, such intelligent methodologies suffer from a few known issues, as described in Table 1. This research proposal attempts to solve the drawbacks of intelligent methodologies adopted in the boiler design and its control. The complete set of gaps that have been identified from the review can be categorized as converging experience, curse of dimensionality, and learning flexibility. In order to overcome these drawbacks, we intended to hybridize multiple intelligent methodologies. The intelligent methodologies include the ANN and firefly (FF) algorithm. The ANN is known for its learning flexibility, but suffers from the curse of dimensionality. This can be overcome by providing training by using robust optimization algorithms. Hence, the FF algorithm is used to perform the task. To ensure the robustness of the methodology, we attempt to hybridize in a sophisticated manner so that the precision of the boiler model can be improved. In another perspective, the boiler design process is separated in our proposal into two steps. In the first step, a blind boiler model is constructed with model parameters. The blind model is formulated based on the inference of the ANN. The ANN is optimized by using the FF algorithm to provide precise fitting of the model with realistic circumstances.

2 Literature Review

In 2015, Beyhan and Kavaklioglu [5] developed the modeling of U-tube steam generators (UTSGs) with online and offline fuzzy-system-based extreme learning machine and ANN. The exogenous input topology combined with a non-linear autoregressive is used to detect the water level of the UTSG system. The performance measures, such as minimum descriptive length and root-mean-squared error, are used and the performances are evaluated using the number of neurons in ANN and number of rules in the fuzzy system. Although extreme learning machines have the benefit of achieving a higher degree of modeling precision, good learning ability, and efficient learning, they have the property of arbitrary initialization leading to an uncertain precision. Secco et al. [30] exploited the computational approach to reduce the NOx emission in a 600 MW tangentially fired pulverized coal boiler. They used genetic algorithms that are able to generate the new boiler settings automatically. The algorithm is combined with computational fluid dynamics (CFD) simulations of the boiler for better target function. The developed approach reduces the NOx emissions with less corrosion and operational cost. Though genetic algorithm is able to handle uncertain system characteristics, it lags under real-time performance. Sayed et al. [29] proposed a new hybrid jump PSO that is based on Gaussian and Cauchy mutation to tune the gains of proportional integral (PI) controllers to the boiler turbine unit. The developed approach is based on the observation of local and global best particles, and the simulation results show better optimization of control parameters. Although PSO has a good convergence rate, it converges to local optima and its high dependency on algorithm parameters and the nature of the search space reduces the interest among researchers.

Table 1: Summary of Literature Review.

Author [Citation]	Adopted methodology	Advantages	Disadvantages
Beyhan and Kavaklioglu [5]	Extreme learning machines	High degree of modeling, better learning ability, and fast learning speed	Uncertainty due to arbitrary initialization
Hengyan et al. [13]	Neural network and genetic algorithm	Ability to handle non-linear and large-scale modeling	Lack of precision in the objective function often results in poor modeling
Liu et al. [19]	Fuzzy-neural network and Gaussian	Efficient modeling and control	Requires precise system knowledge
Kljajic et al. [15]	Neural network	Good prediction reliability and computationally efficiency	Randomness in learning process
Secco et al. [30]	Genetic algorithm	Easy handling of unknown characteristic of system	Limited real-time performance
Sayed et al. [29]	PSO	Good convergence rate	Effects due to premature convergence and curse of dimensionality, high dependency on algorithm parameters, and nature of the search space
Yang et al. [41]	Back-propagation, least square support vector machine, genetic algorithm, fuzzy association rule mining	Accuracy, low cost	Execution time is high and extraction of a large number of redundant rule
Szega and Nowak [33]	Data reconciliation method	Better accuracy, diminished uncertainty	Derivative calculations, Jacobian actualization, matrix inversion, slow rate of convergence, high computational effort
Song et al. [32]	Improved artificial bee colony	Solves non-linear and multifaceted problem	Multisegmented and conditional improvement often leads to complexity
Athanasios et al. [3]	Computational fluid dynamics simulation method	Cost reduction, time reduction, handling of multiple problems, unlimited level of detail	Less accuracy, simplification is needed
Liu and Bansal [18]	Non-dominated sorting genetic algorithm, computational fluid dynamics	Better convergence, solve non-linear problems, non-sensitive toward weights	Requires improvement in terms of precision
Vandani et al. [34]	Genetic algorithm, PSO	Easy handling of unknown characteristic of system, good convergence rate	Limited real-time performance, high dependence on algorithm parameters and nature of search space
Secco et al. [30]	Computational fluid dynamics, genetic algorithm	Ability to handle non-linear and large-scale modeling	Lack of precision in the objective function often results in poor modeling

In 2013, Liu et al. [19] worked on modeling the boiler unit with the nature of 1000 MW and ultra supercritical property. The developed optimizing boiler model was done based on the efficiency of neural networks and the genetic algorithm. The new model works well, handles large-scale system parameters, and rectifies all the drawbacks of conventional analytical techniques; however, it lacks the knowledge or imprecise framing of the objective function leading to poor performance.

In 2012, Kljajic et al. [15] developed a method for finding the efficiency of a boiler that depends on operating performance measurement. They used the strategy of neural networks for analyzing the efficiency and performance of randomly selected 65 boilers that are located at 50 sites in Northern Serbia. New techniques were applied for the rational study of energy. The neural network model had good learning ability; however, the issue of randomness arises due to the arbitrary initialization.

In 2011, Hengyan et al. [13] worked on optimization of the structure of network model for predicting the efficiency of fluidized bed boilers. They used the absolute mean impact value as the performance measure for better predictive ability of the developed model, and applied the genetic algorithm for finding the optimized value. Certain instances of the research works have also contributed to exploit the traditional controlling scheme, such as PI controllers often result in poor controlling. Hence, the methodologies adopted in the current literature for efficient modeling and control of the boiler design process have wide research gaps.

In 2015, Xu et al. [37] proposed a partially underground tower-type boiler to decrease the steam pipeline lengths, and also the boiler height. Here, the advantage of the proposed tower-type boiler for power plants is reducing the steam pressure loss. The experimental results demonstrated that the proposed approach is able to reduce the price of electricity and has the capability to decrease the heat rate.

In 2015, Liu et al. [20] presented a boiler turbo generator unit that is mainly used in many power plants because of its low emission and high cycle effectiveness. Hence, it is necessary to construct a model for an overall control system to ensure efficient operation. Here, the model is derived from the basic physical laws using the data analysis to evade the phase transition problem. Moreover, they presented a non-linear model with low complexity and is appropriate for a control system.

In 2016, Ma et al. [21] proposed a neural network inverse method that is used to improve the power-generating unit. Here, this method is used to restore the proportional–integral–derivative coordinated controller to alter the fuel flow and turbine valve. However, the flaw of the model construction and the imperfect training sample arise as modeling errors. Additionally, the inverse model is applied to real-time controllers because of its high efficiency.

In 2015, Yang et al. [42] proposed CFD; it is used to diagnose the combustion of two wall-firing boilers. Generally, operation parameters with different damper settings are evaluated to identify the air-flow distribution among the burners and fire air ports. Finally, the results are compared with operating data to verify the reliability of the simulation and to categorize the reasons for the various combustion characteristics.

In 2015, Yang et al. [43] developed a novel model for boiler cold end design; its gross energy destruction is 10.3 MW, which is lower than the conventional design, and is the important reason of the better thermodynamic performance and saved energy. Here, preheating of air is categorized into low-temperature air preheater, high-temperature air preheater, and main air preheater. Moreover, the experimental result of these projects shows those aspects of the waste heat recovery systems, and some additional integrated systems have also been proposed.

The FF algorithm and the neural networks, which have been exploited in this paper, remain promising in many applications. They have also undergone various improvements. Parts of the literature that support the use of FF algorithm and the neural network are reviewed briefly.

Darwish [8] have used the FF algorithm to find the optimal multilevel threshold values to enhance Otsu's method. Ranganathan et al. [26] proposed a self-adaptive FF algorithm to identify the best parameters and the optimal possible location for placement of FACTS devices. Alb et al. [1] presented a scalar version of the FF algorithm to solve multiobjective and multimodel optimization problems. Mohammed et al. [23] developed a monopole antenna to optimize the parameters using FF algorithm, and it gave a better result than the PSO algorithm. Fard and Niknam [11] presented a self-adaptive modification approach based on the FF algorithm to investigate the optimal capacitor placement problem. Zhao et al. [45] developed a technique to

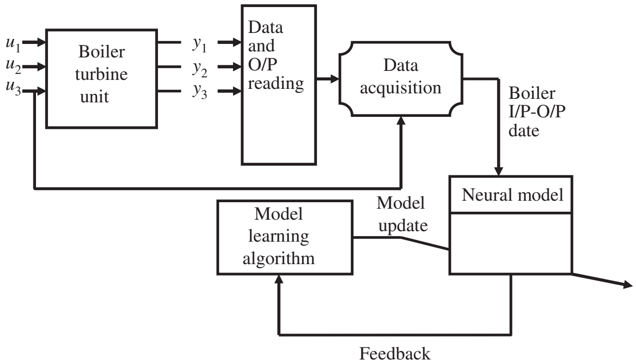

Figure 1: Intelligent Process for Boiler Design.

control and reconstruct both the system states and coefficient matrix using neural network. Yuan and Yu [44] proposed a back-propagation neural network learning scheme to preserve the data in cloud. Xing et al. [36] developed an unsupervised incremental learning neural network method and used it to automatically attain the appropriate expression for learning data without its prior knowledge. Duguleana and Mogan [10] proposed an approach to solve the autonomous movement of robots with the help of a neural network planner. Sokolov-Mladenovic et al. [31] developed the ANN with back-propagation learning algorithm to forecast the gross domestic product growth rate. Yarrapragada and Krishna [27] proposed an interpolation and prediction model by means of neural network.

3 Intelligent Design Process

3.1 System Model

The system model of the intelligent process for boiler design is illustrated in Figure 1. In this system model, there are three inputs represented as u_1 for fuel flow, u_2 for governor valve input, and u_3 for feed water flow, and three output systems represented as y_1 for electric power, y_2 for steam pressure, and y_3 for separator outlet steam temperature. The input and output variables selected have a strong influence on the stability and quality of power plants. The neural model is developed and derived with the data obtained from the output and input variables. The acquired data are subjected to the model learning program and, thus, the neural network model is established.

3.2 NLARX Model by Feedforward Neural Network

The architectural structure of the non-linear autoregressive exogenous input (NLARX) [9] is represented in Figure 2. Let us consider $Y(k)$ as the output of NLARX for k^{th} sample and $X(k)$ as the input to the NLARX model; thus, the NLARX model is given as

$$Y(k) = F(Y(k-1),\ \ldots,\ Y(k-N),\ X(k),\ \ldots X(k-M=1)), \tag{1}$$

where $F(.)$ refers to the functional model of NLARX architecture, and N and M indicate the number of past output and input terms, respectively. These past input terms are used for predicting the current output. The output predictions formed are synthesized from the NLARX model, and they are the results due to changing of the previous outputs and inputs that together form the regression functions with two types of blocks known as linear and nonlinear blocks. Due to the delayed output or input variables, the conventional regressors are formed; however, the

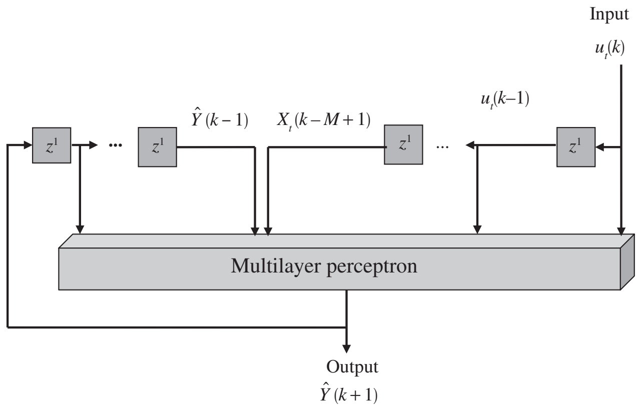

Figure 2: Non-linear ARMAX Model for Modeling the Boiler Plant.

advanced regressors are formed in the arbitrary user-defined function form of delayed output and input variables. Thus, the issue of non-linear unconstrained optimization arise in NLARX model training, and it is represented as

$$\min_{\omega} e(\omega, z_T) = \frac{1}{2T}\sum_{t=1}^{T} \| Y_t(k) - \hat{Y}_t(k|\omega) \|^2, \tag{2}$$

where p, Z_T, $Y_t(k)$, $\hat{Y}_t(k|\omega)$, and ω indicate the number of weighing parameters, training library, desired output, output from NLARX, and weightage, respectively. The $\|\,.\,\|^2$ mentioned in Eq. (2) refers to L2 – norm function, and the training library and the weights are represented as $Z_T = [Y_t(k), X(k)]k = 1, \ldots.., T$ and $\omega = [\omega_1, \ldots, \omega_i, \ldots, \omega_p]$, respectively.

In Eq. (2), an error metric known as the performance index of the network is needed to reduce the negative deviation of performance index to get rid of the metric error. The performance index indicates the network approximation for the provided training patterns, and the network parameters ω have to be changed to minimize the index $e(\omega, Z_T)$ above the complete trajectory for achieving less value.

4 Learning the Plant Characteristics

4.1 Knowledge Base

For effective modeling of the boiler plant, the network has to understand the characteristics of the boiler plant. Understanding the characteristics of the boiler plant is nothing but determining the relationship between the output and the input of the boiler plants. In order to determine the relationship, a precise knowledge base is required. The knowledge base can be constructed using either an empirical model or a theoretical model.

1. **Empirical model:** The selected output and input variables are measured in the boiler plant by considering various parameters such as feed water flow, spray flow, steam pressure in drum, steam pressure in throttle, steam temperature, water level in drum, electrical power, steam pressure, and temperature outlet. With theoretical calculations, the dynamic behavior of the boiler plant cannot be evaluated due to the lack of physical properties, and the dynamic behavior depends on the alterations in the operating point. Therefore, the influence of enthalpy and electrical power on each input is estimated, and when the change in one input occurs, the other input is placed in constant value.
2. **Theoretical model:** Depending on the DIN (1942), the thermal analysis of the boiler BP-1150 is performed [25] and the balancing equation related to energy for the boiler can be represented as from Eqs. (3) to (19); all parameters are referred in Ref. [25].

$$\dot{E}_{IE_1} + \dot{E}_{IE_2} = \dot{Q}_{h\dot{e}_1} + \dot{E}_{el_1} + \dot{E}_{el_2} + \dot{Q}_{hl}. \tag{3}$$

The energy flux in the above equation is represented in the following forms:

Firstly, the input energy flux of a fuel is always proportional to the fuel flux and it is given as

$$\dot{E}_{IE_1} = \dot{C}W_d^*, \tag{4}$$

where W_d^* represents the fuel obtained at lower heating value and it is given as

$$W_d^* = W_d + i_{e_1} + j_{e_2}. \tag{5}$$

Secondly, the input energy flux is always independent to the fuel flux, and this idea gives

$$\dot{E}_{IE_2} = \dot{Q}_{he_2} + N_{pfm}. \tag{6}$$

Thirdly, the flux of the consumed fuel is proportional to the energy loss flux and so

$$\dot{E}_{el_1} = \dot{E}_{gl} + \dot{E}_{enl_1} + \dot{E}_{enl_2}. \tag{7}$$

The loss of energy is due to (a) the loss due to fuel gas and unburned combustibles, as given in Eq. (8); (b) loss because of unburned combustibles and enthalpy in slag, as given in Eq. (9); and (c) loss because of enthalpy and unburned combustibles in fuel dust, as given in Eq. (10):

$$\dot{E}_{gl} = \dot{C}(S_{pe} + S_{ce}) = \dot{C}S, \tag{8}$$

$$\dot{E}_{enl_1} = \dot{C}g_{A_1}(i_{A_1Pe} + i_{A_1Ce}) = \dot{C}g_{\dot{A}_1}i_{\dot{A}_1}, \tag{9}$$

$$\dot{E}_{enl_2} = \dot{C}g_{A_2}(i_{A_2Pe} + i_{A_2Ce}) = \dot{C}g_{A_2}i_{A_2}. \tag{10}$$

The energy loss flux is independent of the fuel flux:

$$\dot{E}_{el_2} = \dot{Q}_{hCS}. \tag{11}$$

Depending upon Ref. [25],

$$\dot{\dot{Q}}_{hl} = 0.0315\dot{Q}_{mup}^{0.7}. \tag{12}$$

Substituting Eqs. (4)–(11) in Eq. (3), we get

$$\dot{C}W_d^* + \dot{Q}_{h\dot{e}_2} + N_{pfm} = \dot{Q}_{h\dot{e}_1} + \dot{C}(S + g_{\dot{A}_1}i_{A_1} + g_{A_2}i_{A_2}) + \dot{Q}_{hcs} + \dot{Q}_{hl}. \tag{13}$$

Thus, the boiler energy efficiency is the ratio of the useful heat flux per input energy of the boiler:

$$\eta_{EK} = \dot{Q}_{h\dot{e}_1}\frac{\dot{Q}_{h\dot{e}_1}}{\dot{C}W_d^* + \dot{Q}_{h\dot{e}_2} + N_{pfm}} = \frac{\dot{Q}_{h\dot{e}_1}}{\dot{E}_{IE_3}}. \tag{14}$$

It can also be written as

$$\eta_{EK} = 1 - \frac{\dot{C}S_{pe}}{\dot{E}_{IE_3}} - \frac{\dot{C}S_{ce}}{\dot{E}_{IE_3}} - \frac{\dot{C}(g_{\dot{A}_1}i_{A_1} + g_{A_2}i_{A_2})}{\dot{E}_{IE_3}}\dot{C} - \frac{\dot{Q}_{hcs} + \dot{Q}_{hl}}{\dot{E}_{IE_3}}, \tag{15}$$

where

$$L_{rel} = \frac{\dot{C}S_{pe}}{\dot{E}_{IE_3}}, \tag{16}$$

$$L_{rel_1} = \frac{\dot{C}S_{ce}}{\dot{E}_{IE_3}} L_{rel_2} = \frac{\dot{C}(g_{A_1} i_{A_1 pe} + g_{A_2} i_{A_2 pe})}{\dot{E}_{IE_3}}, \tag{17}$$

$$L_{rel_3} = \frac{\dot{C}(g_{A_1} i_{A_1 ce} + g_{A_2} i_{A_2 ce})}{\dot{E}_{IE_3}} L_{rel_4} = \frac{\dot{Q}_{hcs} + \dot{Q}_{hl}}{\dot{E}_{IE_3}}. \tag{18}$$

It can be rewritten as

$$\eta_{EK} = 1 - L_{rel} - L_{rel_1} - L_{rel_2} - L_{rel_3} - L_{rel_4}, \tag{19}$$

and the obtained formula is calculated based on the indirect method. The factors that influence the boiler efficiency include loss in fuel gas, L_{rel}, and loss because of unburned combustibles in slag and flue dust, L_{rel_3}.

Though both the models are described here, our paper concentrates on collecting the empirical model based on the published results of Refs. [12, 19].

4.2 NLARX Learning by FF Algorithm

1. **Learning process:** In 1942, McCulloh and Pitts implemented the single artificial neuron mathematical description [7, 14]. The output from one neuron or the input from the other neuron generates signals that are passed to the dendrite of the neuron. The amount of signals reaching the dendrite can be evaluated by calculating their weights and then taking the sum, and the sum of all those signals, when multiplied with their corresponding weights, gives the neuron activation function argument. The net output obtained represents the functional activation of a neuron, and this output is passed to the other new neuron, where they act as the input signal.

   Considering a single neuron as a representation model is challenging because of its computational complexity. Thus, to make it easy, the single neuron is interconnected to a net, which is the organized form of many single neurons. In this organized form of neural network, the signals pass from one layer to the other layer, and the signal indicates the input signal. Commonly, in a neural network, there is one output signal, one input signal, and one or more hidden layers. The feed-forward neural network model, having the feature of multidimensional non-linear approximation, is implemented in the present work.

   A single training is needed for the ANNs, and this ability is unique and more effective than the traditional algorithms. In each technique, there is a need for multiple iterative trainings, which are required for finding the weight of neurons that provides the least difference between the desired output z and the network (model) output y.

   The objective function favors the mean squared error reduction of the answers:

$$E = \frac{1}{2}\sum_{l=1}^{N}(z_j - y_j)^2 \to \min. \tag{20}$$

   Equation (20) consists of a delta factor that is indicated as $\delta = z - y$, and it can be estimated using the expected values z. In hidden layers, the expected values z are not identifiable, and thus, it is not easy to find out the delta factor δ. Hence, the back-propagation delta rule [7, 14] can be used to identify the delta factor values, depending on the weights in between the connections of consecutive hidden layers and the delta factor δ values of the next hidden layer. The back-propagation method includes the evaluation of the output layer delta factor δ values, and then it turns backward leading to error propagation. If any problem in reducing the objective function arises, then it can be solved using the gradient method, and it is given as

$$w(s+1)=w(s)-\eta\nabla E(w(s))+\alpha\Delta w(s-1). \tag{21}$$

The above equation is used for identifying the weight of the neurons. In neural network training, the back-propagation neural network error technique is asserted as accurate. However, a non-linear system exhibits high non-linear relationship among the input and the output data. Hence, a step-size back-propagation algorithm is not competing. Hence, we propose the FF algorithm to replace the back-propagation, and hence the non-linearities can be precisely recognized. The detailed Architecture is illustrated in Figure 3.

2. **FF-based learning:** Depending upon the FF pattern of flashing and behavior, Yang and He [38–40] introduced the FF algorithm in the year 2007, and it follows three rules, as follows:
   - The objective function landscape evaluates the FFs' brightness.
   - The brightness and the attractiveness of FFs are proportional to each other, and both the attractiveness and brightness decrease with increase in distance. The less brightness emitting FFs move toward the high brightness emitting FFs, and if there are no brighter ones, then they will take a random movement.
   - The sexual character of FFs is unisex and, so, the FFs will attract each other commonly.

As the attractiveness of one FF is directly proportional to the intensity of the light emitted by the other FF, the changes in the attractiveness β with respect to the distance r can be calculated using

$$\beta=\beta_0 e^{-\gamma r^2}, \tag{22}$$

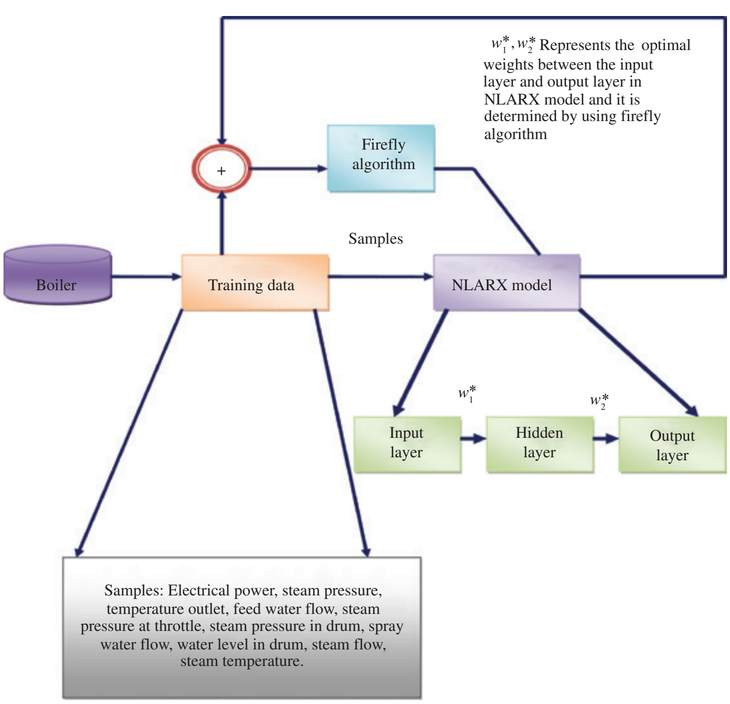

Figure 3: NLARX Learning by FF Algorithm for Modeling of Boiler Design.

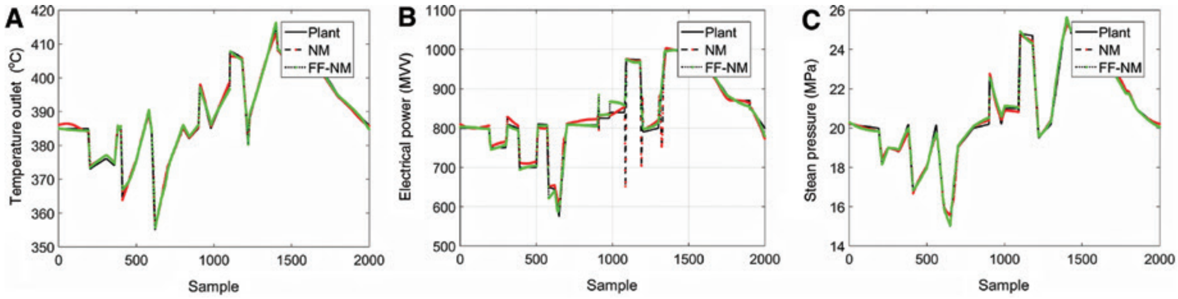

Figure 4: Correlation between the Output of Different Models from Test Case 1.

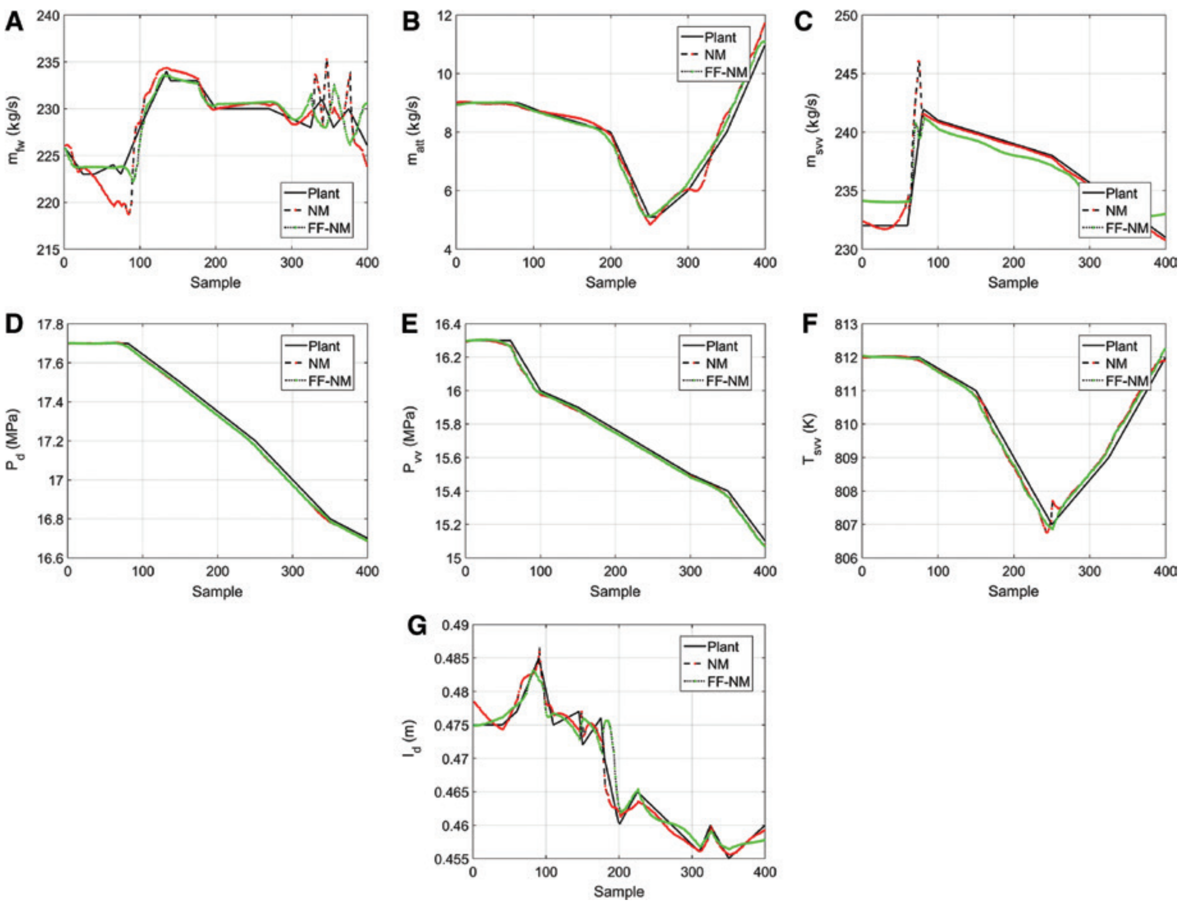

Figure 5: Correlation between the Output of Different Models from Test Case 2 – Set A.

where β_0 represents the attractiveness when $r = 0$. The FFs' movement i is toward the brightness showing FF j, and it can be evaluated using

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha_t \in_i^t . \tag{23}$$

Pseudo code of the FF learning algorithm

$f(x)$, Objective function where $x = (x_1, \ldots, x_d)^t$

Initialize population of FFs $x_i (i = 1, 2, \ldots n)$
Light intensity I_i at x_i is defined by $f(x_i)$
Define light absorption coefficient δ
While $(t < G_{max})$ **do**
For $i = 1$: n, all n FFs **do**
For $j = 1$: i, all n FFs **do**
if $(I_j > I_i)$, move FF i toward j in d dimension;
end if
Attractiveness differs with distance r via $\exp[-\delta r]$
Update light intensity and calculate the new solution
end for j
end for i
Rank FFs and current optimal x
end while

where the second term is formed due to the attraction between the FFs and the third term is in random movement with α_t; $\in_i^t$ represents the numbers selected in a random manner using the uniform or Gaussian distribution at a time period t; and α_t is the parameter for randomization. When $\beta_0 = 0$, the FF chooses

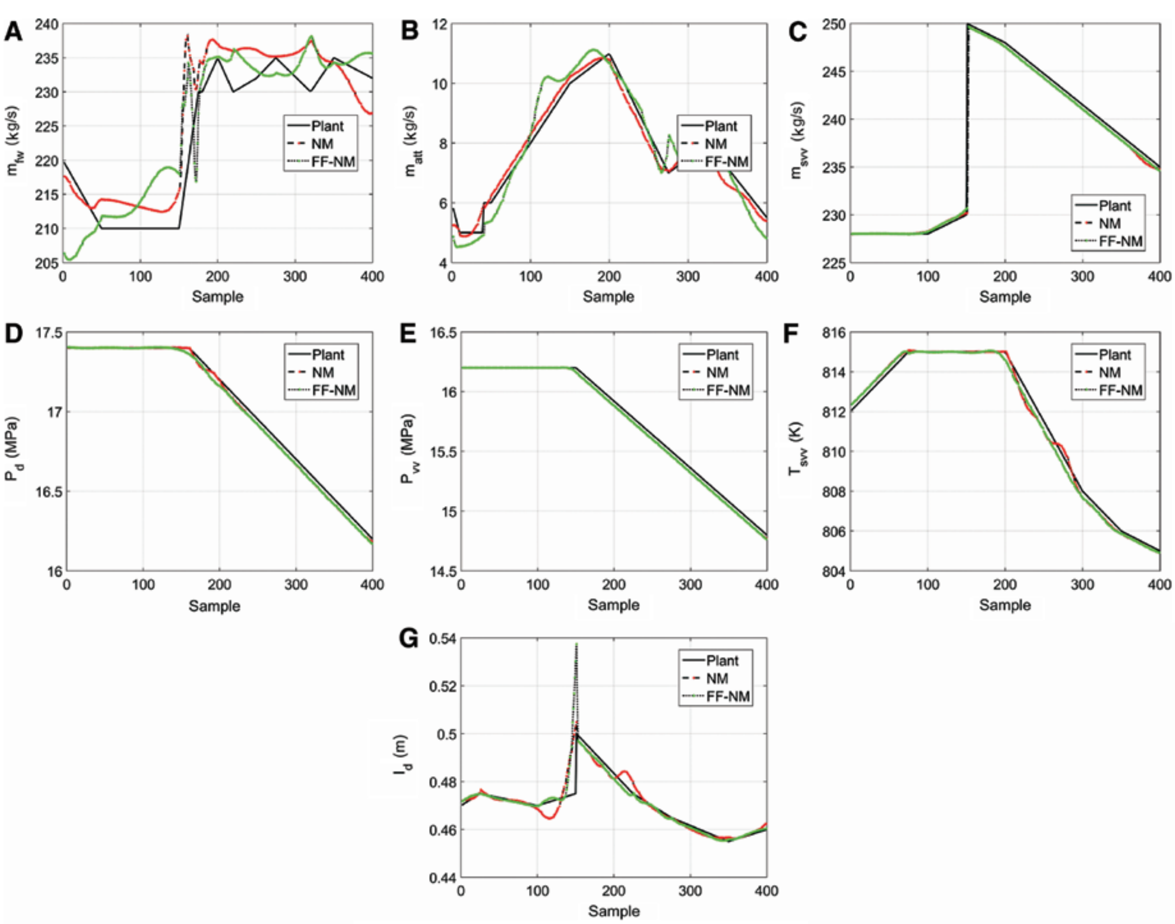

Figure 6: Correlation between the Output of Different Models from Test Case 2 – Set B.

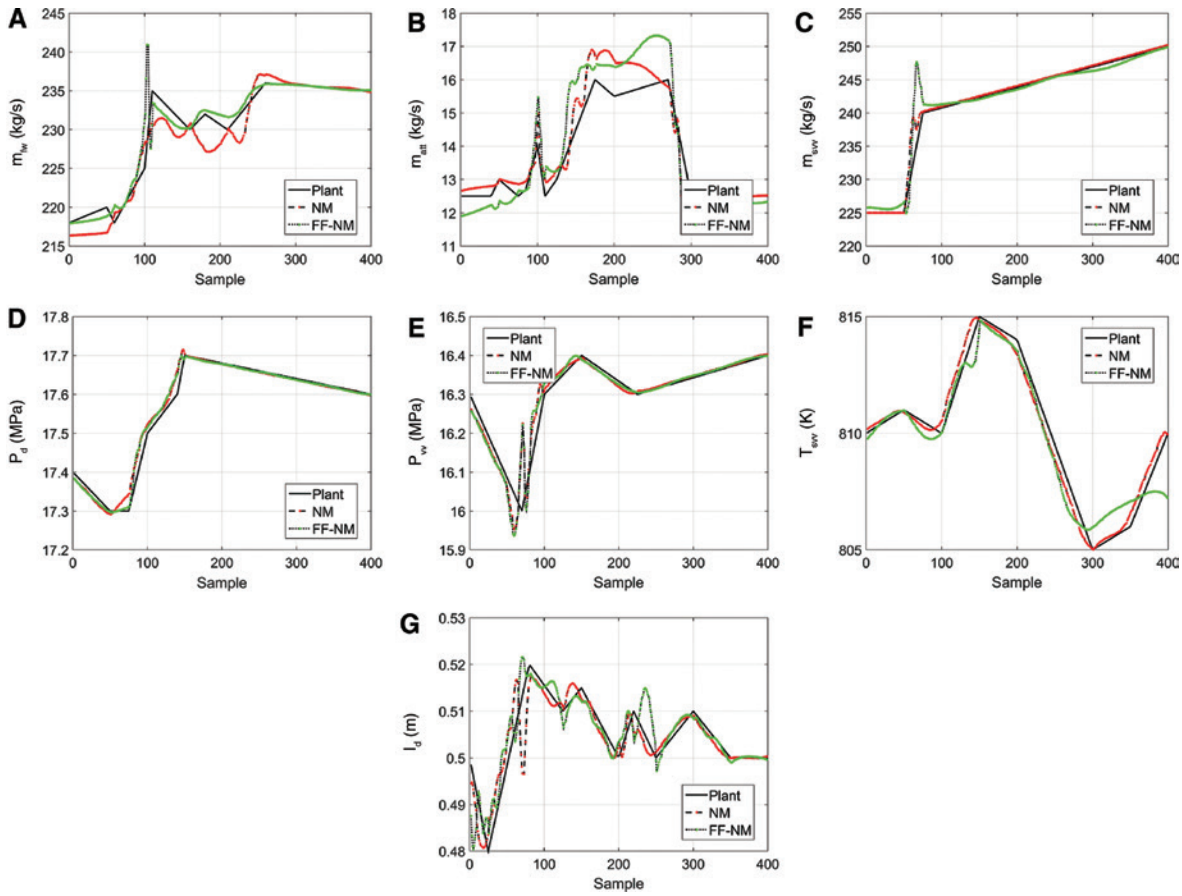

Figure 7: Correlation between the Output of Different Models from Test Case 3.

the random movement and if $\gamma = 0$, it is minimized to a variant of PSO [38]. In addition to this, the $\in_i^t$ randomization can be moved to the other distribution such as Levy flights [38]. In the literature [24], it has been reported that the FF algorithm has been used for training pi-sigma neural network, multilayer perceptron, and back-propagation neural network. However, the NLARX network has not been trained by the FF algorithm as per our review. Nevertheless, the FF algorithm has been used in this paper to improve the performance of the NLARX network.

5 Results and Analysis

5.1 Experiments

The developed experimental model is simulated in MATLAB platform. Totally, 10 parameters are considered to study the developed model efficiency. They are steam flow, temperature outlet, electrical power, steam pressure, feed water flow, steam pressure in drum, spray water flow, steam pressure in throttle, water level in drum, and steam temperature. By supplying various inputs, the aforesaid parameters are acquired in Refs. [12, 19]. We refer to those data as our empirical model, and the experimentation is carried out in three test cases. In the first test case, steam flow, electrical power, and temperature outlet are considered as the boiler

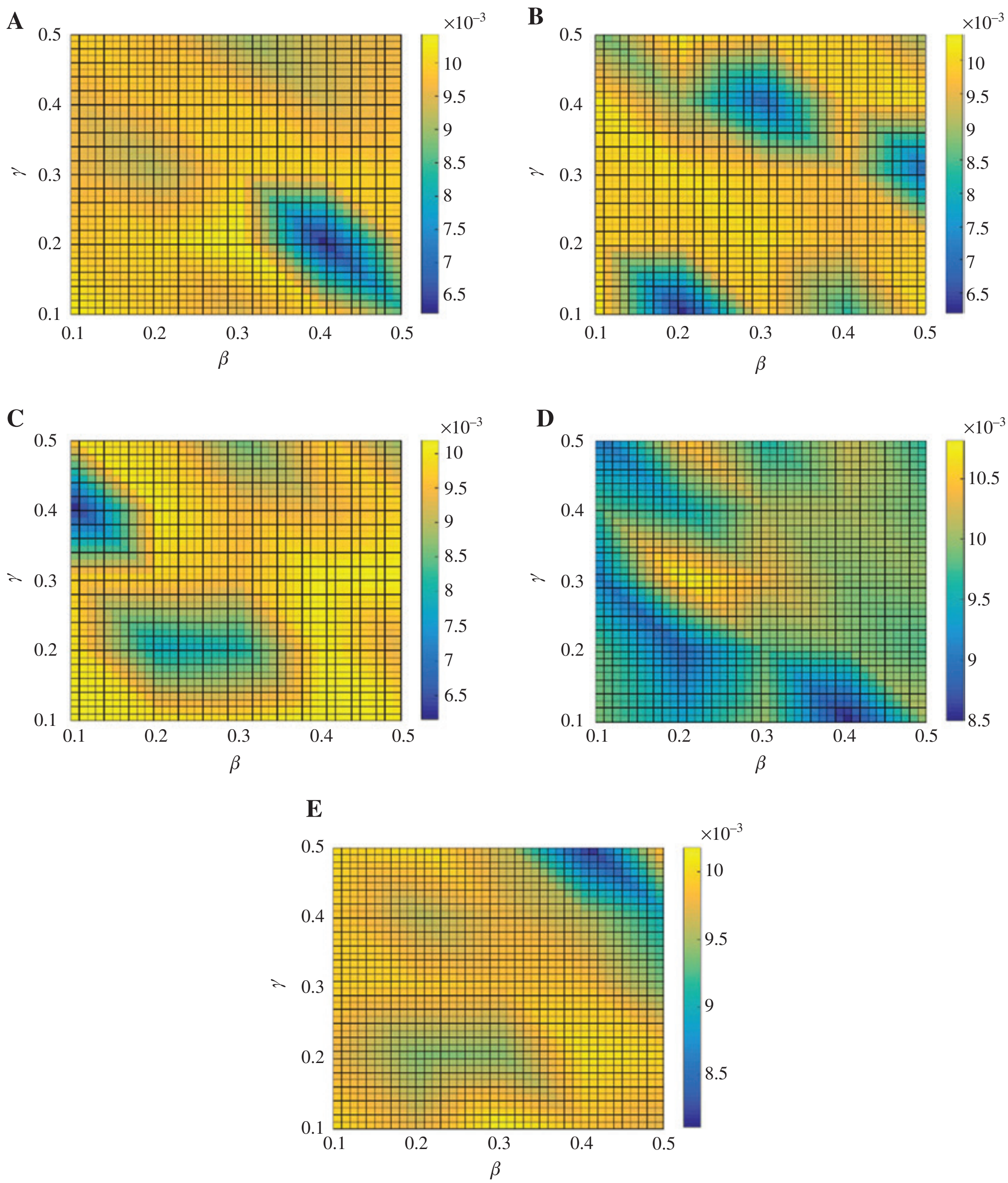

Figure 8: Estimation of Steam Pressure under Varying β and γ with the Reference of α as (A) 0.1, (B) 0.2, (C) 0.3, (D) 0.4, and (E) 0.5.

output, as given in Ref. [19]. The rest of the two test case data are acquired from Ref. [12]. The test case 2 has been segregated into sets A and B, and modeling has been done.

5.2 Design Performance

In test case 1, three parameters – electrical power, steam pressure, and temperature outlet – are taken, and correlations among the output from the plant and modeling techniques such as NM (refers to multilayer per-

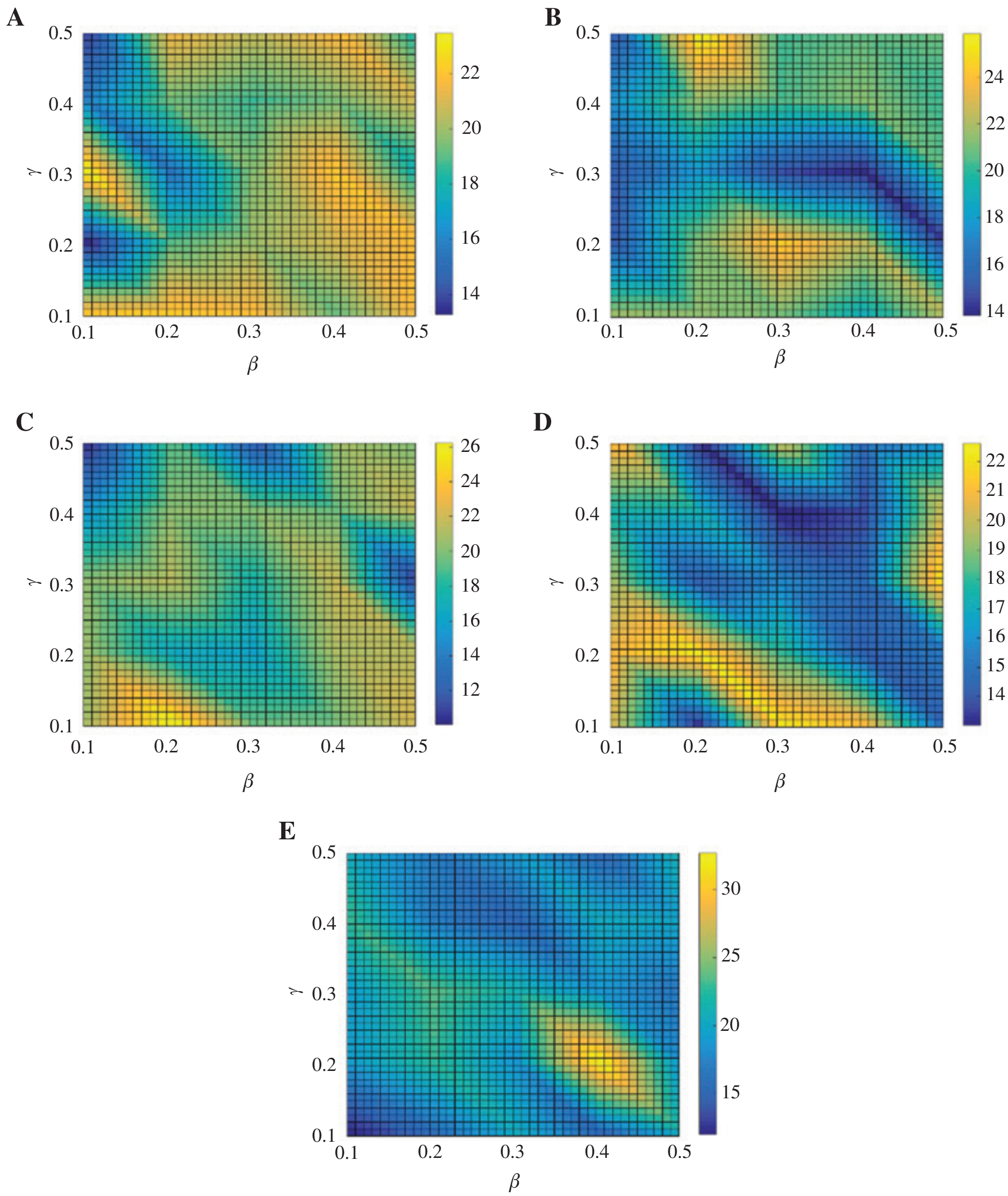

Figure 9: Estimation of electrical power under varying β and γ with the reference of α as (A) 0.1, (B) 0.2, (C) 0.3, (D) 0.4, and (E) 0.5.

ceptron with back-propagation learning algorithm) and FF-NM are evaluated and shown in Figure 4. When the outlet temperature is simulated, the deviation is found at 385°C (during the start of sample iteration) and 365°C (at sample 400) between NM and FF-NM, respectively.

The deviation between NM and FF-NM is found to be at 800 and 850 MW at a sample size of 300 and 1000, respectively, for the electrical power parameter simulation. For steam pressure, the deviation is found at 20 and 25 MPa with respect to the sample size of 300 and 250 for the NM and FF-NM models, respectively.

In test case 2 (for both sets A and B) and case 3, seven parameters are considered and their correlation is shown in Figures 5–7, respectively.

The deviation difference for NM and FF-NM is found to be 1.79% and 2.5%, 0.42% and 1.6%, and 1.21% and 0.85% for feed water flow, water level in drum, and steam flow, respectively. However, for steam pressure

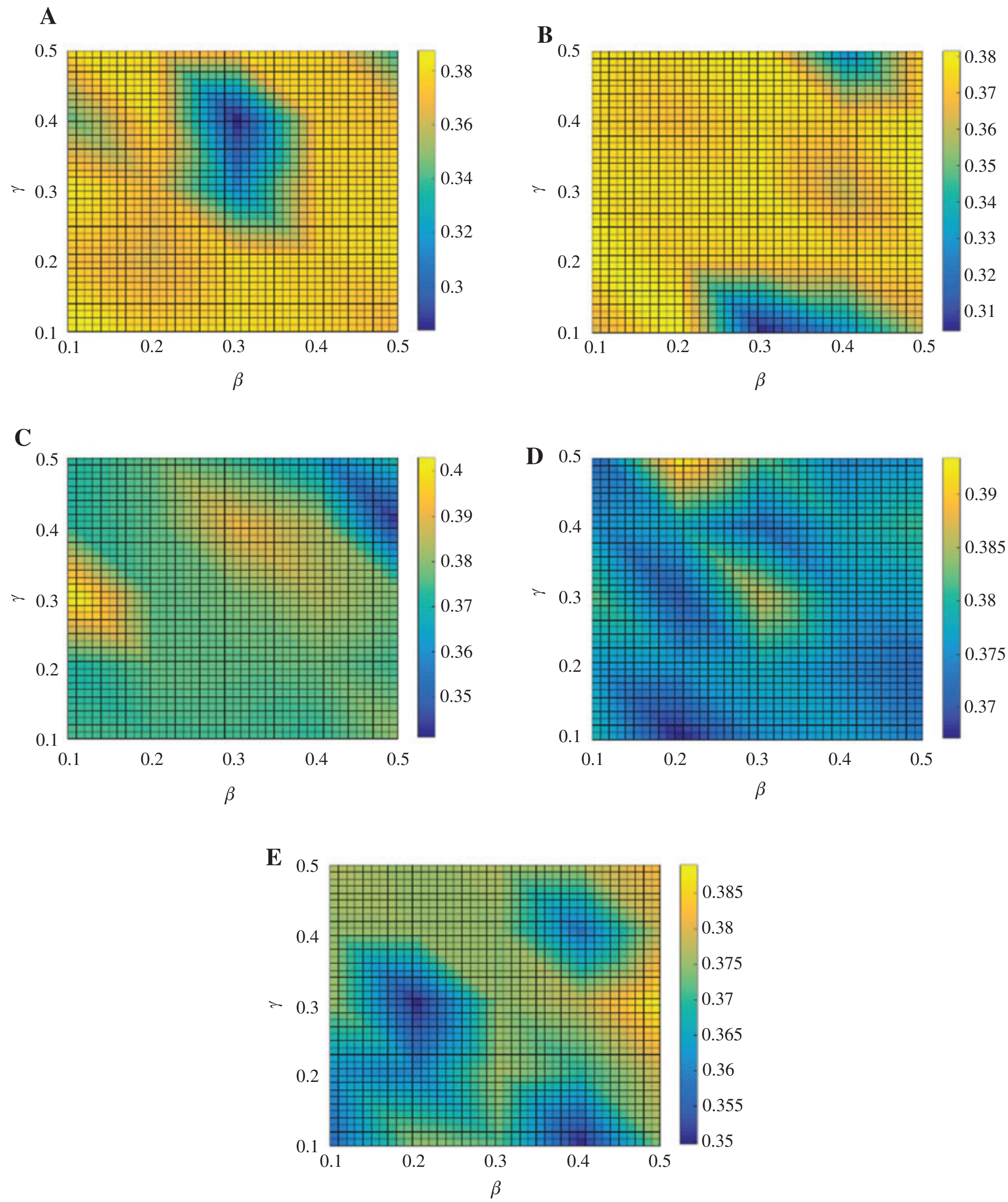

Figure 10: Estimation of Temperature Outlet under Varying β and γ with the Reference of α as (A) 0.1, (B) 0.2, (C) 0.3, (D) 0.4, and (E) 0.5.

in throttle and steam pressure in drum, the plots are very much closer to each other with no deviation. In the case of steam temperature, the estimations are very close for FF-NM. A 0.12% deviation occurs for the NM model curve; for spray water flow, a smaller deviation is noticed. In test case 2 – set A, the curves for the parameters steam flow, steam temperature, steam pressure in drum, and steam pressure in throttle in the two models are closer; however, for water level in drum, feed water flow, and spray water flow, the deviations are found to be 6%, 5.65%, and 15%, respectively, for the FF-NM method, which are rather higher than the deviations between the NM method. In test case 2 – set B, for models NM and FF-NM with respect to the parameters water level in drum, feed water flow, spray water flow, steam flow, steam pressure in throttle, and steam

Table 2: Parameters used in Electric Power under Varying β and γ with the Reference of α.

α	β	γ=1	γ=2	γ=3	γ=4	γ=5
1	1	21.976	13.261	23.46	15.843	13.711
	2	22.13	18.897	15.466	19.307	21.59
	3	21.754	19.921	19.63	18.663	20.686
	4	19.167	20.956	22.144	19.408	21.833
	5	21.789	21.802	17.758	20.933	17.775
2	1	21.602	15.216	15.178	17.613	15.249
	2	21.407	21.184	17.717	21.346	25.854
	3	21.091	24.372	14.833	20.421	20.221
	4	19.06	22.342	13.826	21.291	20.688
	5	22.229	14.306	20.612	20.1	20.907
3	1	20.932	20.477	20.159	15.419	10.059
	2	26.211	16.65	21.284	20.242	18.909
	3	19.383	16.092	17.735	20.094	11.494
	4	19.656	21.011	21.79	19.533	20.617
	5	22.403	21.365	10.547	21.858	19.816
4	1	20.12	20.91	19.349	17.437	21.34
	2	13.367	22.249	14.345	17.307	13.111
	3	22.072	18.057	15.675	13.025	20.25
	4	20.898	14.266	14.69	13.69	14.764
	5	14.295	15.317	22.619	20.478	15.883
5	1	11.961	19.151	19.277	22.882	20.148
	2	15.826	22.615	23.584	17.059	17.12
	3	20.434	18.511	21.358	15.048	19.173
	4	15.267	32.708	18.66	20.42	15.247
	5	20.783	17.946	16.458	19.85	21.585

Table 3: Parameters used in Steam Pressure under Varying β and γ with the Reference of α.

α	β	γ=1	γ=2	γ=3	γ=4	γ=5
1	1	0.010221	0.0098627	0.0096149	0.009576	0.009981
	2	0.0099083	0.010063	0.0091971	0.0098334	0.0097197
	3	0.0094806	0.010432	0.0099833	0.0099227	0.0089701
	4	0.0099792	0.0062381	0.010027	0.0094135	0.0094213
	5	0.0085275	0.0098716	0.0099234	0.0097111	0.0095794
2	1	0.010165	0.0099174	0.0098747	0.010116	0.0086981
	2	0.0061975	0.0098238	0.010045	0.0089234	0.010373
	3	0.0098767	0.010058	0.0097844	0.0069638	0.0099691
	4	0.0083416	0.0096414	0.0096302	0.0099459	0.009885
	5	0.010142	0.0098262	0.0067973	0.010052	0.0088043
3	1	0.010142	0.0099003	0.0097378	0.0061577	0.0099391
	2	0.0099159	0.0077984	0.0097992	0.010029	0.009763
	3	0.009814	0.0080363	0.0095357	0.0094773	0.0084904
	4	0.010191	0.010041	0.010073	0.0093773	0.0096879
	5	0.0099187	0.0092744	0.010111	0.0097761	0.0085963
4	1	0.0098976	0.0098138	0.0091036	0.0097899	0.0090046
	2	0.0093566	0.0089078	0.010817	0.0094791	0.010521
	3	0.0099964	0.0098218	0.010346	0.010093	0.0096076
	4	0.0084993	0.0099224	0.009945	0.01008	0.01019
	5	0.010111	0.0097744	0.009983	0.0098389	0.0096015
5	1	0.0099886	0.009751	0.0099533	0.0099089	0.010006
	2	0.0097203	0.0093931	0.0099207	0.0095661	0.010048
	3	0.010124	0.0094098	0.0098558	0.0097655	0.0096059
	4	0.0098707	0.010057	0.0095606	0.0095606	0.0081088
	5	0.0097222	0.0099687	0.0093404	0.0089802	0.010178

Table 4: Parameters used in Temperature under Varying β and γ with the Reference of α.

α	β	$\gamma=1$	$\gamma=2$	$\gamma=3$	$\gamma=4$	$\gamma=5$
1	1	0.38757	0.37101	0.38398	0.3453	0.38111
	2	0.37562	0.36369	0.36881	0.38025	0.37826
	3	0.37991	0.3785	0.3123	0.28364	0.3787
	4	0.37768	0.37698	0.37767	0.37577	0.37642
	5	0.36795	0.38036	0.37823	0.37252	0.3314
2	1	0.36462	0.3803	0.37597	0.37452	0.3767
	2	0.38146	0.3729	0.37549	0.36872	0.37606
	3	0.30469	0.37423	0.37736	0.37624	0.37863
	4	0.32965	0.37393	0.36136	0.37267	0.3251
	5	0.36105	0.37652	0.37942	0.37854	0.37667
3	1	0.37469	0.37086	0.40286	0.37178	0.3721
	2	0.37422	0.37667	0.37605	0.37607	0.3767
	3	0.37471	0.37622	0.37854	0.39065	0.37208
	4	0.37336	0.37728	0.38378	0.38339	0.36222
	5	0.38075	0.37384	0.37856	0.34118	0.3735
4	1	0.37876	0.37604	0.38174	0.37508	0.37179
	2	0.36714	0.3758	0.37067	0.37791	0.39342
	3	0.37511	0.37811	0.38601	0.37245	0.38219
	4	0.37654	0.37434	0.37642	0.37808	0.37405
	5	0.37324	0.37175	0.37707	0.38137	0.37522
5	1	0.35742	0.36189	0.37495	0.37503	0.37644
	2	0.37479	0.36032	0.35017	0.37527	0.37485
	3	0.3716	0.37556	0.37478	0.37481	0.37668
	4	0.34963	0.36955	0.37771	0.35822	0.37715
	5	0.37585	0.3793	0.38895	0.37895	0.38247

temperature, the deviation is calculated as 4.03% and 1.94%, 2.57% and 7.04%, 6.41% and 3.22%, 1.68% and 4.85%, 0.6% and 4.6%, and 0.06% and 0.24%, respectively.

5.3 Impact of FF Algorithm Parameters on Design Performance

The error rate is analyzed for the proposed model and the graphs are plotted with β on x-axis, γ on y-axis with varied α values (0.1, 0.2, 0.3, 0.4, 0.5) for the parameters temperature outlet, steam pressure, and electrical power, as shown in Figures 8–10, respectively. The results are quantified and tabulated in Tables 2–4.

For the electrical power parameter, the error rate is least when $\gamma=0.2$ and 0.5 with corresponding $\beta=0.1$ and 0.1 for $\alpha=0.1$, and when the α value is set to 0.2, the error is least at $\gamma=0.3$ to 0.28 with corresponding $\beta=0.32$ to 0.44, for $\alpha=0.3$, 0.4, and 0.5, $\gamma=0.5$, 0.3, 0.5 with corresponding $\beta=0.1$, 0.5, 0.3, $\gamma=0.1$, 0.5 to 0.4 to corresponding $\beta=0.2$, 0.21 to 0.3, $\gamma=0.1$ with $\beta=0.1$, respectively. In the case of steam pressure, for $\alpha=0.1$, 0.2, 0.3, 0.4, 0.5, the error is less at $\gamma=0.21$, 0.1, 0.4, 0.1, and 0.5 with corresponding $\beta=0.41$, 0.2, 0.1, 0.4, and 0.42, respectively. For temperature outlet, when $\alpha=0.1$, the error is minimized at $\gamma=0.4$ and $\beta=0.3$ and for $\alpha=0.2$, $\gamma=0.1$ and 0.5 with corresponding $\beta=0.3$ and 0.43. When the α value is 0.5, the error is least at $\gamma=0.3$, 0.1, 0.4 with corresponding $\beta=0.2$, 0.4, and 0.4 and for $\alpha=0.3$ and 0.4, $\gamma=0.1$ and 0.42 with corresponding $\beta=0.2$ and 0.5, respectively.

5.4 Degree of Training Information on Design Performance

The error deviation between the plant and the proposed model, and between NM and the plant is calculated and tabulated in Table 5. Three cases are taken – case 1, case 2, and case 3 – having different parameters, and

Table 5: Error Deviation of Various Design Models with the Actual Boiler Performance.

% of Experimental data	25		50		75	
Methods	**NM**	**FF-NM**	**NM**	**FF-NM**	**NM**	**FF-NM**
Case 1						
Electrical power	450.48	87.55	22.84	19.51	16.76	14.66
Steam pressure	0.03	0.02	0.007	0.006	0.009	0.008
Temperature outlet	0.65	0.54	0.26	0.23	0.37	0.36
Case 2 – Set A						
Feed water flow	3	1.84	0.11	0.13	0.02	0.03
Steam pressure at throttle	0.0006	0.0006	9.9e – 05	0.0001	1.3e – 06	1.1e – 06
Steam pressure in drum	0.0003	0.0003	5.8e – 05	5.9e – 05	6.5e – 08	3.5e – 08
Spray water flow	0.08	0.05	0.008	0.008	6.8e – 05	5.0e – 05
Water level in drum	1.5e – 06	3.8e – 06	3.8e – 07	6.2e – 07	1.9e – 07	1.6e – 07
Steam flow	1	1.49	0.16	0.16	0.005	0.02
Steam temperature	0.05	0.042	0.006	0.006	2.5e – 05	9.6e – 06
Case 2 – Set B						
Feed water flow	21.75	28.47	0.53	0.52	0.01	0.01
Steam pressure at throttle	0.0009	0.0009	0.0001	0.0001	2.5e – 08	2.4e – 07
Steam pressure in drum	0.0006	0.0007	0.0001	0.0001	3.4e – 08	3.2e – 07
Spray water flow	0.07	0.27	0.01	0.01	0.003	0.005
Water level in drum	1.7e – 05	3.4e – 05	3.5e – 06	2.2e – 06	2.3e – 06	1.6e – 06
Steam flow	1.26	1.19	2.62	1.76	2.04	0.72
Steam temperature	0.07	0.08	0.01	0.01	5.9e – 05	5.6e – 05
Case 3						
Feed water flow	3.73	2.39	0.34	0.34	0.05	0.02
Steam pressure at throttle	0.0009	0.001	9.9e – 05	6.9e – 05	8.3e – 07	1.5e – 06
Steam pressure in drum	0.0003	0.0002	4.6e – 05	4.9e – 05	4.0e – 06	3.1e – 06
Spray water flow	0.27	0.58	0.03	0.05	0.008	0.002
Water level in drum	1.1e – 05	1.2e – 05	9.2e – 07	1.0e – 06	6.8e – 08	5.03e – 08
Steam flow	0.94	2.98	0.18	0.15	0.002	0.002
Steam temperature	0.19	0.55	0.03	0.03	0.0002	0.0001

the error deviation is calculated for all these parameters. From the results, it is found that from 25% to 75%, the error is decreased for the proposed model in all cases.

6 Conclusion

This paper discussed about boiler plant modeling strategies for reducing the emissions and increasing the power savings using a novel FF-NM method. The performance of the proposed method has been studied under four modes: test case A, test case 2 – set A, test case 2 – set B, and test case 3 with various parameters including electrical power, temperature outlet, steam pressure, feed water flow, steam pressure at throttle, steam pressure in drum, spray water flow, water level in drum, steam flow, and steam temperature. The results are subjected to comparison with the existing NM and the original plant model. With respect to parameters, the deviation difference is low for FF-NM and the plant. In addition to this, for varying the FF algorithm parameters, the performance is estimated and the minimum error occurrence has been interpreted. The error deviation has been evaluated, and it is noted that the error is decreased with definite parameters. The obtained results prove the efficiency of the proposed modeling technique. The proposed boiler plant model has advantages such as flexibility, accuracy, and the ability without the knowledge of experts. However, the proposed model has not been experimented for its accuracy under external disturbance. In such cases, the precision shall be uncertain, which should be compensated for in the future. Moreover, a variant of the FF algorithm can improve the learning performance and thus the network performance.

Bibliography

[1] M. Alb, P. Alotto, C. Magele, W. Renhart, K. Preis and B. Trapp, Firefly algorithm for finding optimal shapes of electromagnetic devices, *IEEE Trans. Magnet.* **52** (2016), 1–4.

[2] K. J. Astrom and R. D. Bell, Drum boiler dynamics, *Automatica* **36** (2000), 363–378.

[3] N. Athanasios, N. Nikolaos, M. Nikolaosa, G. Panagiotis, and E. Kakaras, Optimization of a log wood boiler through CFD simulation methods, *Fuel Process. Technol.* **137** (2015), 75–92.

[4] Z. N. Bahman and A. Ali, Accurate prediction of the dew points of acidic combustion gases by using an artificial neural network model, *Energy Convers. Manage.* **52** (2011), 911–916.

[5] S. Beyhan and K. Kavaklioglu, Comprehensive modeling of U-tube steam generators using extreme learning machines, *IEEE Trans. Nucl. Sci.* **62** (2015), 2245–2254.

[6] J. S. Chandok, I. N. Kar and T. Suneet, Estimation of furnace exit gas temperature (FEGT) using optimized radial basis and back-propagation neural networks, *Energy Convers. Manage.* **49** (2008), 1989–1998.

[7] W. S. M. Culloch and W. Pitts, A logical calculus of the ideas immanent in nervous activity, *Bull. Math Biophys.* **5** (1943), 115–133.

[8] S. M. Darwish, Combining firefly algorithm and Bayesian classifier: new direction for automatic multilabel image annotation, *IET Image Process.* **10** (2016), 763–772.

[9] J. Deng, R. Stobart and B. Maass, The applications of artificial neural networks to engines, In: *Artificial Neural Networks – Industrial and Control Engineering Applications*, K. Suzuki, ed., In Tech, Rijeka, Croatia, pp. 309–332, 2011.

[10] M. Duguleana and G. Mogan, Neural networks based reinforcement learning for mobile robots obstacle avoidance, *Expert Syst. Appl.* **62** (2016), 104–115.

[11] A. K. Fard and T. Niknam, Optimal stochastic capacitor placement problem from the reliability and cost views using firefly algorithm, *IET Sci. Measur. Technol.* **8** (2014), 260–269.

[12] M. Flynn and M. Malley, A drum boiler model for long term power system dynamic simulation, *IEEE Trans. Power Syst.* **14**, (1999) 209–217.

[13] X. Hengyan, W. Lingmei and C. Huahua, The study of optimizing circulating fluidized bed boiler operational parameters based on neural network and genetic algorithm, In: *Fourth International Conference on Intelligent Computation Technology and Automation*, pp. 287–290, 2011.

[14] J. J. Hopfield, Neural networks and physical systems with emergent collective computational abilities, *Proc. Nat. Acad. Sci.* **79** (1982), 2554–2558.

[15] M. Kljajic, D. Gvozdenac and S. Vukmirovic, Use of neural networks for modeling and predicting boiler's operating performance, *Energy* **45** (2012), 304–311.

[16] I. Kocaarslan and E. Cam, Experimental modelling and simulation with adaptive control of power plant, *Energy Convers. Manage.* **48** (2007), 787–796.

[17] I. Kocaarslan, C. Ertugrul and H. Tiryaki, A fuzzy logic controller application for thermal power plants, *Energy Convers. Manage.* **47** (2006), 442–458.

[18] X. Liu and R. C. Bansal, Integrating multi-objective optimization with computational fluid dynamics to optimize boiler combustion process of a coal fired power plant, *Appl. Energy* **130** (2014), 658–669.

[19] X. J. Liu, X. B. Kong, G. L. Hou and J. H. Wang, Modeling of a 1000 MW power plant ultra super-critical boiler system using fuzzy-neural network methods, *Energy Convers. Manage.* **65** (2013), 518–527.

[20] J. Z. Liu, S. Yan, D. L. Zeng, Y. Hu and Y. Lv, A dynamic model used for controller design of a coal fired once-through boiler-turbine unit, *Energy* **93** (2015), 2069–2078.

[21] L. Ma, K. Y. Lee and Z. Wang, Intelligent coordinated controller design for a 600 MW supercritical boiler unit based on expanded-structure neural network inverse models, *Control Eng. Pract.* **53** (2016), 194–201.

[22] J. C. Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2, pp. 68–73, Clarendon, Oxford, 1892.

[23] H. J. Mohammed, A. S. Abdullah, R. S. Ali, R. A. Abd-Alhameed, Y. I. Abdulraheem and J. M. Noras, Design of a uniplanar printed triple band-rejected ultra-wideband antenna using particle swarm optimisation and the firefly algorithm, *IET Microwav. Antennas Propagat.* **10** (2016), 31–37.

[24] J. Nayak, B. Naik and H. S. Behera, A novel nature inspired firefly algorithm with higher order neural network: performance analysis, *Eng. Sci. Technol.* **19** (2016), 197–211.

[25] D. Norm, DIN 1942 – Acceptance testing of steam generators, edition 02/1994.

[26] S. Ranganathan, M. Surya Kalavathi and C. Asir Rajan, Self-adaptive firefly algorithm based multi-objectives for multi-type FACTS placement, *IET Gener. Transm. Distrib.* **10** (2016), 2576–2584.

[27] H. Rusinowski and W. Stanek, Neural modelling of steam boilers, *Energy Convers. Manage.* **48** (2007), 2802–2809.

[28] K. S. S. Rao Yarrapragada and B. Bala Krishna, Impact of tamanu oil-diesel blend on combustion, performance and emissions of diesel engine and its prediction methodology, *J. Braz. Soc. Mech. Sci. Eng.* **39** (2016), 1–15.

[29] M. Sayed, S. M. Gharghory and H. Kama, Gain tuning PI controllers for boiler turbine unit using a new hybrid jump PSO, *J. Elect. Syst. Inform. Technol.* **2** (2015), 99–110.

[30] S. D. Secco, O. Juan, M. L. Louisy, J. Y. Lucas, P. Plion and L. Porcheron, Using a genetic algorithm and CFD to identify low NOx configurations in an industrial boiler, *Fuel* **158** (2015), 672–683.
[31] S. Sokolov-Mladenovic, M. Milovancevic, I. Mladenovic and M. Alizamir, Economic growth forecasting by artificial neural network with extreme learning machine based on trade, import and export parameters, *Comput. Hum. Behav.* **65** (2016), 43–45.
[32] J. Song, C. E. Romero, Z. Yao and B. He, Improved artificial bee colony-based optimization of boiler combustion considering NOX emissions, heat rate and fly ash recycling for on-line applications, *Fuel* **172** (2016), 20–28.
[33] M. Szega and G. T. Nowak, An optimization of redundant measurements location for thermal capacity of power unit steam boiler calculations using data reconciliation method, *Energy* **92** (2015), 135–141.
[34] A. M. K. Vandani, M. Bidi and F. Ahmadi, Exergy analysis and evolutionary optimization of boiler blowdown heat recovery in steam power plants, *Energy Convers. Manage.* **106** (2015), 1–9.
[35] J. L. Wei, J. H. Wang, and Q. H. Wu, Development of a multi-segment coal mill model using an evolutionary computation technique, *IEEE Trans. Energy Convers.* **22** (2007), 718–27.
[36] Y. Xing, X. Shia, F. Shena, K. Zhouc and J. Zhaoa, A self-organizing incremental neural network based on local distribution learning, *Neural Netw.* **84** (2016), 143–160.
[37] G. Xu, C. Xu, Y. Yang, Y. Fang, L. Zhou and Z. Yang, Thermodynamic and economic analysis of a partially-underground tower-type boiler design for advanced double reheat power plants, *Appl. Thermal Eng.* **78** (2015), 565–575.
[38] X. S. Yang, *Nature-Inspired Metaheuristic Algorithms*, Luniver Press, UK, 2008.
[39] X. S. Yang, Firefly algorithms for multimodal optimisation, In: *Proc. 5th Symposium on Stochastic Algorithms, Foundations and Applications*, 5792, pp. 169–178, 2009.
[40] X. S. Yang and X. He, Firefly algorithm: recent advances and applications, *Int. J. Swarm Intell.* **1** (2013), 36–50.
[41] T. Yang, C. Cui, Y. Shen and Y. Lv, A novel denitration cost optimization system for power unit boilers, *Appl. Therm. Eng.* **96** (2016), 400–410.
[42] J. H. Yang, J. A. Kim, J. Hong, M. Kim, C. Ryu, Y. J. Kim, H. Y. Park and S. H. Baek, Effects of detailed operating parameters on combustion in two 500-MWe coal-fired boilers of an identical design, *Fuel* **144** (2015), 145–156.
[43] Y. Yang, C. Xu, G. Xu, Y. Han, Y. Fang and D. Zhang, A new conceptual cold-end design of boilers for coal-fired power plants with waste heat recovery, *Energy Convers. Manag.* **89** (2015), 137–146.
[44] J. Yuan and S. Yu, Privacy preserving back-propagation neural network learning made practical with cloud computing, *IEEE Trans. Parallel Distrib. Syst.* **25** (2014), 212–221.
[45] Q. Zhao, H. Xu and S. Jagannathan, Near optimal output feedback control of nonlinear discrete-time systems based on reinforcement neural network learning, *IEEE/CAA J. Autom. Sin.* **1** (2014), 372–384.