A Simulation Model to Predict Coal-Fired Power Plant Production Rate Using Artificial Neural Network Tool

Ravinder Kumar[1], Keval Nikam[1,2](✉), and Ravindra Jilte[1]

[1] School of Mechanical Engineering, Lovely Professional University, Phagwara 144411, Punjab, India
ravchauhan8@gmail.com, nikamkeval26@gmail.com

[2] Faculty of Mechanical Engineering, Dr. D. Y. Patil Institute of Engineering, Management and Research, Savitribai Phule Pune University, Akurdi, Pune 411044, India

Abstract. At present, the performance evaluation of a coal-fired power plant is highly required to enhance its efficiency. The present paper deals with the power prediction of a 600 million watts (MW) typical subcritical coal-fired power plant situated in North India using real operational data at different load conditions. The entire complex thermal system comprises various systems like boiler, turbine, condenser, re-heater, deaerator, boiler feed pump, etc. A simulation model is prepared to predict the performance of the power plant. The Artificial Neuron Network tool is used to validate the simulation model for known input and output data. The selected performance criterion and network error is found satisfactory after the analysis of computational results. The coefficient of determination was calculated as 0.99787 which gives an idea of the close relation of one output variable with several different input variables. This paper will definitely help out to those interdisciplinary engineers who are dealing with combining technology with the conventional process.

Keywords: Subcritical coal-fired power plant · Artificial neuron network · Boiler · Turbine

1 Introduction

A coal-based power plant is a complex and highly sophisticated system. Heavy finance is involved annually in the operation and maintenance of such complex power production plants to achieve the desired availability level. Performance prediction of such a thermal system is of great concern because of increasing cost, competition, and public demand in one way, while the risk of failure on the other. In India, there is a heavy load on coal-fired power plants where coal is generally used as a common fuel for electricity generation. This generated electricity plays an important role to raise the modern economy for industry, agriculture, transport, and household for any nation. But, the growing energy demand has increased energy consumption in the entire world. As energy demand is continuously increasing, the improvement in operating characteristics of electrical power

B. Iyer et al. (eds.), *Applied Computer Vision and Image Processing*,
Advances in Intelligent Systems and Computing 1155,
https://doi.org/10.1007/978-981-15-4029-5_15

generation plants has become a mandate in this era. According to the data published by the Central Electricity Authority (CEA) of India, reported that per capita consumption has increased from 15 kWh in 1950 to about 1,122 kWh (kilowatts hours) in the year 2016–17. Out of 597,464 census villages, 592,135 villages (99.25 %) have been electrified as on 31.03.2017. Efforts are been taken by the government of India to fulfill the needs of the citizen by increasing generation about 5.1 billion units in 1950 to 1,242 BU (including imports) in the year 2016–17. Coal-fired power plants are ruling over the power sector from past decades and will continue to remain on top position in India due to the easy availability of coal. The installed capacity of India as on 31.3.2017 was 326,833 MW comprising 59 % of coal-fired power plants as compared to other power sources as shown in Fig. 1.

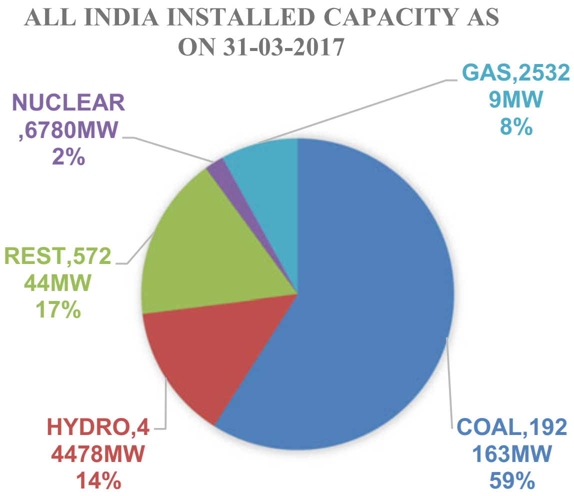

Fig. 1 All India installed capacity as on 31-03-2017 [1]

The subcritical power plants are contributing at the major level in electricity generation in India. Installed unit of a subcritical power plant in India as per data published by CEA were 74 units working under Private companies, 33 units are under State government and 23 units are operating under the Central government. The exact thermodynamic analysis of the subcritical power plant is done using suitable assumptions. Without suitable assumptions, thermodynamic analysis of the subcritical power plant will lead to more number of nonlinear equations and the solution of such equations will lead to an increase in computational time. To overcome this issue, an Artificial Neural Network (ANN) is used to analyze the systems for operational input and output patterns. Using the previously stored operational data, the neural network can be modeled to simulate the power plant operation. ANN models are more dominant than physical models as these can be trained with live operational data. By comparing previous ANN models with the latest model, factors affecting the output can be studied and suitable maintenance majors would be taken in advance. The response time of the ANN model is quick [2]. Some researchers have presented a brief review of applications of ANN in different energy systems [3]. Some of them have proposed energy and exergy analysis using ANN for heat evaluation [4]. Exergy efficiency can also be predicted by using ANN techniques [5]. Multiple regression techniques are also used to predict the energy performance of power generating plants [6]. The use of soft computing techniques like Genetic Algorithm, Particle Swarm Optimization, Fuzzy Logic, and ANN for simulation and prediction of thermodynamic systems is presented in past research work [7, 8]. Specifically, the performance of power generation turbines can also be modeled by using ANN [9]. Researchers nowadays are focusing on carbon capture technology to understand the emissions produced from existing power plant [10]. Emission contents like NO_x (Nitrogen oxide) and CO_2 (Carbon dioxide) from coal-fired power plants can also be predicted by using the ANN technique along with the Genetic Algorithm [11, 12]. It is particularly useful in system modeling while implementing complex mapping, fault detection, and prediction of output [13, 14]. Only a few researchers developed a simulation model for predicting equipment maintenance and their priorities using probabilistic approaches [15]. Several authors have reported the capability of ANN to replicate an established correspondence between points of an input domain and points of an output domain to interpret the behavior of phenomena involved in energy conversion plants [16, 17]. However, ANN models can be developed with definite objective and training with data from existing plants with lesser effort but with great utility. Prediction of output with nearly zero error helps to monitor the performance of power plants [18]. Plant operators can decide to change the water and steam flow rate, temperature and pressure values in accordance with usage of ANN model [19]. Online tracking of the generator output will increase operator awareness, and also plant efficiency and stability in parallel [20]. This kind of prediction method helps in the prediction of amount of energy used and required to obtain the desired output. Recently researchers are implementing ANN to the ultra-supercritical power plant for developing innovative modeling for controlling parameters [21].

In this paper, ANN was trained with the operational data from the subcritical power plant of 600 MW. The objective of the model was to predict mass flow rate, specific enthalpy, pressure and temperature of steam exiting various inlet and outlet of the components such as boiler, high-pressure turbine, intermediate pressure turbine, low-pressure turbine, condenser, re-heater, deaerator, boiler feed pump, etc. In order to have control of the plant with the operator, components should able to communicate based on the history with it. This will increase the plant utilization capacity and finally increase the operating hours. The motivation to select this integration of steam power plant components with the latest technology such as ANN is to improve the overall performance of the subcritical power plant.

2 Experimental Facility

2.1 Typical Plant Description

The unit of 600 MW subcritical power plant was selected for the modeling. The basic description of a subcritical coal-fired thermal power plant is shown in Fig. 2. It uses coal energy to convert it into mechanical energy through the expansion of steam in steam turbines. Coal received from collieries in the rail wagons is routed by belt conveyors. After crushing the coal in coal mills, it is then pushed to the boiler furnace (1), which is comprised of water tube walls all around through which water circulates. The chemically treated water through the boiler walls is converted into high-temperature steam. This steam is further heated in the super-heaters (3). The thermal energy of this steam is utilized to produce mechanical work in high pressure, intermediate pressure, and low pressure turbines. The steam blend collected from the turbine extractions is returned to feedwater heaters. The output of the turbine rotor is coupled to the generator (17) to produce electric energy. The steam after doing useful work in the turbine is condensed to water in condenser (8) for recycling in the boiler. For our study, we had not considered the air preheated circuit and coal feeding system.

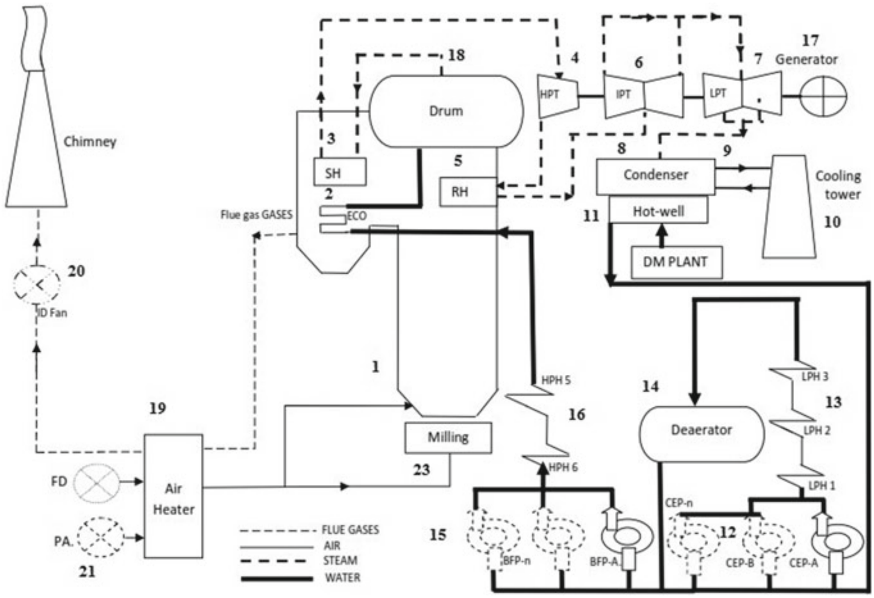

Fig. 2 Typical subcritical coal-fired power plant [22]

2.2 Design of Neural Network Model for 600 MW Plant

The neural network technique is developed from the behavior of the human brain. ANN gets trained by using the previous operational data and develop the relationship between the performance affecting input and output variables. The feed-forward transform function is used to predict the output for known operational inputs parameters. It consists of an input layer, two hidden layers, and an output layer as shown in Fig. 3.

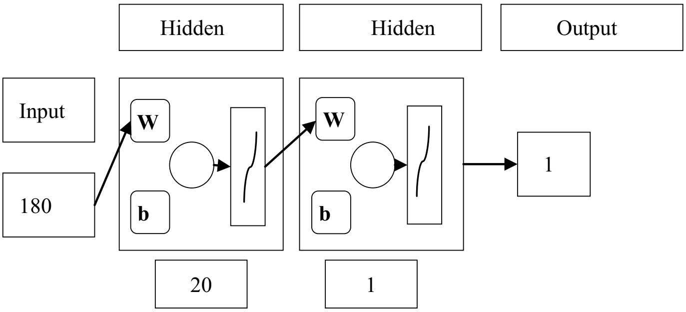

Fig. 3 Typical neuron for the proposed model

Weighted summed is transformed to predict the output in the neural network tool [9]. Hidden Layer Calculations [4]

$$\text{net}_i = \sum x_i w_{ij} \tag{1}$$

$$y_i = f(\text{net}_i) \tag{2}$$

Output Layer Calculations

$$\text{net}_x = \sum y_i w_{jk} \tag{3}$$

$$O_k = f(\text{net}_k) \tag{4}$$

where x_i is the input data, y_i is the output obtained from layer 1, and O_k is the output of layer 2. W is weight, b is bias.

2.3 Measurements

Operational data of 600 MW subcritical power plants were taken for each component. These readings were then imported to the ANN tool present in MATLAB software for constructing a predictive model. The following are the parameters (see Table 1) which were considered while taking a reading.

Table 1 Parameters considered and inputs for predicting output

Measured Parameters	Particulars	Reading	Particulars	Reading	Particulars	Reading	Particulars	Reading	Particulars	Reading	Particulars	Reading	Particulars	Reading
h(Kcal/Kg)	Before steam Generator	269.5	Blend 2 after IPT	728.9	Before Condenser	568.5	After LPH 1	50.5	Blend 1	677	After Boiler Feed Pump	174.5	Blend of HPH 2 send back to Dearator	218.2
C(Temp)		259		297.4		0.9141		50.3		184.3		170.1		210
T/H(Mass F		1979.4		190.8		1241.3		1541.03		78.43		1979		223.9
AT		207.26		8.17		0.105		11.07		2.878		209.6		0
h(Kcal/Kg)	After Steam Generator/ Before Super heater	419.8	After IPT	728.9	After Condenser	46.3	Blend 3	613.6	Before LPH4	677	Before HPH(After 1 BFP)	174.5	Before SG	269.5
C(Temp)		359.3		297.7		46.4		0.969		183.9		170.1		259
T/H(Mass F		0		1458.4		1547		64.478		78.53		1979		1979
AT		188.89		8.32		0.105		0.44		2.729		209.6		207.3
h(Kcal/Kg)	After Superheate r/Before HPT	810.7	Blend 1	677	Before Condenser Extra.Pump	46.3	Before LPH2	613.8	After LPH4	127.5	Blend 1 after IPT	781.9	After SG	419.8
C(Temp)		587		184.3		46.3		0.9701		127		409.9		359.3
T/H(Mass F		1979.4		78.528		1547		64.418		2646		103.1		0
AT		170		2.878		0.105		0.416		9.39		18.16		188.9
h(Kcal/Kg)	Blend 1 after HPT	729.9	Blend 2	638.5	After Condenser Extra.Pump	46.9	After LPH2	73.5	Blend 2 after IPT	728.9	After HPH 1	210.5		
C(Temp)		342.8		99.3		46.6		74.3		297.4		204.7		
T/H(Mass F		223.88		63.678		1547		1547.03		190.8		1979		
AT		49.24		1.119		20.89		10.83		8.17		208.4		
h(Kcal/Kg)	Blend 2 after HPT /Before Reheater	729.9	Blend 3	613.6	Before Gland Steam Condenser	46.9	Blend 2	638.5	Before Dearator	728.9	Blend of HPH 1 send back to Dearator	177.5		
C(Temp)		342.8		0.969		46.6		99.498		296.6		175.4		
T/H(Mass F		1749.6		64.478		1547		63.678		105.4		327		
AT		49.24		0.44		20.89		1.119		7.48		0		
h(Kcal/Kg)	After Reheater/B efore IPT	842.2	Blend 4	64.1	After Gland Steam Condenser	47.3	Before LPH3	638.5	After Dearator	168.1	Blend 1 after HPT	729.9		
C(Temp)		537		64		47.1		98.7		166.6		342.6		
T/H(Mass F		1749.6		11.881		1541		63.678		1979		223.9		
AT		48.35		0.242		11.71		1.059		7.33		48.9		
h(Kcal/Kg)	Blend 1 after IPT	781.7	Blend 5	568.5	Before LPH 1	47.3	After LPH3	98.1	Before Boiler Feed Pump	168.1	After HPH 2	269.5		
C(Temp)		410		0.9141		47.1		97.9		166.6		259		
T/H(Mass F		103.11		1241.3		1541		1547.03		1979		1979		
AT		18.26		0.105		11.71		10.33		7.32		201.9		

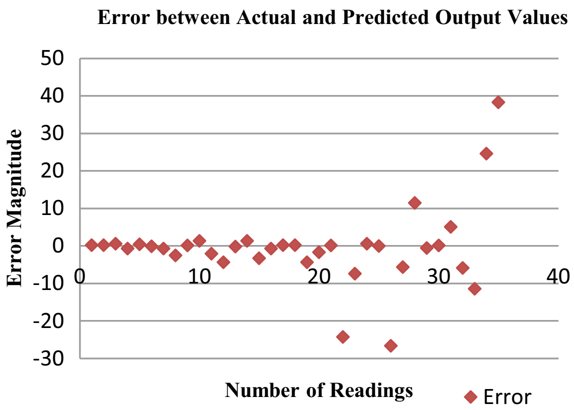

Fig. 4 Graphical representation of error for different readings during training

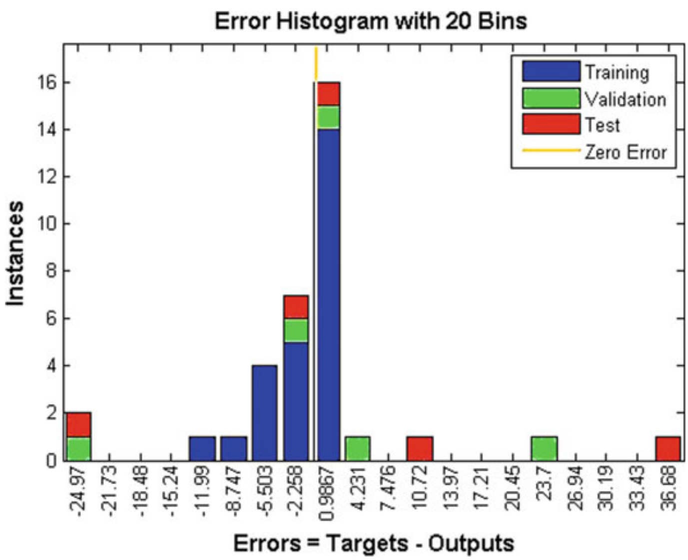

Fig. 5 Error considering 20 neurons between target value and output

3 Results and Discussions

Graphical representation of error between actual and predicted output values for different readings during training is shown in Fig. 4. During the training of neurons, minimum error magnitude was evaluated as 0.11182 for 35 readings as predicted from the ANN model.

As per the discussion of reading in Table 1, the actual output of the plant was observed to be 600 MW. The same said output was predicted from ANN Model with 20 neurons in the hidden layer. It is concluded that considering 20 neurons predicted values come to be true value where the error is equal to zero as shown in Fig. 5. Different neuron combination strategy was used to predict the output as shown in Table 2.

Table 2 Computational table at different combination of neurons

Itr.	Neurons	Training	Validation	Test	ALL R	Predicted values (MW)
1	5	0.9998	0.9959	0.9958	0.9958	661.19
2	10	0.9899	0.9899	0.9541	0.9850	660.51
3	15	0.9983	0.999	0.9911	0.9943	654.00
4	20	1	0.9990	0.9933	0.9978	660
5	25	0.9959	0.9961	0.9733	0.9952	660.76
6	30	0.9983	0.9994	0.9951	0.9943	665.54
7	35	0.9962	0.9992	0.9957	0.9964	656.07
8	40	0.9992	0.9478	0.9933	0.9958	656.48
9	45	0.9984	0.9963	0.9912	0.9972	663.58
10	50	0.8030	0.7904	0.6863	0.7797	780
11	55	0.9985	0.9801	0.9902	0.9959	658.52

In addition to the above work, energy and exergy analysis of power plant is performed and exergetic efficiency is determined as shown in result Table 3. It is clear from Table 3 that ANN is positively applied to existing plants to increase the performance. The exergetic efficiency of components namely High-Pressure Turbine (HPTr), Intermediate Pressure Turbine (IPTr), Low-Pressure Turbine (LPTr), Condensate Extraction Pump (CEP), Boiler Feed Pump (BFP), High-Pressure Heater 1 (HPHeater1), High-Pressure Heater 2 (HPHeater2), Low-Pressure Heater 1 (LPHeater1), Low-Pressure Heater 2 (LPHeater2), Low-Pressure Heater 3 (LPHeater3), Low-Pressure Heater 4 (LPHeater4).

Energetic η and Exegetic ψ efficiency from the sample reading was evaluated as follows:

$$\eta = 41.2\% \quad \text{and} \quad \psi = 39.23\%$$

The small difference in efficiencies is due to chemical exergy of coal being greater than its specific energy measured by its high heating value. From the exegetic efficiency, it is clearly seen that waste heat emissions from the condenser although greater in quantity are low in quality (i.e., have little exergy as compared with other) because of temperature near to surrounding temperature. So improvement in condenser will slightly increase the overall exergy efficiency. From Fig. 6 with minimum deviation from actual reading a straight line is fitted with $R = 0.99787$.

Table 3 Comparison of calculated exergetic efficiency with reference paper

Sr.No.	Components	Calculated exergetic efficiency	Ref. [23]	Ref. [24]	Ref. [25]
1	HPTr	95.04	73.5	72.66	92.11
2	IPTr	94.8	–	–	–
3	LPTr	68.77	–	–	–
4	CEP	67.18	–	–	54.91
5	BFP	88.83	82.5	81.51	–
6	HPHeater1	95.9	97.4	97.65	91.58
7	HPHeater2	92.9	95.3	96.95	86.12
8	LPHeater1	89.99	89.5	89.06	85.41
9	LPHeater2	86.94	67.3	82.79	82.65
10	LPHeater3	86.91	–	–	82.65
11	LPHeater4	85.93	–	–	82.65

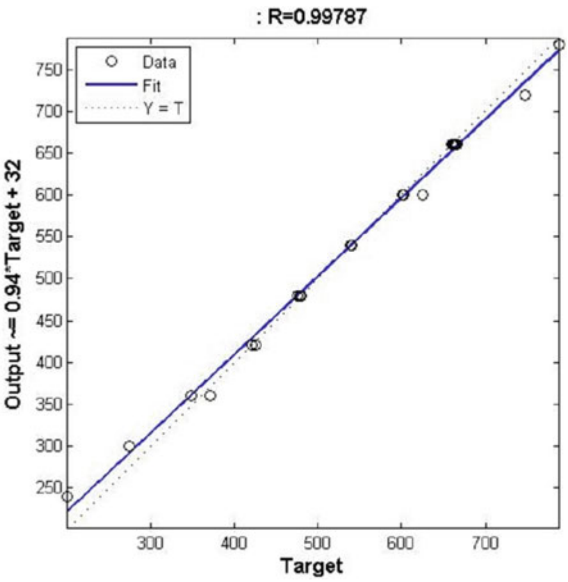

Fig. 6 Curve fitting with input parameter data

4 Conclusion

ANN model was developed with the help of operational data of the existing power plant with different inputs and corresponding outputs in the form of power generated. The main objective of this model was to predict power output for known input parameters. On comparing the error in prediction, it has been found that the ANN model with 20 neurons yields and minimum value of error in actual value recorded. Satisfactory coefficient of determination “R” was found to be 0.99787 which gives an idea of the close relation of one output variable with several different input variables. With this model linked with the control system of the power plant, operators can do changes accordingly in input parameters to achieve the desired power output. As a result of this efficiency and stability of a plant is continuously observed and necessary action could be taken to avoid the losses at different sections of coal-fired power plant.

References

1. Verma, V.S.: Adoption and introduction of supercritical technology in the power sector and consequential effects in operation, efficiency and carbon dioxide emission in the present context. In: Goel, M., Sudhakar, M. (eds.) Carbon Utilization, Green Energy and Technology, pp. 35–43. Springer, Singapore (2017)
2. Ianzhong Cui, X., Shin, K.G.: Contributed paper application of neural networks to temperature control in thermal power plants. Eng. Appl. Artif. lntell. **5**(6), 527–538 (1992)
3. Azadeh, A., Ghaderi, S.F., Anvari, M., Saberi, M.: Performance assessment of electric power generations using an adaptive neural network algorithm. Energy Policy **35**, 3155–3166 (2007)
4. Anead, H.S.: Evaluation and improvement performance of a boiler in a thermal power plant using artificial neural network. Eng. Technol. J. **36**(6), 656–663 (2018)
5. Acır, A.: Application of artificial neural network to exergy performance analysis of coal fired thermal power plant. Int. J. Exergy **12**(3), 362–379 (2013)
6. Kumar, R., Jilte, R., Mayank, B., Coal, Á.: Steady-State Modelling and Validation of a Thermal Power Plant. Springer, Singapore (2019)
7. Naserabad, S.N., Mehrpanahi, A., Ahmadi, G.: Multi-objective optimization of HRSG configurations on the steam power plant repowering specifications. **159** (2018)
8. Qi, J., Zhou, K., Huang, J., Si, X.: Numerical simulation of the heat transfer of superheater tubes in power plants considering oxide scale. Int. J. Heat Mass Transf. **122**, 929–938 (2018)
9. Salim, H., Faisal, K., Jawad, R.: Enhancement of performance for steam turbine in thermal power plants using artificial neural network and electric circuit design. Appl. Comput. Intell. Soft Comput. **2018** (2018)
10. Kumar, R., Jilte, R., Nikam, K.: Status of carbon capture and storage in India’s coal fired power plants: a critical review. Environ. Technol. Innov. **13**, 94–103 (2019)
11. Tunckaya, Y., Koklukaya, E.: Comparative prediction analysis of 600 MW coal-fired power plant production rate using statistical and neural-based models. J. Energy Inst. **88**(1), 11–18 (2015)
12. Shi, Y., Zhong, W., Chen, X., Yu, A.B., Li, J.: Combustion optimization of ultra supercritical boiler based on artificial intelligence. Energy **170**, 804–817 (2019)
13. Chandrasekharan, S., Panda, R.C.: Statistical modeling of an integrated boiler for coal fired thermal power plant. Heliyon **3**(October 2016), e00322 (2017)
14. Nurnie, N., Nistah, M., Lim, K.H., Gopal, L., Basim, F., Alnaimi, I.: Coal-fired boiler fault prediction using artificial neural networks. Int. J. Electr. Comput. Eng. **8**(4), 2486–2493 (2018)
15. Kumar, R., Tewari, P.C.: Markov approach to evaluate the availability simulation model for power generation system in a thermal power plant. Int. J. Ind. Eng. Comput. **3**(3), 743–750 (2013)
16. De, S., Kaiadi, M., Fast, M., Assadi, M.: Development of an artificial neural network model for the steam process of a coal biomass cofired combined heat and power (CHP) plant in Sweden. Energy **32**, 2099–2109 (2007)

17. Basu, S.: Modelling of steam turbine generators from heat balance diagram and determination of frequency response. **2**(1), 1–15 (2018)
18. Kumar, R., Jilte, R., Ahmadi, M.H., Kaushal, R.: A simulation model for thermal performance prediction of a coal-fired power plant, pp. 1–13 (2019)
19. Gurusingam, P., Ismail, F.B., Gunnasegaran, P.: Intelligent monitoring system of unburned carbon of fly ash for coal fired power plant boiler. In: MATEC Web of Conferences, 2017, vol. 02003, pp. 0–5 (2017)
20. Mikulandri, R., Cvetinovi, D., Spiridon, G.: Improvement of existing coal fired thermal power plants performance by control systems modifications zen Lon. Energy **57**, 55–65 (2013)
21. Hou, G., Yang, Y., Jiang, Z., Li, Q., Zhang, J.: A new approach of modeling an ultra-super-critical power plant for performance improvement. Energies **9**(310), 1–15 (2016)
22. Kumar, R.: Performance evaluation of a coal-fired power performance evaluation of a coal-fired power plant. Int. J. Perform. Eng. **9**(4), 455–461 (2013)
23. Aljundi, I.H.: Energy and exergy analysis of a steam power plant in Jordan. Appl. Therm. Eng. **29**(2–3), 324–328 (2009)
24. Hasti, S., Aroonwilas, A., Veawab, A.: Exergy analysis of ultra super-critical power plant. Energy Procedia **37**, 2544–2551 (2013)
25. Topal, H., et al.: Exergy analysis of a circulating fluidized bed power plant co-firing with olive pits: a case study of power plant in Turkey. Energy (2017)