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ORIGINAL CONTRIBUTION

Optimization and Analysis of Design Parameters, Excess Air Ratio, and Coal Consumption in the Supercritical 660 MW Power Plant Performance using Artificial Neural Network

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Abstract This work discusses the supercritical technology that has been instrumental in reducing pollution levels and quick load response from the thermal plant. Various operating parameters such as main steam pressure and temperature; reheat steam pressure and temperature; excess air ratio for a given fuel, feedwater heater bleed steam pressure and temperature are listed. The influence of their optimization is analyzed to reduce the pollution levels to a certain extent. Primarily, this study deals with utilizing artificial intelligence with the existing plant to predict the optimum thermal plant performance. The input parameters that are used in the artificial neural network (ANN) are evaluated to find the energy input through a mixture of coal and air. The ANN algorithm computes different parameters that initiate the optimization, resulting in the least energy input to the plant, as an algorithm fitness function. The built model could also use online optimization in addition to optimizing the design parameters when further modifications are made. This model is used to determine the effect of various excess air ratios and different types of fuels on the performance of the plant. The different boiler losses of boiler from different coal samples and exergy and exergy losses were analyzed at a particular excess air ratio. Finally, this paper predicts that by using ANN tool optimization, around 30% of coal savings are achieved which is equivalent to CO_2 pollution reduction, less reduction of NOx and SOx pollutions, and an increase in plant efficiency by 1.3%.

Keywords Energy efficiency · Turbine extractions · Excess air ratio · Coal analysis · Various operating parameters · Diverse pollutants levels

Abbreviations

CO_2	Carbon dioxide
SOx	Sulfur oxide
NOx	Nitrogen oxide
ANN	Artificial neural network
MW	Megawatt
GA	Genetic algorithm
PWR	Pressurized water reactor
HPH	High-pressure heater
HPT	High-pressure turbine
IPT	Intermediate pressure turbine
LPH	Low-pressure heater
LPT	Low-pressure turbine
TTD	Terminal temperature difference
DCA	Drain cool approach
FWHs	Feed water heaters
BFP	Boiler feed pump
CEP	Condensate extraction pump

List of symbols

%	Percentage
U	Heat transfer coefficient
A	Surface area
°C	Celsius
i	Inlet
o	Outlet
B	Boiler
C	Condenser

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D Deaerator
G Generator
I First case
II Second case
III Third case
IV Fourth case
V Fifth case
D Design case

Introduction

Electricity demand is going to increase day-to-day life, and this demand is one of the most important factors to measure a country's development. Out of all fossil fuels like coal, diesel, and natural gas, coal has one of the profuse resources used for electrical power generation. India has about 8.4% of the coal reserves of the world. Coal demand has been on the rise irrespective of the pollution it causes to the environment. Coal-based steam power plants are generating nearly 70% of total power generation than other fuels like oil and natural gas. Coal-fired power plants in India work on subcritical steam pressure and temperatures, and these plants give less performance and environmental pollution, whereas supercritical once-through units give maximum performance and generate fewer pollutants. Coal combustion in a boiler generates diverse environmental pollutants like carbon dioxide, carbon monoxide, nitrogen oxide, sulfur oxide, and particular matter. Generation of 1 MW of electric power needed 0.59–0.62 tons of specific coal consumption, which may lead to generating 0.59–0.62 tons of carbon dioxide and other pollutants. Increasing CO_2 pollution leads to global warming. Due to the great environmental concern, several researchers were doing their work on coal-fired power plants. By changing the design and operation of the plant, one may increase the performance of the plant and reduce the CO_2 emission to the maximum extent. Several technologies have been developed to reduce the emission of CO_2.

The ultra-supercritical and supercritical once-through units give maximum cycle performance, minimize the cost of power generation, and reduce pollution levels to a certain extent. The widely varying grid frequency in some countries due to broad supply–demand imbalances often forces generators to reduce/increase their station loads too much below/high their defined capacities, resulting in unreliable plant efficiencies. Supercritical once-through drum-less units are very useful for part load generation (Fig. 1).

As a normal practice power, plant efficiencies depend on proximate analysis, ultimate analysis and also on the high heating value of fuel like received basis and dry basis. The detailed coal proximate and elemental analysis is given in Tables 1 and 2. The power plant performance also depends on different parameters like stoichiometric air ratio, and heater bleeds pressure and temperatures, primary steam pressure and temperatures, re-heater steam pressures, and temperatures. The Artificial Intelligence tools are proven to be good to get maximum plant performance by different parameters (nonlinear and complex) a challenging task.

Ceyhun Yilmaz et al. [2] have done design calculation of geothermal power plant on ANN toll, compared those design parameters with the operation parameters, and studied the different reasons for not providing design values from operating values. Finally, they have concluded that as the temperature is increased the exergy efficiency of geothermal power plant also increased. Also, when the plant is operated with the optimized parameters, exergy efficiency of the plant is increased and the plant operating cost is decreased. ANN-based multilayer geothermal power plant has given the best results than numerical optimization techniques as per their analysis. Guotian Yang et al. [3] have studied the application of long short-term memory (LSTM) ANN modeling, which deals relation between operating parameters and NO_x pollution and principal component analysis (PCA) in a 660 MW supercritical boiler. They have concluded that the LSTM model gives better results than the PCA model under the same operating parameters and structure model. Chunlong Liu et al. [4] have studied the excess air ratio in a pulverized coal 800 MW boiler. They have concluded that at excess air low case, coal resident time inside the furnace increases during the low PA velocity; this is beneficial to the bituminous coal combustion inside the boiler and releases a high amount of heat from the furnace. Sahar Safarian et al. [5] have studied the power generation output from the different biomass fuels under various atmospheric conditions. Finally, they have developed an artificial neural network model with an approach to thermodynamic equilibrium. The developed model has a standard deviation of 0.999. Lara Wernicke et al. [6] have done 360 MW coal-fired power plant modeling with ANN in Brazil with the real operation data. They have used the design of the experimental approach on seven operating parameters to get the maximum results in power output and efficiency of the plant. Finally, the response surface methodology gives the best results. Naserbegi and Aghaie [7] have done optimization from multi-objective in Bushehr 1000 MW nuclear power plant to obtain plant efficiency and power output. They have concluded that ANN can find out best operating parameters and later those parameters were done a survey with gravitational search algorithm (GSA) for generating fitness function.

Yan Shi et al. [8] had done a combustion experiment on the ultra-supercritical coal-fired power plant. They had considered the input parameters like unit load, coal

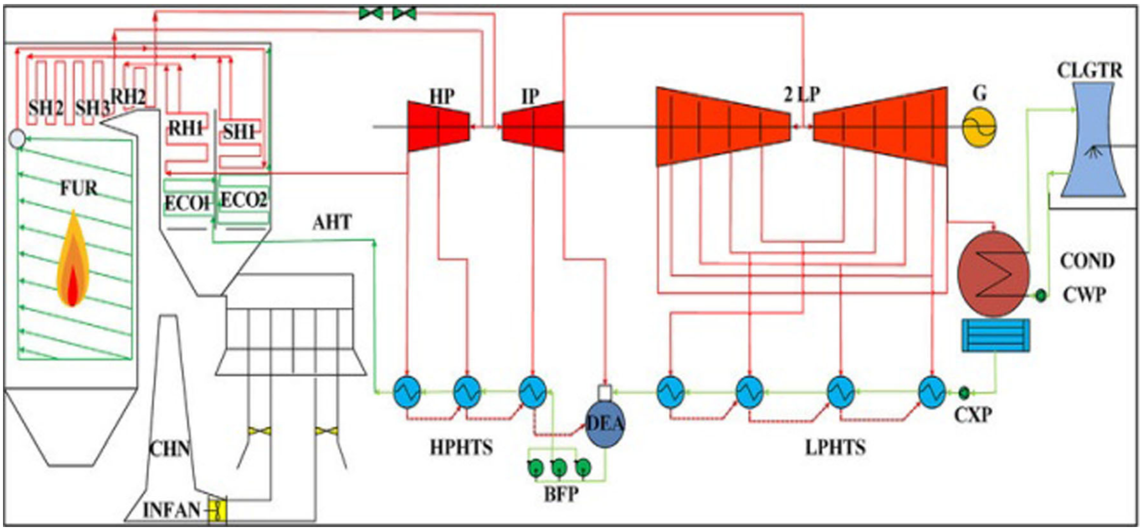

Fig. 1 660 MW supercritical power plant schematic representation

Table 1 Continuous breakdown of coal sample

S.No	Element	%
1	Sulfur	0.5932
2	Oxygen	6.544
3	Carbon	38.012
4	Nitrogen	0.744
5	Hydrogen	2.706

Table 2 Elemental exploration of coal sample

S.No	Element	Value
1	Fixed carbon	25.52%
2	Moisture	12%
3	Ash	30.18%
4	Volatile matter	23.08%
5	G.C.V	3745.3 kcal/kg

properties, excess air, and air distribution system in ANN models, and they studied the thermal efficiency and NOx emission in various operating conditions. Finally, they compared the optimization results with plant results for further improvement of the system. De et.al. [9] had built an ANN model for the steam process of coal biomass co-fired combined heat and power plant to swiftly estimate the performance with precision. De et al. [10] had built an ANN model from the data of existing plants, and ANN models have a fast response than physical model and more flexible to implement physical plant operation. Suresh et al. [11] had done the experiment on high ash coal-fired super critical power plants by using ANN-GA tool. In the novel ANN technique, cycle temperature is used to estimate the energy input from coal. The ANN model of feedforward propagation was trained with the plant data. Minghow et al. [12] had done numerical modeling of a front wall pulverized coal-fired boiler, and they also validated the results with experimental data of operating conditions. Cerri et al. [13] had followed a methodology that replaces traditional model calculated with neural models for methane/air combustion. Convective and turbulent diffusive transport of species was considered for finite volume computational fluid dynamics code. They had developed two versions of mechanisms. The first one is based on traditional differential equations; the second version is based on neural models which can extract and store knowledge. Chen et al. [14] had done a comparison of the CO_2 power cycle which is using low-grade heat and the Rankine organic cycle which is using working fluid as R123. They had concluded that with the use of low-grade heat with equal temperature rejection case, the CO_2 power cycle gives higher output than Rankine organic cycle ANN. Sacco et al. [15] had used GA to augment turbine extraction in a secondary side of a pressurized water reactor.

Jiang Feng wang et al. [16] had experimented on supercritical CO_2 power cycle and exergy destruction in each component from heat recovery vapor generator (HRVG). They concluded that under the specified waste heat conditions, the CO_2 power cycle is improved with energy efficiency as an independent function employing a genetic algorithm. It has been shown that turbine inlet pressure, temperature, and atmospheric temperature are the primary thermodynamic parameters that have a substantial effect on the functioning of the supercritical CO_2 power cycle. Suresh et al. and Sotiris A. Kalagirou [17] had explained AI system applications in combustion systems

Table 3 Design parameters for 660 MW plant

S. No	Design parameters
01	Excess air ratio %: 20
02	Condenser pressure, kPa: 10–13
03	Condenser cooling water inlet, °C: 32.8
04	Condenser cooling water outlet, °C: 42.8
05	Final feed water temperature, °C: 280.9
06	Terminal temperature difference (TTD), °C: 2.8
07	Drain cool approach (DCA), °C: 5.6
08	Bottom-to-fly ash ratio: 20:80
09	Ash composition: Silicon oxide— 60.11%, aluminum oxide—28.96%, iron oxide—4.75%
10	Ambient pressure at atmospheric condition, bar: 1.013
11	Ambient pressure at atmospheric condition, °C: 33
17	High-pressure turbine (HP) efficiency: 99%
18	Intermediate pressure turbine (IP) efficiency: 98%
19	Low-pressure turbine (LP) efficiency: 92%

Table 4 Major operating parameters for 660 MW plant

S. No	Major operating parameters
01	Main steam pressure, bar: 259, and temperature, °C: 571
02	IP Turbine pressure, bar: 47and temperature, °C: 571
03	Deaerator pressure, bar: 9–13
04	Excess air: up to 27%
05	LP heater-1-bled steam pressure, bar: 6
06	LP heater-2-bled steam pressure, bar: 4
07	LP heater-3-bled steam pressure, bar: 3
08	LP heater-4-bled steam pressure, bar: 3
09	HP Heater-1-bled steam pressure, bar: 78.9
10	HP heater-2-bled steam pressure, bar: 58.1
11	HP heater-3-bled steam pressure, bar: 23.4

and internal combustion engines. The combustion system includes boiler, furnace, and incinerators modeling, whereas IC engines include diesel, spark engines, and gas engine modeling and control. Nannariello et al. [18] had applied the neural network analysis technique in modeling, calculating, and approximating construction amenities engineering. This paper also explains how neural networks focused and solve problems in architectural and construction acoustics, civil and structural engineering, etc. Wagner F. Sacco et al. [19] had done work on GA for the determination of optimum mass flow rate of turbine extractions from the pressurized water reactor (PWR) for cycle efficiency improvement. Cayeret al. [20] had analyzed a low-grade steam carbon dioxide trans-critical cycle. They had studied the high-pressure effects on energy efficiency, exergy efficiency, values of total UA (product of overall heat transfer coefficient and heat transfer area) with maximum and minimum temperature. The ultimate aim of this study was to perform optimization of parameters to recover heat maximum. Reddy and Ranjan [21] used the ANN technique to predict solar resources in India. The operation modes of a solar-driven ejector-absorption cycle were modelled using Mohaghegi and Shayegan [22] only as a function of the operating temperatures, and GA was applied to identify the optimal thermodynamic output conditions for steam generators for heat recovery. In order to increase its economic advantages using ANN and GA, Kalogirou [23] optimized the solar energy grid to maximize its economic benefits using ANN and GA.

Kalogirou [24] has done detailed ANN evaluation on different fields of applications, and he has given a detailed review in the boiler furnace where fuel combustion takes place. Mathiadakis et al. [25] had performed an aerodynamic analysis on gas turbine components. The work is mainly highlighted by industrial gas turbine operation. The main objective was to identify the deposits on gas turbine blades that were influential in power generation and monitoring of the compressor fouling. Fantozzi and Desideri [26] had done the ANN capability by repeating the process from input to output from energy conservation plants until satisfactory output comes. Zang et al. [27–30] had experimented on a solar-based thermodynamic cycle on electricity generation and heat using CO_2as running fuel. Holland [31] had introduced a genetic algorithm that simulates the biological evaluation naturally. The genetic algorithm operated on a Darwinian survival principle on a solution to deliver the best predictions to the solutions. The genetic algorithm differed from other optimization techniques because through this method the solutions are not

Table 5 Different coal samples for 660 MW plant operation

S.No	Description	Design coal		Coal sample-1		Coal sample-2		Coal sample-3	
		As received (%)	Dry basis (%)	As received (%)	Dry basis (%)	As received (%)	Dry basis (%)	As received (%)	Dry basis (%)
Proximate analysis									
1	Fixed carbon	17.3	19.807	26.40	30.226	20.1	23.013	23.28	26.654
2	Ash	44.3	50.7235	26.65	30.512	39.70	45.453	32.0	36.637
3	Moisture	19.4	–	23.35	–	20.20	–	22.72	–
4	Volatile matter	19	21.753	23.60	27.02	20.0	22.898	22.0	25.188
Ultimate analysis									
1	Carbon	30.5	34.92	39.02	44.669	30.62	35.057	34.0	38.927
2	Hydrogen	2.79	3.194	2.83	3.2401	2.90	3.3203	2.80	3.0258
3	Oxygen	3.00	3.434	6.77	7.7511	5.28	6.0452	7.32	8.3808
4	Nitrogen	0.51	0.5839	0.77	0.8759	0.78	0.893	0.66	0.7556
5	Sulfur	0.5	0.5725	0.62	0.7058	0.52	0.594	0.50	0.5725
6	Ash	44.3	50.7235	26.65	30.512	39.7	45.453	32.0	36.637
7	Inherent moisture	19.4	–	23.35	–	20.20	–	22.72	–

from a single point but also from the sub-optimal solutions. Xinying Xu et al. [32] had studied combustion efficiency and various pollutant emissions from thermal power plants. They had done combustion optimization by artificial intelligence method and distribution combustion optimization method. The Mapreduces programming framework was used to parallelize the proposed algorithm model and increase its capability to facilitate big data.

In this paper, the ANN simulator model for the entire plant is developed. The entire power plant is classified into two categories, boiler and its auxiliaries, steam turbine, steam generator, and its auxiliaries. Firstly, two ANN models have been developed for both boiler and turbine areas operating under various constraints. The first boiler ANN model should be linked to a turbine model, for utilizing boiler feedwater in the boiler and steam used in steam turbine, later cross-validation and testing were done with a reliable dataset.

Simulation of Power Plant

Several supercritical 660 MW units and ultra-supercritical 800 MW units are in operation currently, and 1000 MW ultra-supercritical power plants are in the development stage. The required pressure, temperature, and mass flow rates of individual components were specified, and the design and operating parameters for the simulation of the plant are given in Tables 3 and 4. The rated main steam pressure is 259 bar, and the temperature is 571°C. The plant is considered to be a single reheat and double condensing, and condensation at the exit of the condenser is assumed as a saturated state. Further leakage losses from the boiler and pressure drop across the pipelines could be neglected. The drain cool approach of LP heaters could be neglected as they are giving fewer temperature changes. The auxiliary power consumption for the entire plant would be 7.2% of the gross generation of the plant (including all auxiliaries which are considered from unit auxiliary transformers). For the simulation of plants, different excess air ratios and different Indian coals are considered and different heaters' bleed pressures were considered along with and without heaters services. Table 5 shows the different coal samples.

$$\text{Plant energy efficiency} = \frac{\text{Net electricity output to the grid}}{\text{The mass flow rate of coal X HHV (dry basis of the coal)}} \quad (1)$$

$$\text{Plant exergy efficiency} = \frac{\text{Net electricity output to the grid}}{\text{The mass flow rate of coal X Specific exergy of the coal}} \quad (2)$$

Methodology

A power plant has various complex subsystems like a coal handling plant, ash handling plant, reverse osmosis plant, demineralized plant, etc. The plant simulation data obtained from design and various operating conditions are used to train the artificial neural network to find the energy

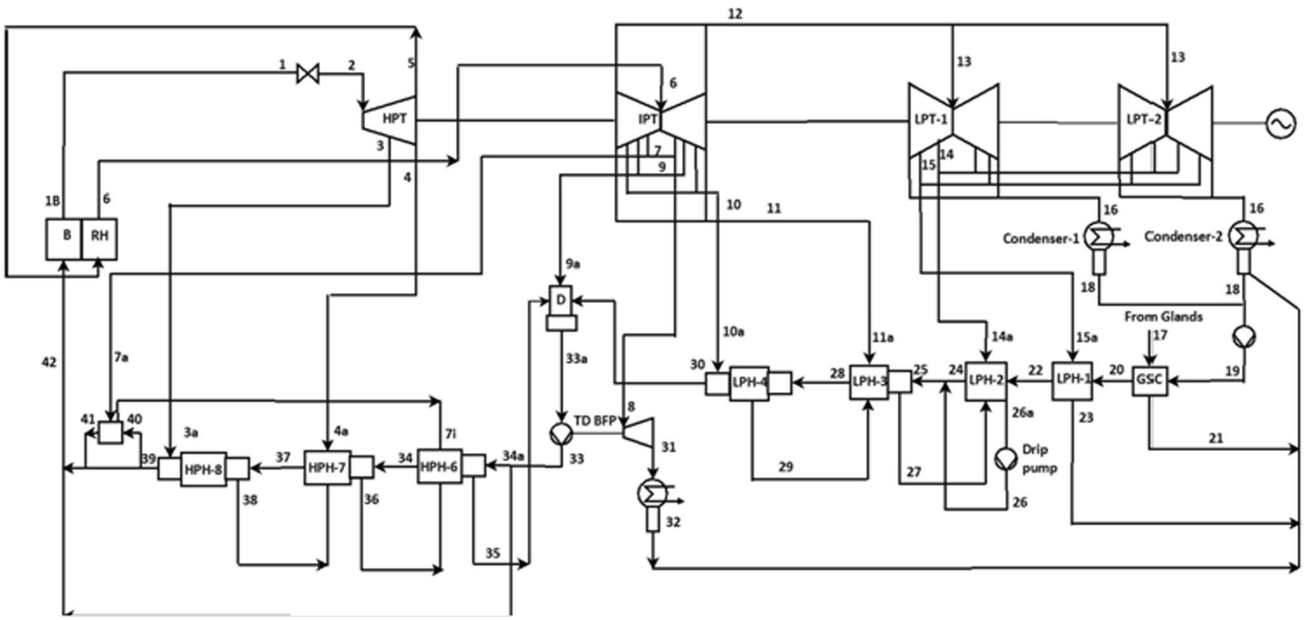

Fig. 2 A 660 MW supercritical power plant schematic representation

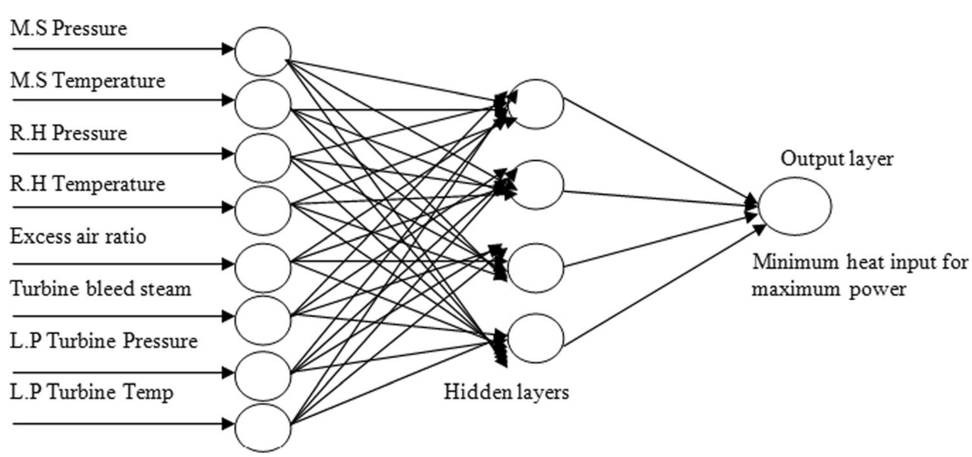

Fig. 3 660 MW Neuro-genetic optimization methodology

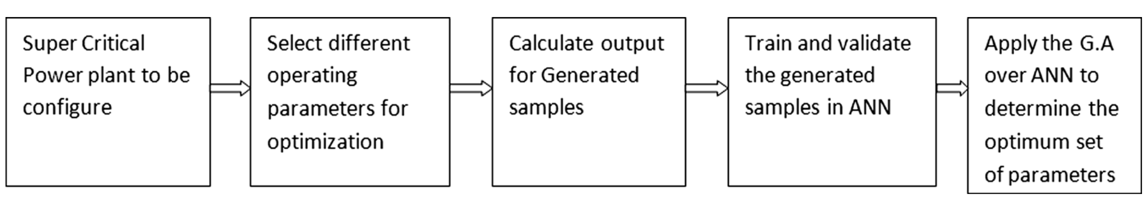

Fig. 4 Neuro-genetic optimization methodology in 660 MW power plant

input through coal. The finest set of several factors at different load conditions giving the least energy input to the power plant is predicted by using artificial neural network as a fitness function with the genetic algorithm. The optimum plant efficiency is obtained from the set of different parameters that could be optimized. The optimization of the total plant is divided into (i) boiler-side optimization and (ii) turbine-side optimization. Boiler-side optimization can deal with the different types of coals, excess air ratio, main steam pressure, main steam temperature, re-heater steam pressure, and re-heater steam temperatures. Turbine-side optimization can deal with heater-bled steam pressure and temperatures, LP turbine steam pressure, and temperatures.

Table 6 Generation versus excess air heater data with and without extractions

Power generation	Excess air ratios in different cases						Heater without extraction, Energy input (10^5)kwh in different cases						Heater without extraction, energy input (10^5)kwh in different cases					
	I	II	III	IV	V	D	I	II	III	IV	V	D	I	II	III	IV	V	D
660 MW	21	20	22	21	21	20	6.825	6.762	6.688	6.680	6.675	6.793	3.534	3.498	3.496	3.492	3.488	3.522
600 MW	22	23	24	21	22	21	6.708	6.652	6.645	6.652	6.642	6.669	3.514	3.482	3.481	3.478	3.472	3.508
545 MW	23	24	25	22	24	22	6.621	6.565	6.552	6.548	6.428	6.569	3.502	3.424	3.42	3.41	3.400	3.495
500 MW	24	25	25	26	24	24	6.527	6.478	6.465	6.455	6.452	6.498	3.482	3.414	3.41	3.41	3.400	3.472
475 MW	26	25	26	27	25	25	6.457	6.388	6.285	6.185	6.085	6.397	3.355	3.22	3.21	3.2	3.188	3.348
450 MW	27	28	28	26	27	26	6.387	6.312	6.288	6.188	6.088	6.322	3.344	3.2	3.122	3.12	3.110	3.240
425 MW	28	29	28	27	26	27	6.33	6.266	6.122	6.022	6.018	6.278	3.301	3.194	3.19	3.18	3.150	3.205
400 MW	29	29	29	28	30	28	6.25	6.172	6.165	6.065	6.052	6.196	3.285	3.152	3.144	3.14	3.120	3.181

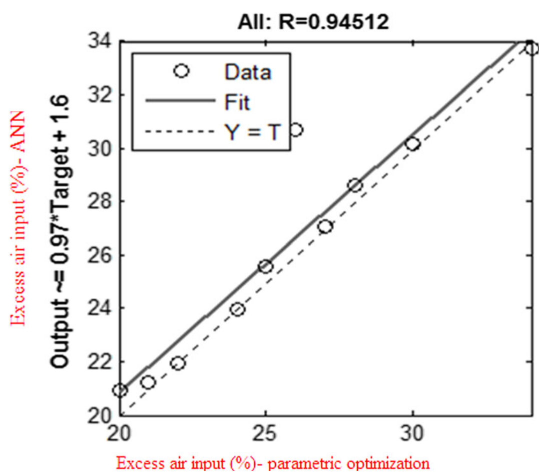

Fig. 5 Regression fit based on the ANN model for excess air using 660 MW boiler

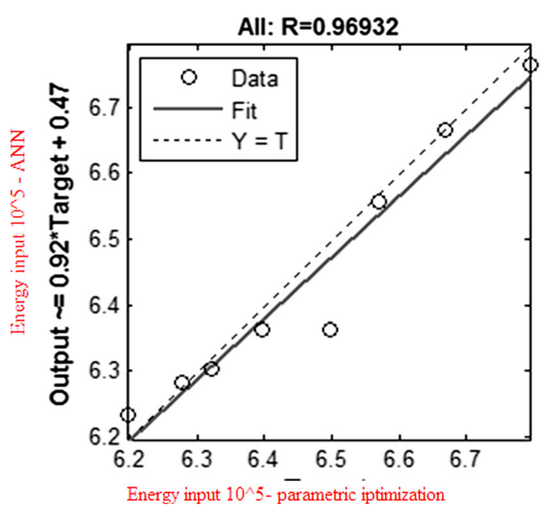

Fig. 6 Regression fit for without extraction of feedwater heater 660 MW plant based on the ANN model

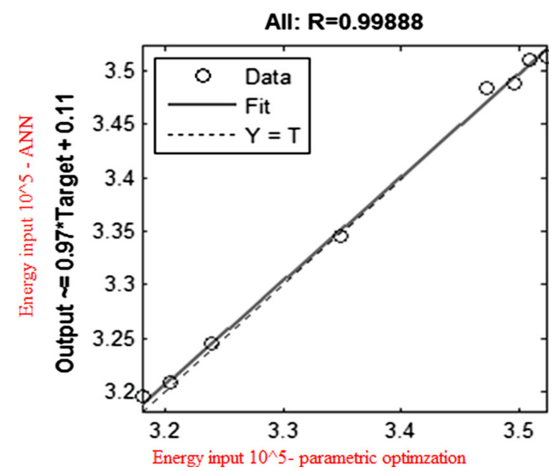

Fig. 7 Regression fit for extraction of feedwater heater 660 MW plant based on the ANN model

Artificial Neural Network (ANN)

ANN is a tool that deals with the inputs and outputs by training similar to the neural structure of the human brain. ANN consists of several interconnected neurons with a proper weight, which are in linear or nonlinear transfer functions, and these are capable of controlling the linear or nonlinear performance of a system. Multilayer feedforward networks are a type of network, which is using this study. The networks consist of an input layer, a hidden layer, and an output layer. Once the inputs are introduced into the networks, they will be multiplied by their weights and then they are added and moved to give an output. The data used as inputs are transferred layer by layer, and the output is achieved. ANN is a good modeling scheme used to test models faster and easier than any other system. The achieved outputs are compared with the preferred output values and are used to modify the weights of the network to lessen the extent of the fault. Hence, through this "supervised learning" iterative process, a satisfactory level of

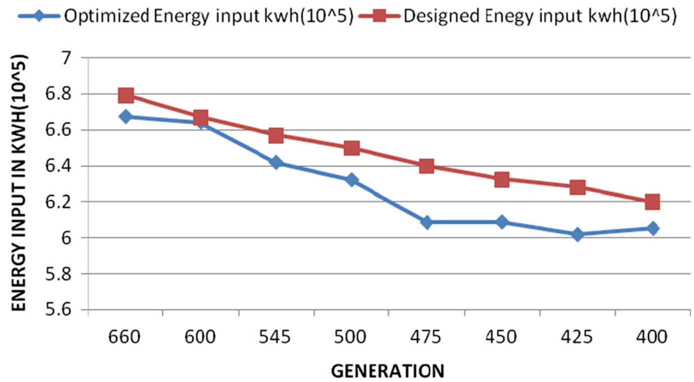

Fig. 8 Optimization convergence curve of 660 MW power plant except FWHs

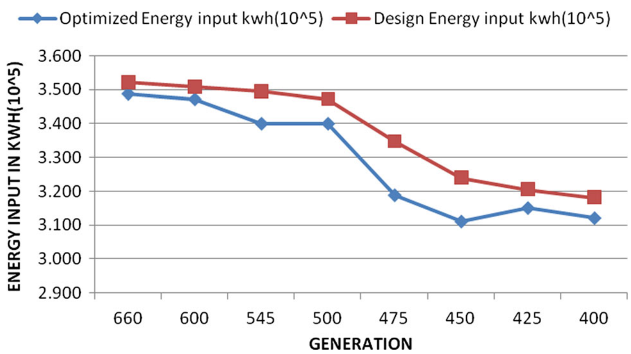

Fig. 9 Optimization convergence curve of 660 MW power plant with FWHs

faults is identified. In general, the excess air ratios vary from 10 to 30% depending on the combustion conditions inside the boiler. The combustion conditions depend on the various elements in the coal, the oxy-fuel ratio of the boiler, availability of load demands from the grid, and unexpected outages of the power plant. A nonlinear regression problem is considered in this paper as the excess air ratios and turbine extractions are varying continuously.

ANN Simulator Development for Thermal Power Plant

The main drive of this analysis is to build the ANN simulator model for the entire plant. The total power plant is divided into two categories: the first one is a boiler and its auxiliaries, and the second one is a steam turbine and its auxiliaries, including a steam generator. First, two ANN models have been developed by studying different cases from both boiler and turbine areas. The first boiler model could be linked to a turbine model utilizing feed water that goes to the boiler and steam from the boiler supplied to the steam turbine. To alter the dataset as consistent, data preprocessing is necessary for artificial neural network training. Then particular dataset is used for training ANN's with cross-validation and testing. A satisfactory result has been obtained by trial and error.

Selection of Data for ANN Training from Real Plant

The ANN deals with the interrelationship between a set of input and output parameters. It can be achieved from training; thus, the appropriate selection of data for training from the existing plant is most central for the prediction of the accuracy of the final ANN-developed model. Required data daily for 20–30 min for 30 days have been obtained from the thermal plant which has been acknowledged. To develop a precise ANN model, the following stages are carried out from the plant data.

(a) Data filtering, (b) data selection with a suitable representation of each category, (c) selection of transfer functions and rang, (d) testing of selected data, (e) selection of input and output parameters. The 660 MW supercritical thermal power plant line diagram is useful in the analysis and optimization (Fig. 2).

Neuro-Genetic Optimization

A wide range of operating parameters are needed to use neuro-genetic optimization for finding the best output. In this work, the wide ranges of operating parameters are considered from the existing operation of the plant. Forgetting the best output of the plant, the entire plant is divided into boiler and turbine stages. In the first stage, optimized values of operating parameters were found from MS pressure/temperature, RH steam pressure/temperature, and excess air ratio by considering a different range of operating parameters, whereas in the second stage optimized values from turbine-side parameters like LP turbine pressure/temperature and turbine-bled steam pressure/temperature were found by considering a different range of operating parameters.

The 660 MW artificial neural network diagram consists of 8 input variables with 4 hidden neurons and one output variable (Fig. 3). The neural network is obtained from the Levenberg–Marquardt backpropagation algorithm with 4 hidden neurons for the plant that can solve excess air, with considering and without considering feedwater heaters.

Table 7 Various losses in boiler according to various coal samples

S. No	Description	Unit	660 MW Sample1	660 MW Sample2	660 MW Sample3	660 MW Sample4
	Proximate analysis					
	Fixed carbon	%	17.3	26.4	20.1	23.28
	Ash	%	44.3	26.65	39.7	32.0
	Volatile matter	%	19.0	23.6	20.0	22.0
	Moisture—inherent	%	19.4	23.35	20.2	22.72
	Gross calorific value—A.R.B	Kcal/Kg	3630.52	3856.68	3700.82	3820.0
	Ultimate analysis					
	Carbon—ultimate	%	30.50	39.02	30.62	34.00
	Sulfur—ultimate	%	0.5	0.62	0.52	0.50
	Hydrogen—ultimate	%	2.79	2.83	2.90	2.80
	Nitrogen—ultimate	%	0.51	0.77	0.78	0.66
	Oxygen—ultimate	%	3.00	6.77	5.28	7.32
	Boiler efficiency by heat loss method					
I	Unburnt carbon losses	%	3.040	1.722	2.791	1.706
II	Fly ash caused sensible heat loss	%	0.251	0.134	0.207	0.155
III	Bed ash caused sensible heat loss	%	0.492	0.279	0.436	0.335
IV	Moisture in combustion air caused loss	%	0.061	0.066	0.056	0.056
V	Moisture in fuel caused loss	%	3.385	3.819	3.441	3.738
VI	Hydrogen in fuel caused loss	%	4.382	4.166	4.446	4.146
VII	Dry flue gas caused loss	%	4.200	4.216	3.793	3.450
VII	Radiation loss	%	0.250	0.250	0.250	0.250
	Total loss		83.939	85.347	84.580	86.164

Table 8 Energy balance comparison

Components	Reference case	Case-1	Case-2	Case-3
Plant efficiency	38.9	39.2	39.5	40.3
Plant heat rate, kcal/kwh	2147	2165	2195	2210
Heat rejected through stack	10.8	10.2	9.88	9.92
Heat rejected through bottom ash (L.O.I)	1.4	1.1	0.8	0.7
Radiation and unaccounted loss	3.8	3.3	3.1	2.7

The population size of the genetic algorithm is 20, and approaches considered 1000 for getting accurate results. Figure 4 shows the application of the 660 MW parameters in a neural network tool from MATLAB software. Table 6 shows the data at different cases (case-I to case-v and design case-D) of excess air ratios, heater with extractions, and heater without extractions.

The data fit obtained between physical operating and ANN model for excess air is shown in Fig. 5. In this case, different excess air ratios were considered at different loads; iteration has been done with all cases by comparing the design case. Finally, the regression fit of case no.5 has given 94.5% accuracy than other cases. ANN model is the better way to find out the operating parameters.

The data fit obtained between physical operating and ANN model for feedwater without extractions is shown in Fig. 6. In this case, different feed water extractions were considered at different loads and iteration has been done with all cases by comparing design cases. Finally, the regression fit of case V has given 96.9% more accuracy than the other cases.

The data fit obtained between physical operating and ANN model for feed water with extractions is shown in Fig. 7. In this case, different feed water extractions were considered at different loads and iteration has been done

Table 9 Optimized 660 MW plant process data

S. No	Component	Energetic power input (MW)	Energetic power output (MW)	Exergy power input (MW)	Exergy power output (MW)
1	Boiler	1791.28	1562.35	2088.8	898.3
2	Combustion	1791.28	1787.72	2089.3	1256.8
3	Heat transfer	1791.28	1562.35	1256.8	906.6
4	HPT	209.88	206.28	225.3	206.3
5	IPT	326.16	318.034	312.5	294.5
6	LPT – 1/2	2 × 68.98	2 × 66.98	2X97.9	2X84.2
7	Turbine	674	659	733.6	669.2
8	CEP	1.731	1.13	1.8	1.2
9	LPH-1	26.41	25.145	3.3	2.1
10	LPH -2	33.82	32.68	6.2	5.2
11	LPH -3	80.25	79.85	30.3	28.0
12	LPH -4	52.21	50.85	22.2	18.3
13	Drip pump	0.125	0.122	0.112	0.09
14	Deaerator	462.3	457.8	75.9	68.1
15	BFP	20.87	20.25	20.9	18.9
16	HPH-6	52.56	51.85	41.2	36.8
17	HPH -7	88.68	86.82	88.3	71.3
18	HPH -8	89.31	88.48	38.5	34.4
19	Condenser-1/2	391.097	279.634	20.8	15.6
20	Net Plant	1791.28	659	2090.3	660

Table 10 Results comparison between parametric optimization and neuro-genetic optimization

S.N0	Parameter	Parametric optimization	Neuro-genetic optimization
1	Boiler outlet steam pressure (bar)	257.6	257.6
2	Boiler outlet steam temperature (°C)	571	569
3	Condenser pressure (M Pa)	0.0103	0.0103
4	Excess air (%)	23	20
5	LPH-1 extraction pressure (bar)	0.42	0.39
6	LPH-2 extraction pressure (bar)	1.02	0.96
7	LPH-3 extraction pressure (bar)	3.02	2.15
8	LPH-4 extraction pressure (bar)	6.58	6.28
9	Deaerator extraction pressure (bar)	13.74	12.82
10	HPH-1 extraction pressure (bar)	28.78	26.31
11	HPH-2 extraction pressure (bar)	60.12	59.15
12	HPH-3 extraction pressure (bar)	91.20	86.34
13	Plant exergy efficiency(%)	32.0	31.60
14	Plant energy efficiency(%)	36.78	36.59

with all cases by comparing design cases. Finally, the regression fit of case V has given 99.8% more accuracy than the other cases.

Initially, the optimized parameters are identified for an operational power plant by considering design parameters that were supplied by the OEM supplier. Then, the final optimized parameters are obtained through an artificial neural network. The optimized parameters obtained for a specific system are repeated subsequently for all the systems throughout the plant (viz. excess air, turbine bleed parameters with or without FWHs) depicted in the convergence curves and curve fittings (Figs. 8 and 9). The physical model of a power plant model is built using the design parameters obtained by the ANN tool. While comparing both operation parameters optimization and neuro-genetic optimization, there is a small difference that can be observed from the calculated values for energy and exergy efficiencies. The neuro-genetic optimization methodology is to reduce computation effort as parametric optimization requires several calculations to find out the best method and gives a quick response.

Effects of different types of Coal Samples on Boiler Efficiency

Boiler efficiency depends on the losses that are caused by the type of coal samples under a constant load operation. The various losses in the boiler are (i) unburnt carbon loss, (ii) sensible heat loss due to fly ash, (iii) sensible heat loss due to bottom ash, (iv) moisture loss in the air, (v) moisture loss in fuel, (vi) hydrogen loss in fuel, (vii) dry flue gas loss, (viii) radiation loss, from Table 7. Case-I gives less boiler efficiency than case-IV due to dry flue gas losses more. The dry flue gas mainly depends on excess air ratio and exit flue gas temperature at the induced draft fan. The optimized excess air ratio of 21% was obtained from the regression fit-based ANN. A detailed boiler performance for the different coal samples and the losses of energy-exergy were estimated at that optimized specific excess air ratio [33]. Finally, the total plant performance was calculated.

$$\begin{aligned}&\%\ \text{Excess air supplied (EA)}\\&\quad=\frac{\text{O2 \% at Economiser}}{(21-\text{O2 \% at Economiser})}\end{aligned}\tag{3}$$

$$\begin{aligned}&\text{The actual mass of air supplied/kg of fuel to the Boiler}\\&\quad=\frac{1+\text{Excess air supplied}}{100}*Theoreticalairsupplied\end{aligned}\tag{4}$$

In order to obtain the performance of the plant and perform its analysis, different coal samples were considered. Energy loss is considered as the ratio of energy rejected by the system to the coal energy going to supply in terms of input. Table 8 shows the energy balance for four cases, whereas exergy loss is considered as the ratio of exergy destruction to the coal exergy input supplied to the system. Table 9 shows the detailed energetic and exergetic evaluations. It is observed that there is an improvement of plant energy efficiency by 1.42% and exergy efficiency by 2.9% with 26.65% ash coal instead of 44.3% ash coal. The reduction of ash percentage from 44.3 to 26.65%, leading to a saving of auxiliary power consumption by 0.5%. The lessening of ash percentage in coal decreases the combustibles in bottom ash and increases in combustibles in coal. This would reduce the power consumption by mills and significantly reduce the exergy destruction in the combustion space and also increase the overall plant efficiency. There is one drawback to reducing the ash content of the fuel, and the flue gas temperature increases with the same excess air and fuel input. This may affect the tube material and may even damage the tube itself. To avoid this condition, the airflow and fuel flow adjustments have to be monitored continuously concerning the flue gas temperature.

Results

In this study, after performing a detailed ANN analysis of various process parameters, results with good accuracy are found finally than with a parametric optimization. The detailed parametric and neuro-genetic optimizations are displayed in Table 10. Boiler outlet steam pressure is constant as there is coal firing in both cases in the furnace. The other remaining parameters are changed according to combustion conditions inside the boiler. Boiler performance could rise by reducing the ash content in the coal sample and at the specified controlled flue gas outlet temperature (129–138 °C) and based on sulfur dew point corrosion. Plant efficiency increased by reduction of losses like stack heat losses, bottom ash losses, and radiation losses. Major exergy loss occurred in the boiler than any other components due to irreversibility in combustion space. Results indicated that with the 2088.8 MW exergy input supply to the boiler through coal combustion in the furnace, the exergy output from the boiler is 898.3 MW. Hence, there is nearly 1190.5 MW of wastage from the boiler. Similarly, a major energy loss occurred in the condenser than any other component. A 391.097 MW energy input is supplied to the condenser through turbine exhaust steam from the last blade, and the energy output from the condenser is 279.634 MW. Hence, nearly 111.46 MW of energy wastage occurred through the circulating water in the condenser. From the study, 0.4% exergy efficiency and 0.19% energy efficiency improvement were achieved from the neuro-genetic optimization approach.

Conclusion

A 660 MW power plant optimization scheme based on artificial intelligence is a proven effective methodology than a parametric optimization technique, whereas the neuro-genetic optimization method lessens the computational work than optimization of parameters, without reducing the accuracy of results by using the online artificial intelligence technique. This analysis is performed on different coal samples of different compositions. The power plant performance shows a reduction of ash from 44.3 to 26.65% and an increase in plant efficiency from 83.93% to 85.34%. The enhanced performance of the powerplant gives coal saving around 30% and improves overall plant heat rate from 2210 to 2165 kcal/kWh. Also, there is a decrease in auxiliary power consumption, 0.5%, and an increase in the overall plant efficiency to 1.3%. The energy loss of the plant reduces to 1.41% which minimizes the exergy destruction in the combustor to the maximum extent. Hence, around 0.4% exergy efficiency and 0.19% energy efficiency improvement were achieved from the neuro-genetic optimization approach.

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Declarations

Conflict of interest The authors hereby affirm that they have no known competing financial interests or personal relationships that could have seemed to affect the work described in this paper.

References

1. C. Wang, M. Liu, B. Li, Thermodynamic analysis on the transient cycling of coal-fired powers: simulation study of a 660 MW supercritical unit. Energy **122**, 505–527 (2017)
2. C. Yilmaz, I. Koyuncu, Thermoeconomic modeling and artificial neural network optimization of Afyon geothermal power plant. Renew. Energy **163**, 1166–1181 (2021)
3. G. Yang, Y. Wang, X. Li, Prediction of the NOx emissions from thermal power plant using long-short term memory neural network. J. Energy. **192**, 116597 (2019)
4. C. Liu, Z. Li, W. Kong, Y. Zhao, Z. Chen, Bituminous coal combustion in a full-scale start-up ignition burner: Influence of the excess air ratio. Energy **35**, 4102–4106 (2010)
5. S. Safarian, S.M.E. Saryazdi, R. Unnthorsson, C. Richter, Artificial neural network integrated with thermodynamic equilibrium modeling of downdraft biomass gasification-power production plant. Energy **213**, 118800 (2020)
6. L.W. Vieira, A.D. Marques, P.S. Schneider, A.J. da SilvaNeto, F.A.C. Viana, M. Abde-jawad, J.D. Hunt, J.C.M. Siluk, Methodology for ranking controllable parameters to enhance operation of a steam generator with a combined artificial neural network and design of experiments approach. Energy and AI **3**, 100040 (2021)
7. A. Naserbegi, M. Aghaie, Multi-objective optimization of hybrid nuclear power plant coupled with multiple effect distillation using gravitational search algorithm based on artificial neural network. Therm Sci Eng Prog **19**, 100645 (2020)
8. Y. Shi, W. Zhong, X. Chen, A.B. Yu, J. Li, Combustion optimization of ultra supercritical boiler based on artificial intelligence. Energy **170**, 804–817 (2019)
9. S. De, M. Kaidi, M. Fast, M. Assadi, Development of an artificial neural network model for the steam process of a coal biomass co-fired combined heat and power (CHP) plant in Swedan. Energy **32**, 2099–2109 (2007)
10. S. De, M. Kaidai, M. Fast, M. Assadi, Development of an artificial neural network model for the steam process of a coal biomass co-fired combined heat and power (CHP) plant in Sweden. Energy **32**, 2099–2109 (2007)
11. M.V.J.J. Suresh, K.S. Reddy, A.K. Kolar, ANN-GA based optimization of a high ash coal fired supercritical power plant. Appl. Energy **88**, 4867–4873 (2011)
12. X.U. Minghou, J.L.T. Azevedo, M.G. Carvalho, Modelling of a front wall fired utility boiler for different operating conditions. Comput. Methods Appl. Mech. Eng **190**, 3581–3590 (2001)
13. G. Cerri, V. Michelassi, S. Monacchia, Kinetic combustion neural modeling integrate into computational fluid dynamics. J. Power Energy **217**, 185–192 (2003)
14. X. Chen, P. Lundqvist, A. Johansson, P. Platell, A Comparative study of the carbondioxide transcritical power cycle compared with an original Rankine cycle with R123 as working fluid in waste heat recovery. Appl. Therm. Eng. **26**, 2142–2147 (2006)
15. W.F. Sacco, C.M.N.A. Pereira, P.P.M. Soares, R. Schirru, Genetic algorithms applied to turbine extraction optimization of a pressurized water reactor. Appl. Energy **73**, 217–222 (2002)
16. J. Wang, Z. Sun, Y. Dai, S. Ma, Parametric optimization design for supercritical CO2 power cycle using genetic algorithm and artificial neural network. Appl Energy **87**, 1317–1324 (2010)
17. S.A. Kalogirou, Artificial intelligence for the modeling and control of combustion process: a review. Prog. Energy Combust. Sci. **29**(6), 515–566 (2003)
18. J. Nannariello, F.R. Frike, Introduction to neural network analysis and its applications to building services engineering. Build. Serv. Eng. Res. Technol. **22**(1), 58–68 (2001)
19. W.F. Sacoo, C.M.N.A. Pereira, P.P.M. Soares, R. Schirru, Genetic algorithms applied to turbine extraction optimization of a pressurized-water reactor. Appl. Energy **73**, 217–222 (2002)
20. E. Cayer, N. Galanis, M. Desilets, H. Nesreddine, P. Roy, Analysis of a carbondioxide transcritical power cycle using a low temperature source. Appl Energy **86**, 1055–1063 (2009)
21. K.S. Reddy, M. Ranjan, Solar resource estimation using artificial neural networks and comparison with other correlation models. Energy Conv. Manage **44**, 2519–2530 (2003)
22. M. Mahagheghi, J. Shayegan, Thermodynamic optimization of design variables and heat exchangers layout in HRSG's for CCGT, using Genetic algorithm. Appl. Thermal Eng **29**, 290–299 (2009)
23. S.A. Kalogirou, Optimization of solar systems using artificial neural network and genetic algorithms. Appl. Energy **77**, 383–405 (2004)
24. S.A. Kalogirou, Application of artificial neural networks for energy systems. Appl. Energy **67**, 17–35 (2000)
25. K. Mathiadakis, A. Stamatis, A. Tsalavoutas, N. Arekisn, Performance analysis of industrial gas turbines for engine condition monitoring. Proc. Inst. Mech. Eng. AJ Power Energy **215**, 173–184 (2001)
26. F. Fantozzi, U. Desideri, Simulation of power plant transient with artificial neural networks: application to an existing combined cycle. Inst. Mech. Eng. AC **212**(5), 299–313 (1998)
27. X.R. Zang, H. Yamagucliti, D. Uneno, K. Fujima, M. Enomoto, N. Sawadan, Analysis of a naval solar energy-powered Rankine cycle for combined power and heat generation using supercritical carbon dioxide. Renew. energy **31**, 1839–1854 (2006)

28. X.R. Zang, H. Yamaguchi, D. Uneno, Thermodynamic analysis of the CO2 based Rankine cycle powered by solar energy. Int. J. Energy Res. **31**, 1414–1424 (2007)
29. Y. Chen, P. Lundqvist, A. Johansson, P. Platell, A comparative study of the carbondioxide transcritical power cycle compared with an original Rankine cycle with R123 as working fluid in waste heat recovery. Appl. Therm. Eng. **26**, 2142–2147 (2006)
30. E. Cayer, N. Galanis, N. Desilets, H. Nesreddine, P. Roy, Analysis of a carbondioxide transcritical power cycle using a low temperature source. Appl. Enegy **86**, 1055–1063 (2009)
31. J.H. Holland, *Adaption in Nature and Artificial Systems, an Introductory Analysis with Applications to Biology, Control and Artificial Intelligence* (MIT press, Massachusetts, 1992)
32. X. Xu, Q. Chem, M. Ren, L. Cheng, J. Xie, Combustion optimization for coal fired power plant boiler based on improved distributed ELM and distributed PSO. Energies-17th march 2019
33. Energy Auditor Books from Beauru of Energy Efficiency, ministry of power, Government of India