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ANN-GA based optimization of a high ash coal-fired supercritical power plant

M.V.J.J. Suresh, K.S. Reddy *, Ajit Kumar Kolar

Heat Transfer and Thermal Power Laboratory, Department of Mechanical Engineering, Indian Institute of Technology Madras, Chennai 600 036, India

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ABSTRACT

The efficiency of coal-fired power plant depends on various operating parameters such as main steam/reheat steam pressures and temperatures, turbine extraction pressures, and excess air ratio for a given fuel. However, simultaneous optimization of all these operating parameters to achieve the maximum plant efficiency is a challenging task. This study deals with the coupled ANN and GA based (neuro-genetic) optimization of a high ash coal-fired supercritical power plant in Indian climatic condition to determine the maximum possible plant efficiency. The power plant simulation data obtained from a flow-sheet program, "Cycle-Tempo" is used to train the artificial neural network (ANN) to predict the energy input through fuel (coal). The optimum set of various operating parameters that result in the minimum energy input to the power plant is then determined by coupling the trained ANN model as a fitness function with the genetic algorithm (GA). A unit size of 800 MWe currently under development in India is considered to carry out the thermodynamic analysis based on energy and exergy. Apart from optimizing the design parameters, the developed model can also be used for on-line optimization when quick response is required. Furthermore, the effect of various coals on the thermodynamic performance of the optimized power plant is also determined.

1. Introduction

Electricity drives the economic growth of a developing country like India, which is witnessing a robust economic growth rate of 8% and above. India has huge coal reserves – about 7.1% of the world's total [1] and thus, coal-fired power plants contribute to about 70% of the total power generation [2]. Currently all the coal-fired power plants in India operate on subcritical (SubC) steam parameters with the exception of two recent plants that use supercritical (SupC) steam parameters. Most of the coal-fired power plants that use indigenous high ash (HA) (~45%) coal have plant efficiencies (net) less than 35% (based on HHV of coal). Rapid depletion of fossil fuel resources and consequent increase in CO_2 emissions necessitate installation and operation of more efficient power plants. The first coal-fired SupC power plant recently commissioned by National Thermal Power Corporation (NTPC) in India has a gross power output of 660 MWe with steam parameters of 242.2 bar/537 °C/565 °C [3]. However, the steam parameters adopted for the new SupC units in India are on the lower range of SupC conditions compared to the state-of-the-art power plants elsewhere. Hence, there is an ample scope to optimize the operating parameters of the SupC power plants further to improve the plant efficiencies significantly.

The efficiency of a power plant depends on various operating parameters such as main steam/reheat steam pressures and temperatures, turbine extraction pressures, and excess air ratio for a given fuel. But simultaneous optimization of these operating parameters to achieve the maximum plant efficiency is a challenging task. The use of Artificial Intelligence (AI)-based tools like artificial neural networks (ANN) and genetic algorithms (GA) have been found very promising to solve a variety of such complex/ill-defined problems [4–8]. ANN is widely applied in design, optimization, classification, forecasting, and control systems. De et al. [9] developed an ANN model for the steam process of a coal biomass co-fired combined heat and power plant to quickly predict the performance with good accuracy. Reddy and Ranjan [10] used ANN to estimate solar resource in India. The performance parameters of a solar-driven ejector-absorption cycle were modeled as functions of only the working temperature using ANN by Sözen and Akçayol [11]. GA is a stochastic global search method that simulates the natural biological evolution. It searches from a population of solutions rather than from a single point and thus prevents the convergence to suboptimal solutions. Sacco et al. [4] applied GA to optimize turbine extraction in a secondary side of pressurized-water reactor. Mohagheghi and Shayegan [12] applied GA to calculate the optimal thermodynamic performance conditions for heat recovery steam generators. The optimization of thermodynamic parameters of the supercritical CO_2 power cycle was reported by Wang et al. [8] using ANN and GA. Kalogirou [13] optimized a solar-energy system to maximize its economic benefits using ANN and GA.

This study presents a coupled neuro-genetic optimization methodology involving ANN and GA to determine the maximum

* Corresponding author. Tel.: +91 44 2257 4702; fax: +91 44 2257 4652.
E-mail address: ksreddy@iitm.ac.in (K.S. Reddy).

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possible plant efficiency of a high ash coal-fired SupC power plant in Indian climatic condition where the design ambient temperature is considered as 33 °C. A unit size of 800 MWe currently under development in India is considered for the neuro-genetic optimization. Furthermore, the effect of various coals on the thermodynamic performance of the optimized plant is also determined based on energy and exergy analysis. It is to be noted that the majority of the causes of irreversibilities like heat transfer through a finite temperature difference, chemical reactions, friction, and mixing are accounted by only exergy analysis [14].

2. Methodology

Power plant is a complex system that involves various interconnected circuits each of which consists of different components. Hence, a flow-sheeting computer program, 'Cycle-Tempo' is used to perform a component-wise modeling followed by a system simulation. 'Cycle-Tempo' is a well-structured package for the steady state thermodynamic modeling and analysis of systems for the production of electricity, heat and refrigeration [15]. The power plant simulation data obtained from 'Cycle-Tempo' is used to train the ANN to predict the energy input through fuel (coal). The optimum set of various operating parameters that result in the minimum energy input to the power plant is then determined by using the trained ANN model as a fitness function with the GA. The maximum plant efficiency is then finally obtained from the power plant simulation in 'Cycle-Tempo' using the set of optimum parameters. The neuro-genetic optimization of the entire plant is carried out in two stages. In the first stage, optimal excess air ratio, intermediate pressure turbine (IP) steam parameters (reheat pressure and temperature), and low pressure (LP) turbine inlet steam pressure are calculated assuming high pressure (HP) turbine steam parameters (main steam temperature and pressure). Once the HP, IP, and LP turbine steam parameters are determined, then the turbine extraction steam pressures are calculated for the individual feedwater heaters as a part of the second stage.

Table 1
Major assumptions for the SupC power plant simulation.

Ambient pressure of the reference environment (bar)	1.013
Ambient temperature of the reference environment (°C)	33
Relative humidity of the ambient air (%)	60
Chemical composition of the reference-environment model: (mole fraction)	
N_2	0.7562
O_2	0.2030
H_2O	0.0312
CO_2	0.0003
Others	0.0093
Ash composition: (by weight)	
SiO_2	70
Al_2O_3	30
Bottom to fly ash ratio	20:80
Excess air (%)	20
Condenser pressure (kPa)	10.3
Temperature gain of the condenser cooling water (°C)	10
Final feedwater temperature (°C)	305
Terminal temperature difference (TTD): (°C)	
Low pressure (LP) closed feedwater heaters (FWHs)	3
High pressure (HP) closed FWHs	0
Drain cooler approach (DCA) temperature of closed FWHs (°C)	5
Isentropic efficiencies: (%)	
High pressure (HP) turbine	90
Intermediate pressure (IP) turbine	92
Low pressure (LP) turbine	90
Turbine driven boiler feed pump (BFP)	80
Fans	80
Pumps	85
Generator efficiency (%)	98.7

Table 3
Assumed ranges of the operating parameters to be optimized.

Parameter	Range
Excess air	Up to 25%
IP turbine (RH) steam pressure	15–25% of the HP turbine (main) steam pressure
IP turbine (RH) steam temperature	580–620 °C
LP turbine steam pressure	3–5 bar
De-aerator pressure	9–12 bar
LP FWH1	0.103–0.42 bar
LP FWH2	0.42–1.19 bar
LP FWH4	3–6.1 bar
HP FWH1	11–30.35 bar

3. Power plant simulation

The configuration of the first 660 MWe SupC power plant commissioned by NTPC in India is considered for optimizing the various operating parameters [3]. Also, the simulations were carried out for higher capacity of 800 MWe for the same plant configuration which is currently under development in India. The process flow diagram of the power plant is prepared in 'Cycle-Tempo' and the required operating parameters (such as pressures, temperatures, and efficiencies) for individual components are specified.

Table 2
Characteristics of Indian coals.

	Reference high ash (HA)		Sample-1		Sample-2		Sample-3		Sample-4	
	As-received (wt.%)	Dry (wt.%)	As-received (wt.%)	Dry (wt.%)	As-received (wt.%)	Dry (wt.%)	As-received (wt.%)	Dry (wt.%)	As-received (wt.%)	Dry (wt.%)
Proximate analysis										
Fixed carbon	24.00	27.27	30.00	31.71	32.80	35.73	42.80	47.40	48.30	49.19
Volatile matter	21.00	23.86	23.90	25.27	27.30	29.74	26.40	29.24	34.10	34.73
Ash	43.00	48.87	40.70	43.02	31.70	34.53	21.10	23.36	15.80	16.08
Moisture	12.00	–	5.40	–	8.20	–	9.70	–	1.80	–
Ultimate analysis										
Carbon	34.46	39.16	40.40	42.71	46.30	50.44	54.60	60.47	66.50	67.72
Hydrogen	2.43	2.76	2.60	2.75	2.70	2.94	3.00	3.32	4.10	4.18
Oxygen (by difference)	6.97	7.92	9.50	10.04	9.70	10.56	10.00	11.07	9.70	9.88
Nitrogen	0.69	0.78	1.00	1.06	1.00	1.09	1.20	1.33	1.70	1.73
Sulfur	0.45	0.51	0.40	0.42	0.40	0.44	0.40	0.44	0.40	0.41
Ash	43.00	48.87	40.70	43.02	31.70	34.53	21.10	23.37	15.80	16.08
Moisture	12.00	–	5.40	–	8.20	–	9.70	–	1.80	–
HHV (MJ/kg)	13.96	15.83	15.79	16.64	17.90	19.44	21.10	23.30	26.78	27.20
Exergy (MJ/kg)	15.26	17.30	17.14	18.08	19.11	20.77	22.14	24.45	27.64	28.08

The major assumptions used for the simulation of power plant are listed in Table 1. The HP turbine (main) steam pressure and temperature are considered as 290 bar and 600 °C, respectively that correspond to the state-of-the-art power plants. Furthermore, pressure drop in the pipes is neglected whereas the same in steam generator is assumed equal to that in the reference single reheat SupC power plant [16]. The constraint of DCA temperature does not apply to the low pressure feedwater heater (LP FWH) immediately located after the condenser as the condensate is assumed to be in saturated state at the condenser exit. An auxiliary power consumption of 7.5% is assumed for the optimized SupC power plant and the power consumption by miscellaneous balance of plant (such as plant control systems, lighting, and heating, ventilating, and air conditioning (HVAC)), steam turbine auxiliaries and transformer losses is considered as 5 MWe (included in the auxiliary power consumption) [17]. The characteristics of the reference HA Indian coal along with other coals from various coal mines in India that are used for the simulation are presented in Table 2 [3,18].

The performance of the studied coal-fired power plant is evaluated in terms of plant energy and exergy efficiencies as follows:

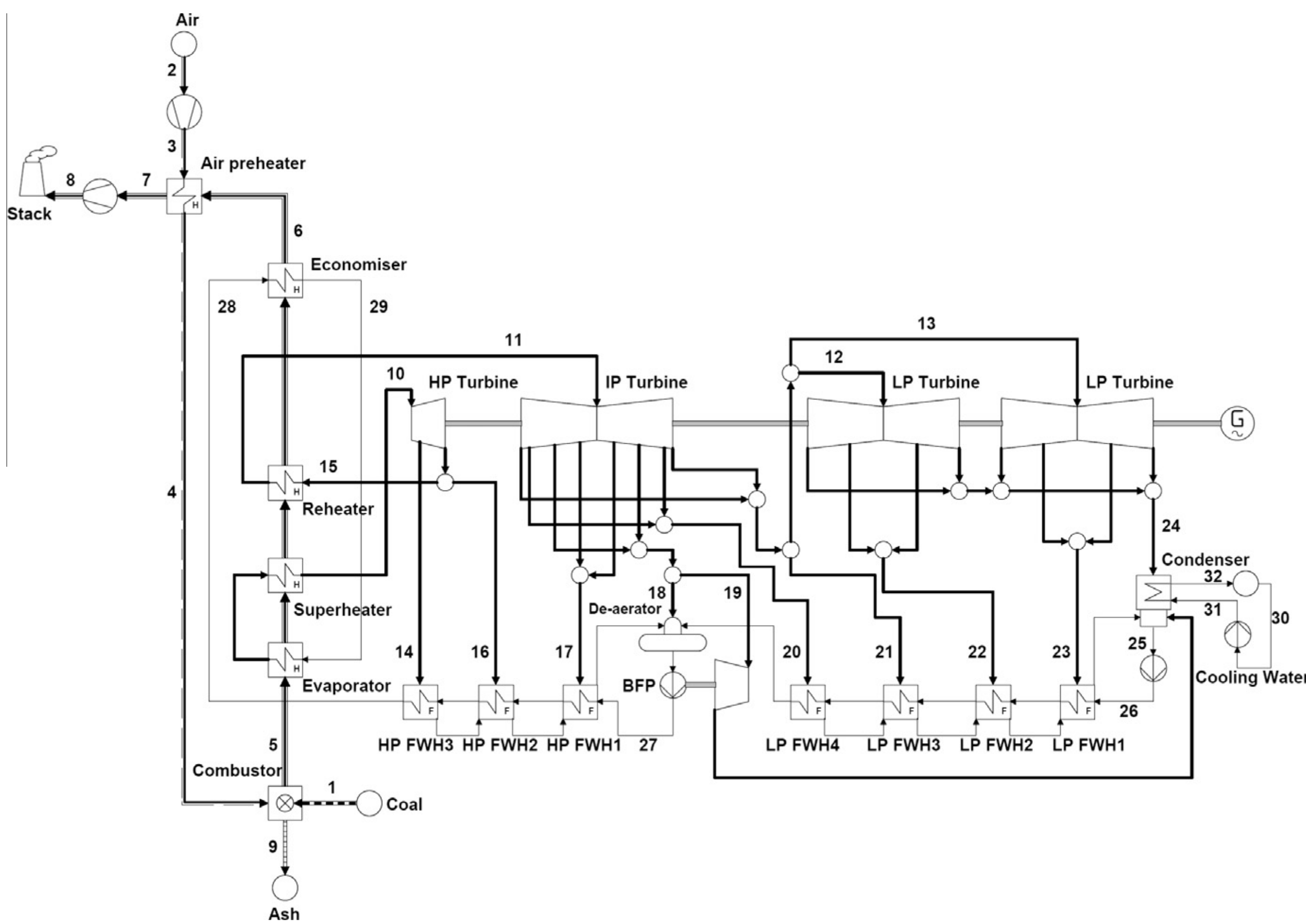

Fig. 1. Schematic representation of the 800 MWe supercritical power plant.

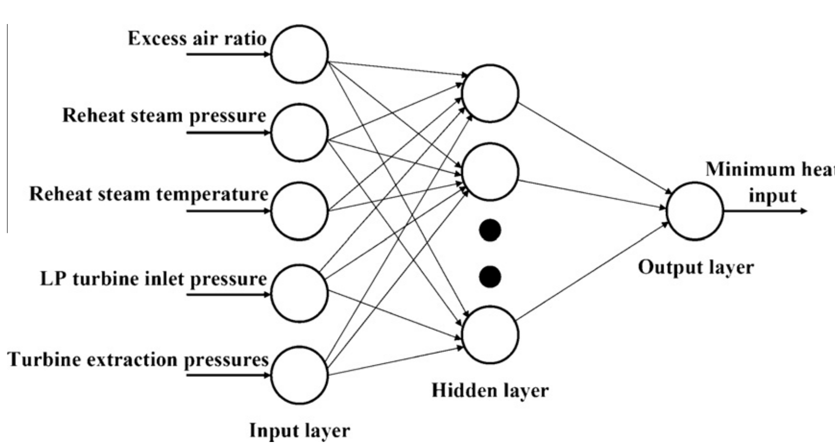

Fig. 2. Schematic of the ANN architecture.

Plant energy efficiency,

$$\eta = \frac{\text{Net electricity output}}{\text{Mass flow rate of coal} \times \text{HHV(dry basis) of the coal}} \quad (1)$$

Plant exergy efficiency,

$$\varepsilon = \frac{\text{Net electricity output}}{\text{Mass flow rate of coal} \times \text{Specific exergy of the coal}} \quad (2)$$

In India, as a normal practice, power plant industry quotes the power plant efficiencies on the basis of higher heating value (HHV) of fuel. Hence, to reflect the typical values of power plant efficiencies in India, HHV (dry basis) has been used throughout the study instead of LHV.

4. Neuro-genetic optimization

A prior knowledge of the typical range of operating parameters is required or the same needs to be identified prior to the use of neuro-genetic optimization methodology. In the present study, the ranges of operating parameters determined by the authors in their earlier work [16] have been used for neuro-genetic optimization. The optimized parameters of the studied power plant configuration are determined in two stages using neuro-genetic approach. In the first stage, optimized values of operating parameters such as excess air ratio, IP turbine (reheat steam) pressure/temperature, and LP turbine pressure are determined assuming the typical ranges as shown in Table 3 [16] whereas in the second stage, the optimized extraction pressures of turbine bleed streams to feedwater heaters (FWHs) are determined.

Fig. 1 shows the schematic of the SupC power plant configuration and the typical ANN architecture considered for the present study is shown in Fig. 2. The neuro-genetic optimization approach shown in Fig. 3 is applied using MATLAB's Neural Network and Genetic Algorithm toolbox [19]. The neural network is trained using Levenberg–Marquardt backpropagation algorithm with four and six hidden neurons for plant without and with FWHs, respectively whereas the population size in genetic algorithm is considered to be 20 with an elite count and crossover fraction as 2 and 0.8, respectively. The comparison of data fit obtained between Cycle-Tempo simulations of power plant cycle without FWHs and ANN model is shown in Fig. 4. It is observed that the ANN model is in very good agreement with the Cycle-Tempo simulations and hence GA is applied over the ANN model to determine the optimum set of

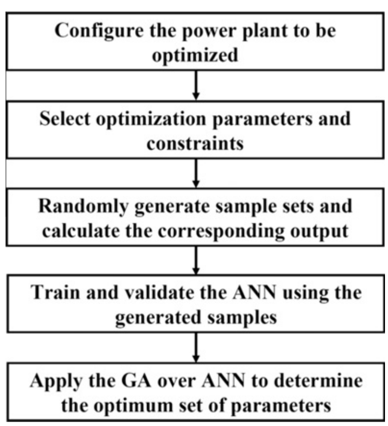

Fig. 3. Neuro-genetic optimization methodology adopted for the studied plant.

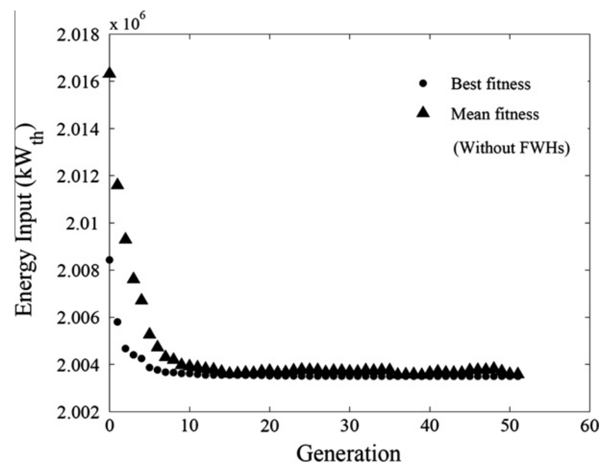

Fig. 5. Convergence curve of optimization of power plant parameters except FWHs.

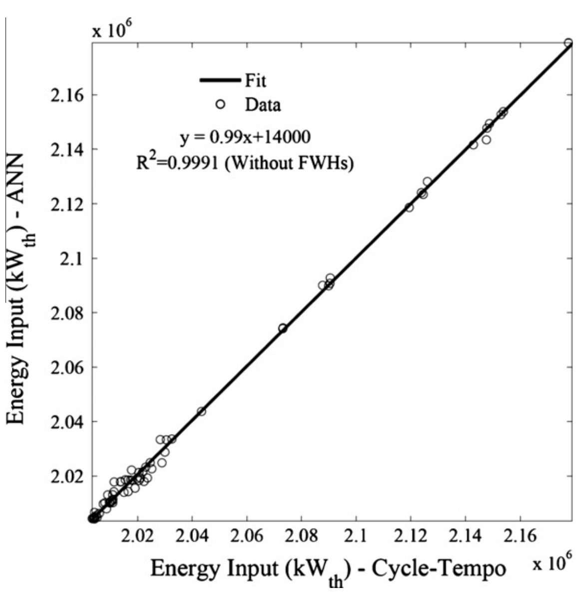

Fig. 4. Regression fit based on the ANN model of power plant except FWHs.

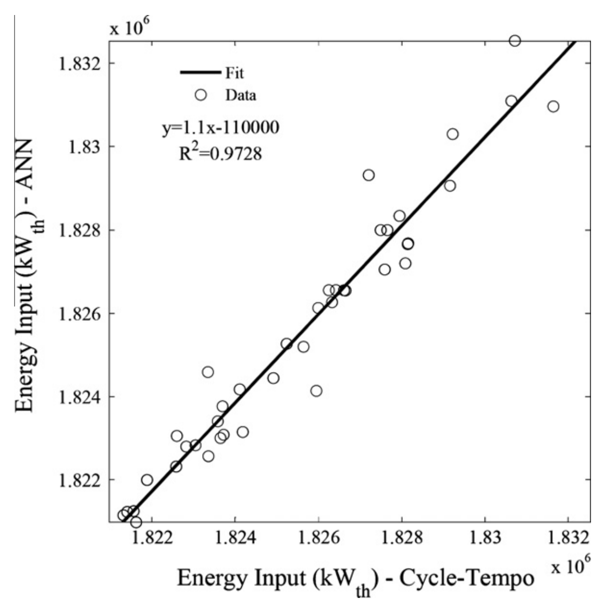

Fig. 6. Regression fit based on the ANN model of power plant including FWHs.

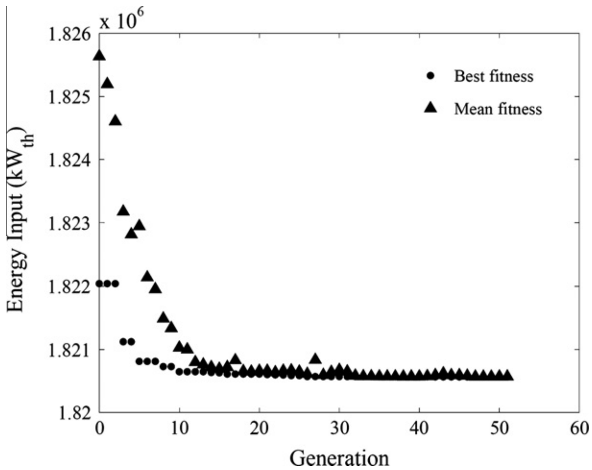

Fig. 7. Convergence curve of optimization of power plant parameters including FWHs.

operating variables. The objective function is to minimize the energy input to the power plant without the feedwater heaters (FWHs) and subject to the constraints considered in Table 3. The corresponding convergence of the GA is shown in Fig. 5. Once the optimized turbine parameters are identified, the neuro-genetic optimization approach is repeated for the entire plant including the FWHs. In order to identify the optimized extraction pressures for FWHs, an equal temperature distribution is assumed for individual FWHs (wherever applicable) after determining the de-aerator pressure. The corresponding data fit and GA convergence curves for the total plant including FWHs are shown in Figs. 6 and 7, respectively. Furthermore, the comparison of results obtained with the coupled neuro-genetic optimization and the 'Cycle-Tempo' simulation is also carried out to determine the accuracy of the adopted methodology. The variation in the output of the objective function, i.e. the minimum energy input to the power plant using reference HA Indian coal was less than 1%. The stream data of the optimized power plant configuration is shown in Table 4.

The comparison of results of neuro-genetic optimization and the parametric optimization reported by the authors in their earlier work [16] is shown in Table 5. It is observed that neuro-genetic optimization results in almost the same plant energy and exergy efficiencies. Moreover, the variations in optimized operating parameters obtained using both the methods are very minimal. The neuro-genetic optimization methodology results in the significant reduction of computation effort compared to the parametric optimization wherein a number of cases are required to be simulated corresponding to the variations in individual operating parameters. The major advantage of the neuro-genetic algorithm is the possibility of on-line optimization when quick response is required. However, the physical model of the power plant needs to be built prior to the on-line optimization.

5. Effect of various coals on the thermodynamic performance of the optimized plant

The power plant efficiency gets affected considerably by the variation in fuel composition and it is difficult to account the loss that involves unburnts without using any assumptions that in turn may lead to uncertainties. It is to be noted that the energy loss in the steam generator due to the combustibles in ash, radiation and convection losses, and unaccounted losses is considered as

Table 4
Stream data of the optimized SupC power plant.

Stream No. (as indicated in Fig. 1)	Pressure (bar)	Temperature (°C)	Mass flow rate (kg/s)	Energy flow rate (MW_{th})	Exergy flow rate (MW_{th})
Coal/bottom ash					
1	1.030	33.0	118.2	1870.8	2044.4
9	1.013	1050.0	11.6	15.4	9.2
Air/flue gas					
2	1.013	33.0	687.0	31.2	0
3	1.040	35.9	687.0	33.2	1.6
4	1.030	273.9	687.0	202.6	46.2
5	1.010	1784.9	793.6	2030.0	1404.4
6	1.000	320.0	793.6	351.9	137.7
7	1.000	122.7	793.6	182.5	74.4
8	1.060	130.0	793.6	188.6	79.6
Water/steam					
10	290.0	600.0	636.9	2110.9	983.7
11	62.0	620.0	523.6	1865.6	787.6
12	3.0	209.5	190.3	522.8	122.2
13	3.0	209.5	190.3	522.8	122.2
14	92.2	409.8	44.8	134.8	54.6
15	62.0	353.9	523.6	1525.5	586.6
16	62.0	353.9	68.5	199.7	76.8
17	25.6	480.3	29.8	97.6	35.8
18	11.0	362.3	20.5	62.5	19.6
19	11.0	362.3	45.9	139.7	43.9
20	6.1	288.8	21.4	61.9	17.2
21	3.0	209.5	25.4	69.7	16.3
22	1.1	114.2	23.7	60.8	10.5
23	0.3	69.1	17.1	40.8	4.2
24	0.103	46.4	339.9	772.9	32.0
25	0.103	46.4	473.3	26.5	0.5
26	11.0	46.5	473.3	27.1	1.0
27	360.0	191.2	636.9	440.6	104.8
28	360.0	305.0	636.9	772.9	241.7
29	342.5	340.0	636.9	893.2	299.4
30	1.013	33.0	20808.3	0	0
31	2.030	33.0	20808.3	2.7	2.1
32	1.030	43.0	20808.3	870.3	14.0

Table 5
Comparison between parametric and neuro-genetic optimization.

Parameter	Parametric optimization	Neuro-genetic optimization
Excess air (%)	20	18
HP turbine inlet steam pressure and temperature (bar/°C)	290/600	290/600
IP turbine inlet steam pressure and temperature (bar/°C)	61/620	62/620
LP turbine inlet steam pressure (bar)	3	3
Condenser pressure (bar)	0.103	0.103
Extraction pressure to LP FWH 1 (bar)	0.43	0.30
Extraction pressure to LP FWH 2 (bar)	1.26	1.05
Extraction pressure to LP FWH 3 (bar)	3.00	3.00
Extraction pressure to LP FWH 4 (bar)	6.62	6.10
Extraction pressure to de-aerator (bar)	12.00	11.00
Extraction pressure to HP FWH 1 (bar)	28.90	25.60
Extraction pressure to HP FWH 2 (bar)	62.50	62.00
Extraction pressure to HP FWH 3 (bar)	92.20	92.20
Plant energy efficiency (%)	39.5	39.6
Plant exergy efficiency (%)	36.1	36.2

1.5% of energy input through the coal for the optimized power plant configuration. Since exergy analysis gives more insights into the process, the present study is extended to determine the effect of coal composition on the thermodynamic performance of the optimized power plant based on both energy and exergy.

Different coal samples considered in Table 2 are used to evaluate the performance. The results of energy and exergy balance are shown in Tables 6 and 7, respectively with cases representing the values corresponding to respective coal samples. The energy losses are calculated as the ratio of energy rejected to the energy content of input fuel whereas the exergy losses are calculated as the ratio of irreversibilities to the exergy content of the fuel. It is observed that there is an increase of 1.2% points in plant energy efficiency using coal with an ash content of 16% compared with the reference coal with an ash content of 49% (dry-basis). The corresponding increase in plant exergy efficiency is 3.3%.

The variation of fuel consumption with different coal samples is shown in Fig. 8. A significant reduction of about 42% in coal consumption is observed using coal with an ash content of 16% (sample-4) compared to the reference coal that in turn results in a reduction of auxiliary power consumption. The reduction of energy loss through the bottom ash also contributes to the increase in plant energy efficiency. However, exergy balance gives additional insights into the process. There is a significant reduction in exergy loss in the combustor with the decrease in ash content of coals which is due to the increase in combustibles. However, the heat transfer irreversibility in the steam generator increases for the plant using relatively low ash coals compared to the reference HA coal. This is due to the relatively higher flue gas temperature using low ash coals (higher reaction temperature) compared to the reference coal and hence higher temperature difference between the flue gas and the steam for the same excess air ratio and steam parameters of the turbine cycle.

Table 6
Comparison of energy balance.

Components (%)	Reference high ash (HA)	Case-1	Case-2	Case-3	Case-4
Power (efficiency)	39.6	39.8	40.3	40.7	40.8
Heat rejected in cooling water	46.5	46.6	46.9	47.0	46.8
Heat rejected through stack	10.1	10.0	9.8	9.8	10.2
Heat rejected through bottom ash	0.8	0.7	0.5	0.3	0.2
Other losses (by difference)	3.0	2.9	2.5	2.2	2.0

Table 7
Comparison of exergy balance.

Components (%)	Reference high ash (HA)	Case-1	Case-2	Case-3	Case-4
Power (efficiency)	36.2	36.6	37.7	38.7	39.5
Loss in combustor	33.1	32.5	31.0	29.4	28.3
Loss in steam generator (excluding combustor)	16.8	16.9	17.4	17.9	18.3
Loss through stack	3.9	4.0	4.2	4.4	4.5
Loss in turbine	3.5	3.5	3.6	3.7	3.7
Loss in condenser and cooling water	1.9	1.9	1.9	2.0	2.0
Loss in feed water heaters	1.0	1.0	1.0	1.0	1.1
Loss through bottom ash	0.5	0.4	0.3	0.2	0.1
Other losses (by difference)	3.1	3.2	2.9	2.7	2.5

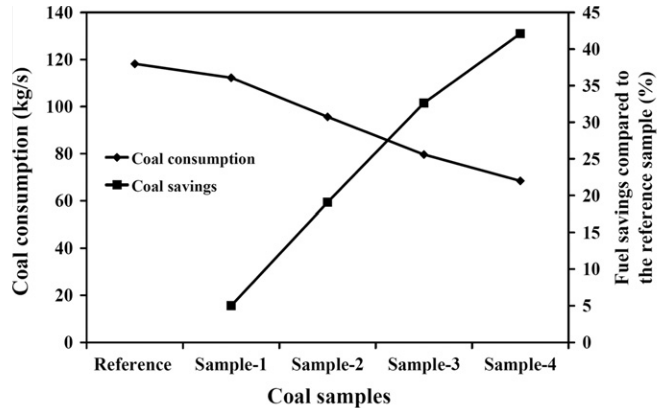

Fig. 8. Variation of coal consumption with different samples.

6. Conclusions

Thermodynamic optimization of power plant based on coupled artificial neural network and genetic algorithm (neuro-genetic) is found to be an efficient methodology compared to the routine parametric optimization. Neuro-genetic optimization methodology significantly reduces the computational effort without compromising the accuracy of the results along with the major advantage of on-line optimization. Furthermore, the thermodynamic analysis carried out to study the effect of coal composition on the power plant performance shows a reduction of about 42% in fuel consumption using coal with 16% ash compared with the coal having 49% ash. The corresponding increase in plant energy and exergy efficiencies are 1.2% and 3.3% points, respectively. It is also observed that the exergy loss in the combustor may be a suitable indicator to determine the effect of variation in coal composition on the power plant performance.

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