Innovative Systems Design and Engineering
ISSN 2222-1727 (Paper) ISSN 2222-2871 (Online)
Vol.6, No.11, 2015
www.iiste.org

Thermodynamic Optimization of Steam Boiler Parameter Using Genetic Algorithm

Darlington Egeonu * Chukwumaobi Oluah Patrick Okolo Howard Njoku
Department of Mechanical Engineering, University of Nigeria, Nsukka, Enugu State, Nigeria

Abstract

In this paper, genetic algorithm implemented in Matlab is used for the optimization of the boiler unit at Egbin power plant. Based on thermodynamic consideration of a boiler, the thermal efficiency of the boiler for 2008 and 2009 is computed. The thermal efficiency is defined as the objective function and is maximized using genetic algorithms subject to a list of constraints for obtaining the numerical values of the optimum operating parameters. These determined optimum operating parameters will serve as basis for improving the performance of the power plant and this is the significance of this study. The effects of genetic algorithm options (such as initial population, elite children, and crossover ratio) on the optimization results are also established. It is observed that applying genetic algorithm in the thermodynamic optimization of a case study (Egbin power plant) boiler, the percentage increase in the thermal efficiency is 4.76% and 3.89% in comparison with the existing values for the studied boiler at Egbin thermal power plant for 2008 and 2009 respectively.

Keywords: Thermodynamics, Optimization, Genetic Algorithm, Steam Boiler, Power Plant.

1.0 INTRODUCTION

Thermodynamic optimization is primarily concerned with determining the thermodynamically optimum size or operating regime of a certain engineering system, 'optimum' here means the condition in which the system loses the least power while still performing its fundamental engineering function (Buljubasic and Delalic, 2008). It turns out that in many systems, various mechanisms and design features that account for irreversibility compete with one another. Accordingly, the thermodynamic optimization of interest here is the operating condition of a steam boiler that will yield the best thermal efficiency of the boiler.

A steam boiler in its original meaning is a pressurized system in which thermal energy, resulting from combustion of organic fuels, is transferred through heat surfaces to a working fluid which evaporates in the system with the steam further overheated to a certain temperature, steam under pressure is then usable for transferring the heat to a process.

The basic element of a steam boiler is furnace, in which fuel combustion takes place in presence of oxygen, usually from air, releasing energy of a chemical reaction which raises enthalpy of a heat receiver to a level suitable for transferring the heat to a heat exchanger surface. In other elements of a steam boiler, flue gas is being cooled giving heat to heat further receivers through heat surfaces. Those elements are: economizers, evaporators, steam super-heaters and reheaters as well as air heaters. The most common working fluid (heat receiver) is water which evaporates in the boiler, and is being further over heated so the final product is saturated or super-heated steam (Buljubasic and Delalic, 2008).

The performance parameters of boiler, like efficiency and evaporation ratio reduces with time due to poor combustion, heat transfer surface fouling and poor operation and maintenance. Even for a new boiler, reasons such as deteriorating fuel quality, water quality etc. can result in poor boiler performance. Most power plants have highly nonlinear dynamics with numerous uncertainties. However, no mathematical model can exactly describe such a complicated physical process, and there will always be modeling errors due to un-modeled dynamics and parametric uncertainties (Weng et al., 1996).

To properly characterize the essential dynamic behavior of power plants with accurate representation of plant components/parts, detailed models are needed (Maffezzoni, 1997). Besides, detailed modeling of plants dynamics is often not efficient for control synthesis.

There are complicated models based on finite element approximations to partial differential equations. These models are in the form of large simulation codes for plant design, simulators and commissioning. However, they are not normally used in control design approach because of their complexity (Astrom and Bell, 2000).

The analytical plant model can be formulated based on the fundamental laws of physics such as mass conservation, momentum, and energy semi-empirical laws for heat transfer and thermodynamics state conversion (Astrom and Bell, 2000). In order to build such analytical models, it is necessary to define their parameters with respect to boundaries, inputs, and outputs. Generally, the developed models need to be tuned by performing tests to validate for steady state and transient responses (Lu and Hogg, 2000; De Mello, 1991).

When the identified model for system component is nonlinear in the parameters, using conventional methods like standard least squares technique will not provide superior results. In these cases, evolutionary algorithm based methodologies are investigated as potential solutions to obtain good estimation of the model parameters (Horst et al., 2000). Genetic algorithms have an advantage that it does not require a complete system model and can be employed to globally search for the optimal solution (Borsi, 1974).

In this paper, energy analysis will be used to determine the thermal efficiency of steam boiler and optimize it using genetic algorithm with Egbim power plant as a case study.

1.1 GENETIC ALGORITHMS (GAs)

The GAs is a stochastic global search method that mimics the metaphor of natural biological evolution (Gen and Cheng, 2000). GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) better and better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation.

Genetic Algorithms is an optimization technique that is based on the evolution theory. Instead of searching for a solution to a problem in the "state space" (like the traditional search algorithms do), a GA works in the "solution space" and builds (or better, "breeds") new, hopefully better solutions based on existing ones (Haupt and Haupt, 2004).

The general idea behind GAs is that we can build a better solution if we somehow combine the "good" parts of other solutions (schemata theory), just like nature does by combining the DNA of living beings.

Individuals, or current approximations, are encoded as strings, chromosomes, composed over some alphabet(s), so that the genotypes (chromosome values) are uniquely mapped onto the decision variable (phenotypic) domain. The most commonly used representation in GAs is the binary alphabet {0, 1} although other representations can be used, e.g. ternary, integer, real-valued etc.

The search process will operate on the encoding of the decision variables, rather than the decision variables themselves, except, where real-valued genes are used.

Having decoded the chromosome representation into the decision variable domain, it is possible to assess the performance, or fitness, of individual members of a population. This is done through an objective function that characterizes an individual's performance in the problem domain. In the natural world, this would be an individual's ability to survive in its present environment. Thus, the objective function establishes the basis for selection of pairs of individuals that will be mated together during reproduction.

During the reproduction phase, each individual is assigned a fitness value derived from its raw performance measure given by the objective function. This value is used in the selection to bias towards more fit individuals. Highly fit individuals, relative to the whole population, have a high probability of being selected for mating whereas less fit individuals have a correspondingly low probability of being selected.

Once the individuals have been assigned a fitness value, they can be chosen from the population, with a probability according to their relative fitness, and recombined to produce the next generation. Genetic operators manipulate the characters (genes) of the chromosomes directly, using the assumption that certain individual's gene codes, on average, produce fitter individuals. The recombination operator is used to exchange genetic information between pairs, or larger groups, of individuals. The simplest recombination operator is that of single-point crossover. A further genetic operator, called mutation, is subsequently applied to the new chromosomes. Mutation causes the individual genetic representation to be changed according to some probabilistic rule. In the binary string representation, mutation will cause a single bit to change its state, $0 \Rightarrow 1$ or $1 \Rightarrow 0$. Mutation is generally considered to be a background operator that ensures that the probability of searching a particular subspace of the problem space is never zero. This has the effect of tending to inhibit the possibility of converging to a local optimum, rather than the global optimum.

After recombination and mutation, the individual strings are then, if necessary, decoded, the objective function evaluated, a fitness value assigned to each individual and individuals selected for mating according to their fitness, and so the process continues through subsequent generations. In this way, the average performance of individuals in a population is expected to increase, as good individuals are preserved and bred with one another and the less fit individuals die out. The GA is terminated when some criteria are satisfied, e.g. a certain number of generations, a mean deviation in the population, or when a particular point in the search space is encountered. A flow chart of the operations of genetic algorithm is shown in figure 1.

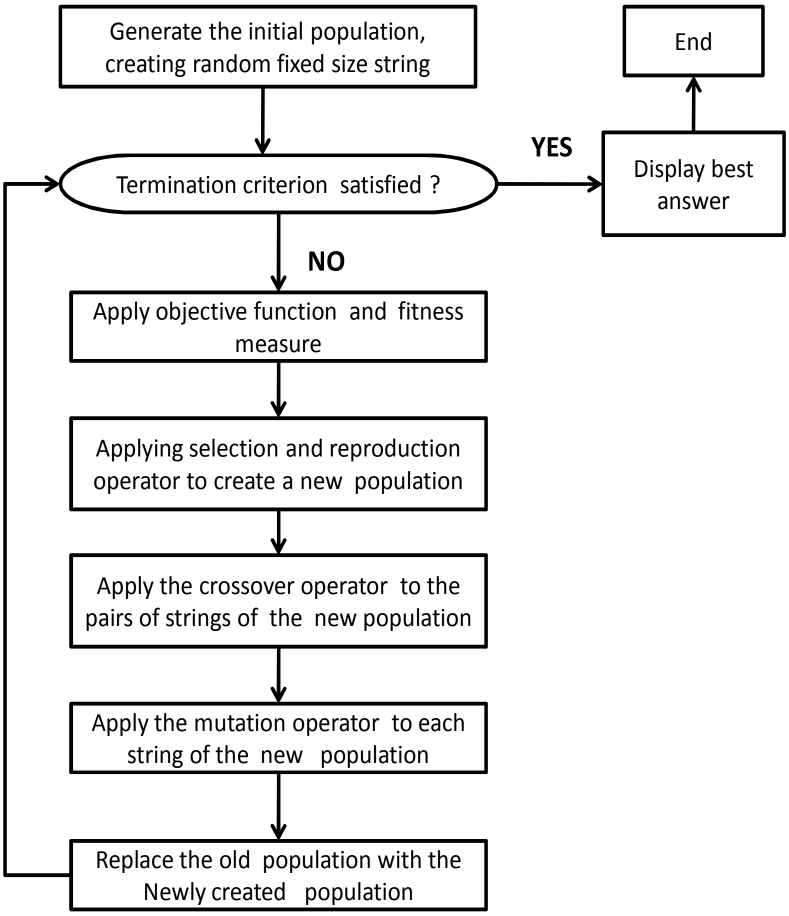

Figure 1: **GENETIC ALGORITHMS FLOW CHART** (Hassanein, Aly and Abo-Ismail, 2012).

1.2 CASE STUDY DESCRIPTION

This study is on the steam boiler of a 220MW steam power plant which converts the feed water at temperature 204^{o}C to superheated steam at pressure 12,990 kPa and temperature 541^{o}C, and also converts cold reheat steam to hot reheat steam at pressure 3,398 kPa and temperature 541^{o}C. The steam boiler, shown in figure 2, comprises the following major elements: Burners (B), furnace (F), secondary super heater (SSH), primary super heater (PSH), re-heater (RH), drum (D), economizer (ECO) and air heater (AH). The burners are dual fuel firing as they could operate on HPFO (high pour fuel oil), LPFO (low pour fuel oil), or gas. They are of three levels; A, B & C, LEVELS A&C has six burners each while level B has three burners .The Water enters at ECO where it is heated at temperatures below the boiling point. Heated water is sent to D of which any steam formed is removed by the hydro-cyclone separators in the drum. Heated water then flows to F through down-comers by natural circulation where water turns into steam. The steam water mixture rises into a steam boiler drum where water separates from steam (by cyclone separators) and generation of dry saturated steam is ensured by passing the steam through knockout drums and scrubbers. Dry saturated steam then moves to primary super heater and then to the secondary super heater, from that point superheated steam at 12,990kPa and 541^{o}C leaves the steam boiler to High pressure turbine. Cold reheat steam leaves the high pressure turbine back to the boiler re-heater (RH) and leaves the boiler as hot reheat steam at 3,398kPa and 541^{o}C to the intermediate pressure turbine. Steam leaves intermediate pressure turbine to low pressure turbine from where it moves to the condenser where it condensed to water at very low pressure. Make up water is now added to the condensed water (when necessary) which passes through series of low pressure heaters, de-aerator, boiler feed pump, high pressure heaters and then moves back to the economizer.

The schematics of the boiler and the flow diagram of the plant are shown in figure 2 below.

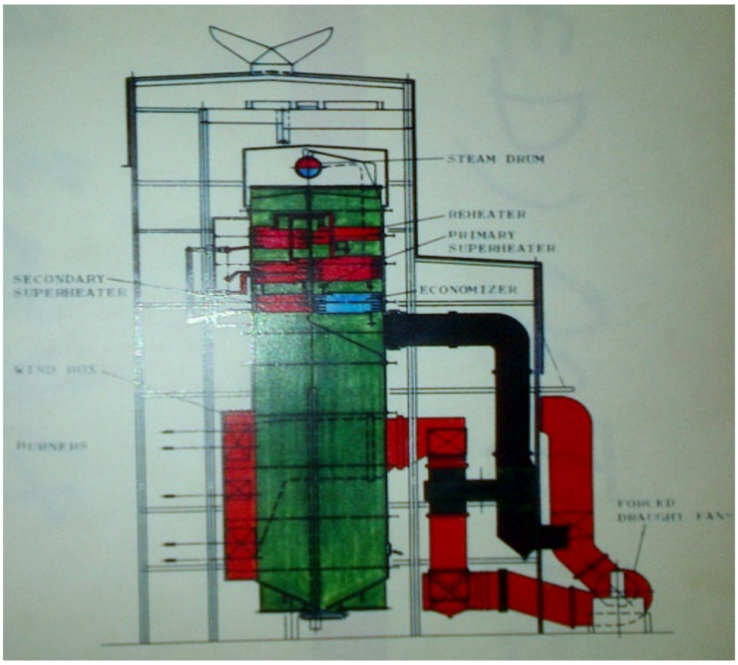

Figure 2: Schematics of Boiler Unit
(Source: Egbin Power Plant Catalogue, 1985)

2.0 ANALYSIS

In this study, two years (2008-2009) daily operational data of Egbin power plant was collected and used in the analysis and optimization of steam boiler using genetic algorithm tool box in Matlab.

The mathematical representation of the mass and energy flow consists of a set of equations. Figure 3 shows the heat exchanger network used to model the energy system of the steam boiler of figure 2.

2.1 MASS AND ENERGY FLOWS:

Mass balance of the mathematical model of the system is as follows:

$$\dot{m}_{sh} = \dot{m}_w \quad (1)$$

$$\dot{m}_a = L \cdot \dot{m}_f \quad (2)$$

$$\dot{m}_{cp} = V \cdot \dot{m}_f \quad (3)$$

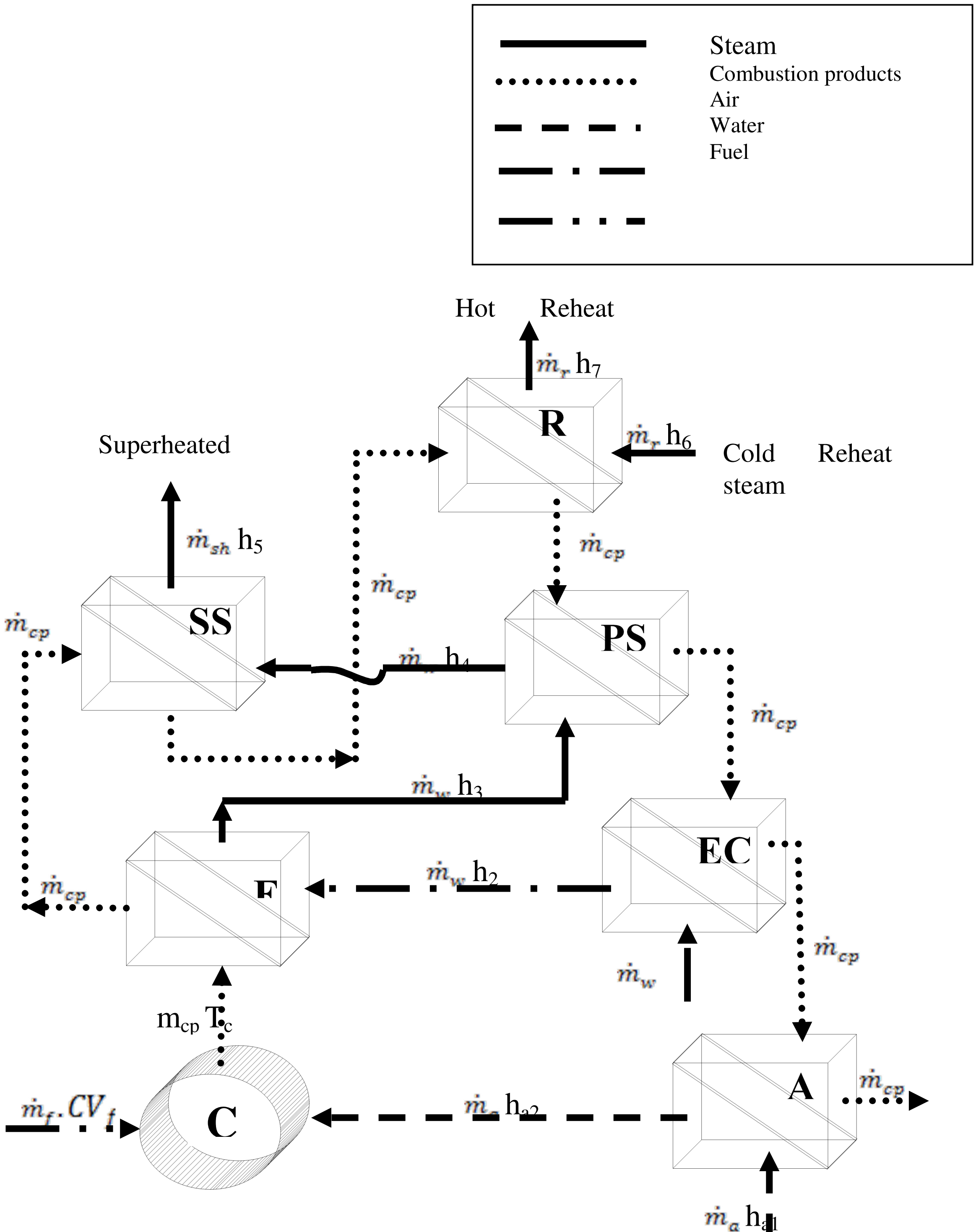

Figure: 3: Schematic diagram of heat exchanger network of the steam boiler

Where

$\dot{m}_w$ [kg/s] is the mass flow of water or steam, $\dot{m}_a$ [kg/s] is the mass flow of air, $\dot{m}_r$ [kg/s] is the mass flow of reheat steam, L [kg/kg] is the mass of air required for combustion products for 1 kg of fuel, $\dot{m}_f$ [kg/s] is the consumption of fuel, $\dot{m}_{cp}$ [kg/s] is the mass flow of combustion products, V [kg/kg] is the mass of combustion products for 1 kg of fuel, $\dot{m}_{sh}$ [kg/s] is the mass flow of steam at a superheater exit, CV_f [kJ/kg] is the heating value of the fuel,

Equation (2) presents the mass balance of air for combustion; Equation (3) presents mass balance of product of combustion.

Energy balance of the mathematical model of the system is as follows:

Furnace F:

$$\dot{m}_{cp}.C_{pcp}\left(T_c - T_{cp}\right) = \dot{m}_w(\mathrm{h}_3 - \mathrm{h}_2) \quad (4)$$

SSH : (pressure = 12990kPa)

$$\dot{m}_{cp}.C_{pcp}\left(T_{cp1} - T_{cp2}\right) = \dot{m}_{sh}(\mathrm{h}_5 - \mathrm{h}_4) \quad (5)$$

RH : (pressure = 3398kPa)

$$\dot{m}_{cp}.C_{pcp}\left(T_{cp2} - T_{cp3}\right) = \dot{m}_{sh}(\mathrm{h}_6 - \mathrm{h}_7) \quad (6)$$

PSH :

$$\dot{m}_{cp}.C_{pcp}\left(T_{cp3} - T_{cp4}\right) = \dot{m}_w(\mathrm{h}_4 - \mathrm{h}_3) \quad (7)$$

Economizer , Eco:

$$\dot{m}_{cp}.C_{pcp}\left(T_{cp4} - T_{cp5}\right) = \dot{m}_w(\mathrm{h}_2 - \mathrm{h}_1) \quad (8)$$

Air heater, AH

$$\dot{m}_{cp}.C_{pcp}\left(T_{cp5} - T_{cp6}\right) = \dot{m}_a(\mathrm{h}_{A2} - \mathrm{h}_{A1}) \quad (9)$$

The constraints of the mathematical model are given by the following equations

$$T_c > T_{cp1}\,; T_{c1} > T_{cp2}\,; T_{cp2} > T_{cp3};\ T_{cp3} > T_{cp4}\,;\ T_{cp4} > T_{cp5};\ T_{cp5} > T_{cp6} \quad (10)$$

where C_{pcp}[J/kgK] is the specific heat of combustion products, T_c [K] is the temperature of combustion, T_{cpi}[K] is the temperature of combustion products, T_{a1}[K] is the temperature of cold air, T_{a2}[K] is the temperature of heated air, h_2[kJ/kg] is the specific enthalpy of heated water, h_3 [kJ/kg] is the specific enthalpy of saturated steam, h_6 [kJ/kg] is the specific enthalpy of superheated steam at exit of the steam boiler and temperatures of water and steam at actual place of the steam boiler.

In order to determine the efficiency of the boiler, the following assumptions were made:

- The heat exchangers of the steam boiler are counter-flow type;
- The kinetic and potential energies of the fluid streams are negligible;
- The process is a steady flow process;
- There are no heat losses through connecting piping and passages.

From first law of thermodynamics,

$$\Delta U_s = Q - W \qquad (11)$$

For a steady flow process as considered here;

i. The total energy content Es of the system remains constant during the process. Therefore

$$\frac{dE_S}{dt} = 0 \qquad (12)$$

ii. The boundary remains unchanged with time, so that no boundary work is done during a steady flow process, and therefore

$$(\dot{W}_{boundary})_{in} = 0 \qquad (13)$$

iii. All properties at the inlet and the exit of the system remain unchanged with time. Therefore, enthalpy (h), velocity (c) and height (z) are constants.

Applying the above characteristics of a steady flow process in equations (5) and (6) to equation (4) yields;

$$\dot{Q}_{in} + \left(\dot{W}_{shf}\right)_{in} + \dot{m}_i\left(h_i + \frac{C_i^2}{2} + gz_i\right)_{in} - \dot{m}_e\left(h_e + \frac{C_e^2}{2} + gz_e\right)_{out} = 0$$

(14)

Where $\dot{W}_{shf}$ is shaft work, and the subscripts 'i' and 'e' denotes the inlet and exit, respectively. m_i is the same as $\dot{m}_e$. Let us represent these two equal mass flow rates by the symbol m, which can be considered as the constant mass flow rate through the steady flow process. Applying the above in equation (7) the energy balance is attained, that is the first law of thermodynamics applied to a steady flow process with a single inlet and a single exit, as

$$\dot{Q}_{in} + \left(\dot{W}_{shf}\right)_{in} = \dot{m}\left(h_e - h_i + \frac{C_e^2 - C_i^2}{2} + g(Z_e - Z_i)\right) \qquad (15)$$

There is no shaft work involved in a boiler. The potential and kinetic energy changes across these devices are negligible in comparison to the change in enthalpy. So that the steady flow energy equation for flow through a boiler becomes

$$\dot{Q} = \dot{m}(h_e - h_i) \tag{16}$$

$$Boiler\ Efficiency = \frac{Heat\ Output}{Heat\ Input} \tag{17}$$

Where heat input (Q_{in}) is the heat supplied by the fuel and heat output (Q_{out}) is the heat gained by water and steam.

$$\eta = \frac{Q_{out}}{Q_{in}} \tag{18}$$

Which can be written as

$$\eta = \frac{\dot{m}(h_e - h_i)}{\dot{m}_f \times CV_f} \tag{19}$$

Applying these to our case study boiler

$$\eta = \frac{\dot{m}_{sh}(h_5 - h_1) + \dot{m}_r(h_7 - h_6)}{\dot{m}_f \times CV_f} \tag{20}$$

2.2 Genetic Algorithm Optimization

For the thermodynamic optimization, the objective function which is to be maximized is the thermal efficiency of the steam boiler given by

E = -((x(1)*(x(2)- x(3))) + (x(4)*(x(5)- x(6))))/ (x(7) * x(8)) (21)

Subject to the following constraints:

For 2008 data;

$$\left.\begin{array}{l} x(5) > x(6),\ x(2) > x(3),\ x(5) > x(1);\ 174.3 \le x(1) \le 174.3; \\ 3386 \le x(2) \le 3449;\ 599.2 \le x(3) \le 1085;\ 157.7 \le x(4) \le 157.7; \\ 3489 \le x(5) \le 3550;\ 3166 \le x(6) \le 3166;\ 11.94 \le x(7) \le 12.5; \\ 48851.036 \le x(8) \le 48851.036 \end{array}\right\} \quad (22)$$

For 2009 data;

$$\left.\begin{array}{l} x(5) > x(6),\ x(2) > x(3),\ x(5) > x(1);\ 174.3 \le x(1) \le 174.3; \\ 3395 \le x(2) \le 3539;\ 617.9 \le x(3) \le 900.7;\ 157.7 \le x(4) \le 157.7; \\ \\ 3373 \le x(5) \le 3635;\ 3166 \le x(6) \le 3166;\ 11.94 \le x(7) \le 12.5; \\ 48851.036 \le x(8) \le 48851.036 \end{array}\right\} \quad (23)$$

For 2008-2009 data:

$$\left.\begin{array}{l} x(5) > x(6),\ x(2) > x(3),\ x(5) > x(1);\ 174.3 \le x(1) \le 174.3; \\ 3386 \le x(2) \le 3539;\ 617.9 \le x(3) \le 1085;\ 157.7 \le x(4) \le 157.7; \\ \\ 3373 \le x(5) \le 3635;\ 3166 \le x(6) \le 3166;\ 11.94 \le x(7) \le 12.7; \\ 48851.036 \le x(8) \le 48851.036 \end{array}\right\} \quad (24)$$

Where

E = thermal efficiency (η), x(1) = $\dot{m}_{sh}$ = Quantity of steam generated per second from superheater in kg/s, x(2) = h_5 = Enthalpy of saturated steam from superheater in kJ/kg of steam, x(3) = h_1 = Enthalpy of feed water in kJ/kg of water, x(4) =$\dot{m}_r$ = Quantity of steam generated per second from reheater in kg/s, x(5) = h_7 = Enthalpy of hot reheat steam in kJ/kg of steam, x(6) = h_6 = Enthalpy of cold reheat steam in kJ/kg of steam, x(7) =$\dot{m}_f$ = Quantity of fuel used per second in kg/s, x(8) = CV_f = Calorific value of the fuel (CV) in kJ/kg of fuel. Equation (11) which is defined as the thermal efficiency of the boiler (objective function) was coded in Matlab and optimized using genetic algorithm tool box.

3.0 RESULTS / DISCUSSION

3.1 RESULTS

Thermal efficiency of the boiler for the 365 days of years 2008 and 2009 has been calculated using equation (10) and the results plotted (see figures 4 and 5 respectively). From the plot of Variation of Thermal Efficiency with Days shown in figures 4 and 5 respectively, the maximum thermal efficiencies are 86.8% (on the 90^{th} day) and 87.67% (on the 216^{th} day), while the average thermal efficiencies are 78% and 84.32% .

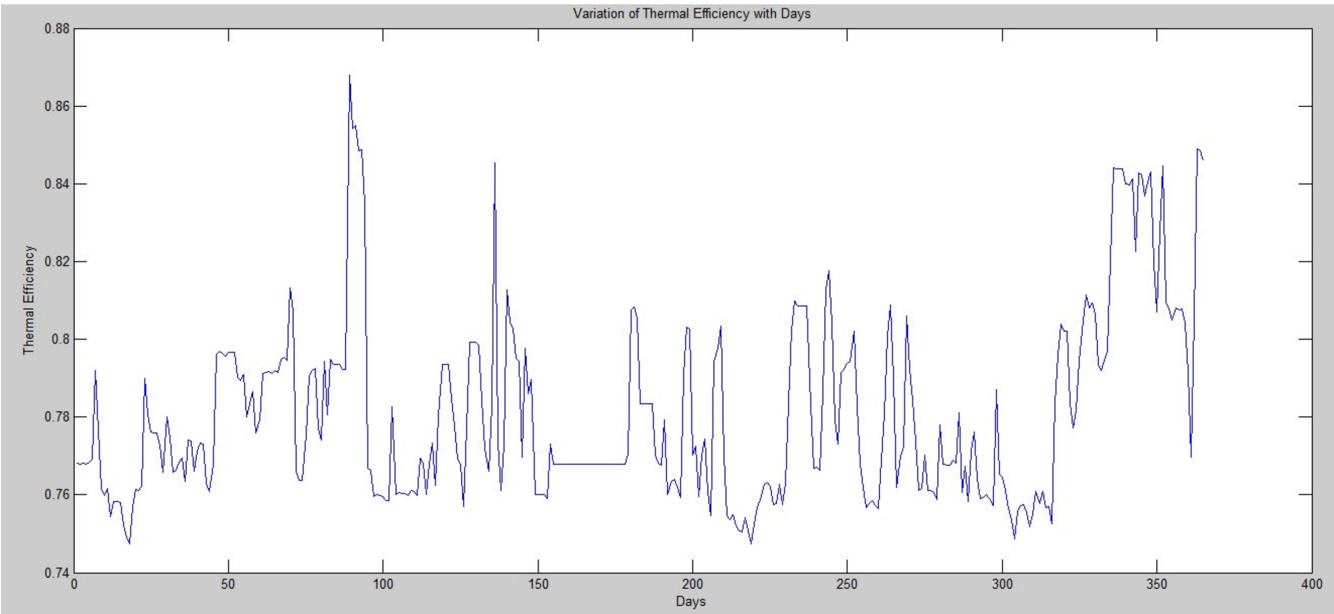

Figure 4: Variation of Thermal Efficiency with Days for 2008

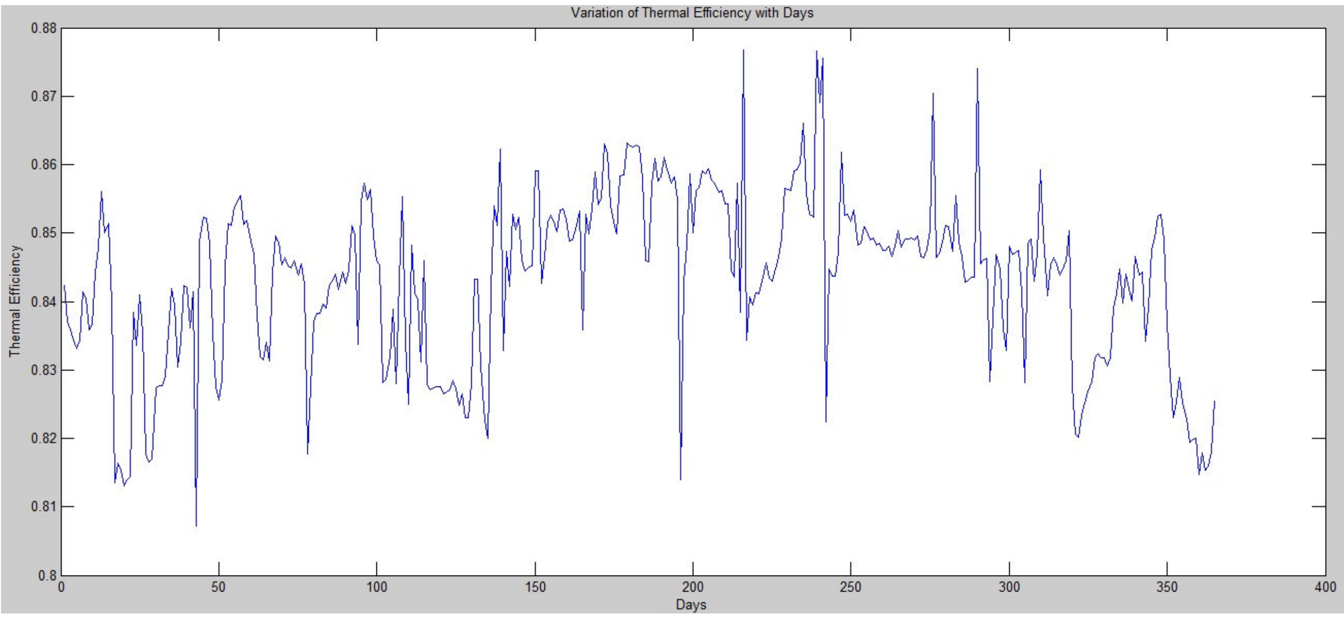

Figure 5: Variation of Thermal Efficiency with Days for 2009

After Optimization with genetic algorithm in MATLAB, the plots of Best Fitness and Mean Fitness, Average Distance Between Individuals, Current Best Individual, and Best, Worst and Mean were obtained as shown in figures 6 and 7 for 2008 and 2009 respectively.

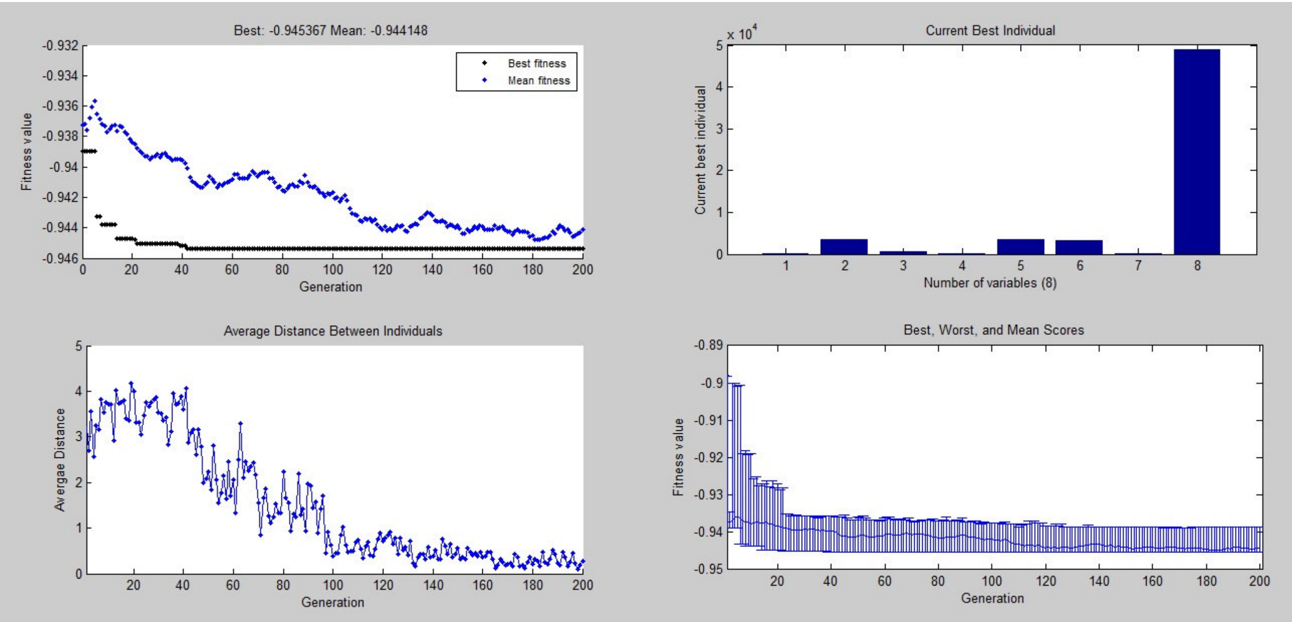

Figure 6: Optimization plots for 2008

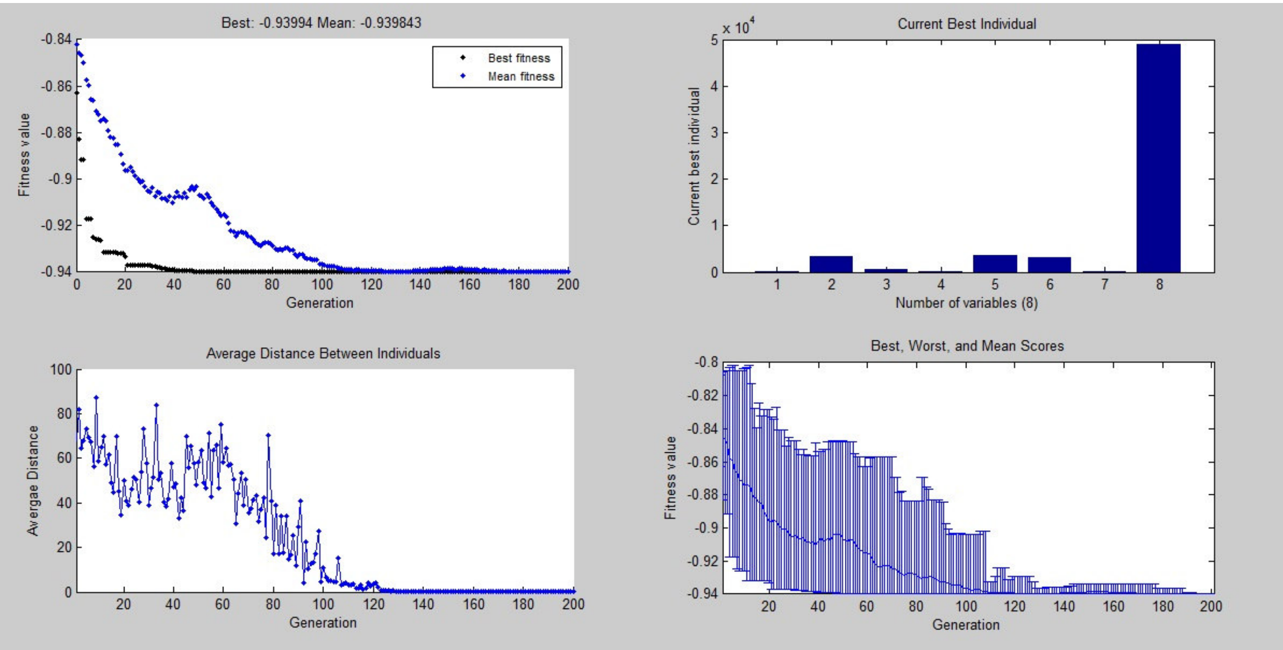

Figure 7: Optimization plots for 2009

From the plot of Best Fitness and Mean Fitness shown in figures 6 and 7 for 2008 and 2009 respectively, the best fitness value obtained is 0.945367 while the mean fitness value obtained is 0.944148 for the year 2008 whereas, the best fitness value obtained is 0.93994 while the mean fitness value obtained is 0.939843 for the year 2009.

From the plot of Average Distance Between Individuals for 2009 shown in figure 7, the overall average distance between individuals is 88, it decreases as optimization progresses. The average distance between successive individuals decrease and increase as optimization progresses, it is approximately zero from 130th generation. From the plot of Average Distance Between Individuals for 2008 shown in figure 6, the overall average distance between individuals is 4.5, it follows similar trend as that of figure 7.
From the plot of Best, Worst and Mean scores shown in figure 6 and 7, there is an improvement in all the scores as the optimization progresses, the difference between the best score and the worst score is also reduced for both plots. The scores are approximately equal as optimum point is reached at about 195th generation for 2009 while the difference is negligible for 2008.
Figures 6 and 7 for 2008 and 2009 respectively; show a plot of Current Best Individual, which is the best individual after optimization. The best individual could be said to be a vector whose length is the number of variables (or chromosomes) in the problem, applying the fitness function to the best individual results to the score of the best individual which is the value of the best fitness function. The best individual varies as optimization progresses. The genes (vector entries) and score of the best individual are recorded in tables 1 and 3.
Tables 1 and 3 show a comparison of results, for 2008 & 2009 respectively, between values of decision variables before and after optimization, the optimized values of decision variables are based on the GA parameter values.

Table 1: Comparison of Results Between Values of Decision Variables Before and After Optimization for 2008

Variables		Before Optimization		After Optimization	
		Average	Maximum	Mean	Best
x(1)	$\dot{m}_{sh}$ (kg/s)	174.3	174.3	174.3	174.3
x(2)	h_5 (kJ/kg)	3423.81	3423	3433.13	3433.13
x(3)	h_1 (kJ/kg)	966.37	655.5	559.20	559.20
x(4)	$\dot{m}_r$ (kg/s)	157.7	157.7	157.7	157.7
x(5)	h_7 (kJ/kg)	3522.15	3522	3533.018	3533.02
x(6)	h_6 (kJ/kg)	3166.0	3166.0	3166.0	3166.0
x(7)	$\dot{m}_f$ (kg/s)	12.7	12.7	12.7	12.7
x(8)	CV_f (kj/kg)	48851.036	48851.036	48851.036	48851.036
E	H	0.78	0.868	0.944148	0.945367

The enthalpy values have been converted to temperatures at operating pressures for optimized mean values and shown in Table 2;

Table 2: Optimum Boiler Parameters for 2008

Variables	Enthalpy (kJ/kg)		Temperature (°C)	Pressure (kPa)
FEED	h_1	559.20	133	
SUPERHEATER	h_5	3433.13	534.3	12601
COLD REHEAT	h_6	3166.0	375.2	3398
HOT REHEAT	h_7	3533.018	535.7	3398

Table 3: Comparison of Results Between Values of Decision Variables Before and After Optimization for 2009

Variables		Before Optimization		After Optimization	
		Average	Maximum	Mean	Best
x(1)	$\dot{m}_{sh}$ (kg/s)	174.3	174.3	174.3	174.3
x(2)	h_5 (kJ/kg)	3436.951	3450	3453.1151	3453.1162
x(3)	h_1 (kJ/kg)	749.3159	667	657.7572	657.7574
x(4)	$\dot{m}_r$ (kg/s)	157.7	157.7	157.7	157.7
x(5)	h_7 (kJ/kg)	3512.742	3539.0	3552.9351	3552.9351
x(6)	h_6 (kJ/kg)	3166	3166	3166.0	3166.0
x(7)	$\dot{m}_f$ (kg/s)	12.7	12.7	11.9400	11.94
x(8)	CV_f (kj/kg)	48851.036	48851.036	48851.036	48851.036
E	H	0.843213	0.876679	0.939843	0.93994

The enthalpy values have been converted to temperatures at operating pressures for optimized mean values and shown in Table 4;

Table 4: Optimum Boiler Parameters for 2009

Variables	Enthalpy (kJ/kg)		Temperature (°C)	Pressure (kPa)
FEED	h_1	657.7572	156	
SUPERHEATER	h_5	3453.1151	541.8	12601
COLD REHEAT	h_6	3166.0	375.2	3398
HOT REHEAT	h_7	3552.9351	544.4	3398

Data for 2008 – 2009 has been merged, making available an initial population of 730 individuals. Variation of Thermal Efficiency with Days has been plotted as shown in figure 8.

The minimum thermal efficiency is 74.73% obtained on the 18th day of 2008, the maximum thermal efficiency is 87.67% obtained on the 216th day of 2009 (581st day of overall data), the average thermal efficiency is 81.21%.

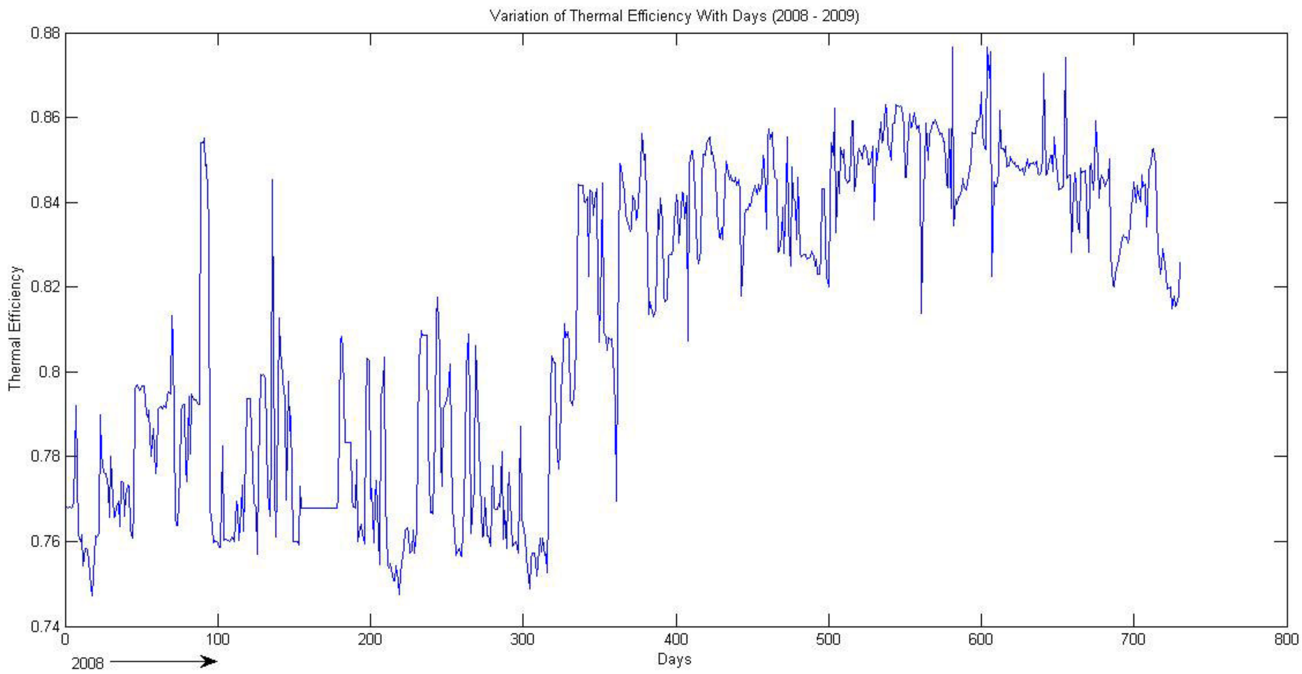

Figure 8: Variation of Thermal Efficiency with Days (2008-2009)

After Optimization with genetic algorithm in MATLAB, the plots of Best Fitness and Mean Fitness, Average Distance Between Individuals, Current Best Individual, and Best, Worst and Mean were obtained as shown in figure 9 for 2008 - 2009.

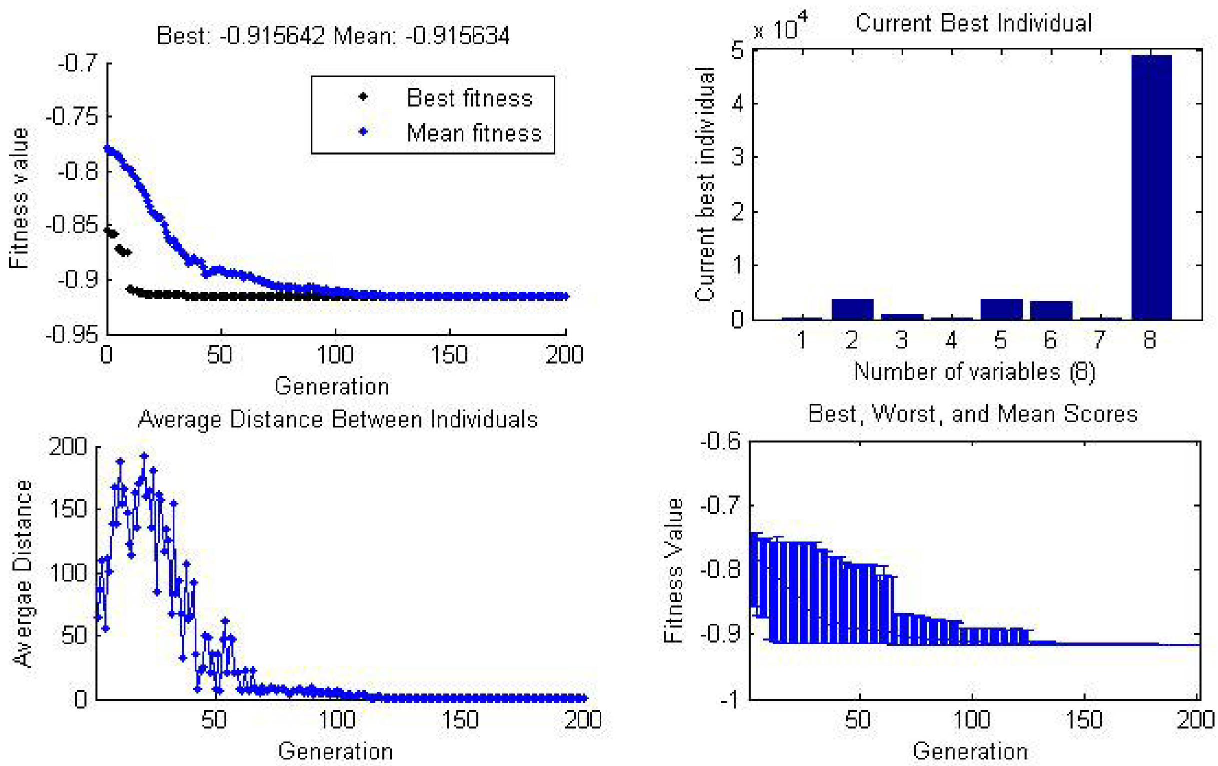

Figure 9: Optimization plots for 2008-2009 (Combined)

From the plot of Best Fitness and Mean Fitness shown in figure 9, the best fitness value obtained is 0.915642 while the mean fitness value obtained is 0.915634.

From the plot of Average Distance Between Individuals shown in figure 9, the overall average distance between individuals is 200 and reduces to 60 from the 42nd generation, it decreases as optimization progresses. The average distance between successive individuals decrease as optimization progresses, it is approximately zero from 120th generation.

From the plot of Best, Worst and Mean scores shown in figure 9, there is an improvement in all the scores as the optimization progresses, the difference between the best score and the worst score is also reduced. The scores are approximately equal as optimum point is reached at about 190th generation.

Table 5 shows a comparison of results between values of decision variables before and after optimization, the optimized values of decision variables are based on the GA parameter values shown above.

Table 5: Comparison of Results Between Values of Decision Variables Before and After Optimization for 2008 - 2009 Combined

Variables		Before Optimization			After Optimization
		Minimum	Average	Maximum	Mean
x(1)	$\dot{m}_{sh}$ (kg/s)	174.3	174.3	174.3	174.3
x(2)	h_5 (kJ/kg)	3423	3430.389	3450	3433.3158
x(3)	h_1 (kJ/kg)	1085	857.9285	667	698.5364
x(4)	$\dot{m}_r$ (kg/s)	157.7	157.7	157.7	157.7
x(5)	h_7 (kJ/kg)	3522	3517.4548	3539.0	3530.0167
x(6)	h_6 (kJ/kg)	3166	3166	3166	3166.0
x(7)	$\dot{m}_f$ (kg/s)	12.7	12.7	12.7	11.9400
x(8)	CV_f (kj/kg)	48851.036	48851.036	48851.036	48851.036
E	H	0.747338	0.812053	0.876679	0.915634

Converting the enthalpy values to temperatures at operating pressures for optimized mean values is shown in Table 6;

Table 6: Optimum Boiler Parameters for 2008 - 2009 (Combined)

Variables	Enthalpy (kJ/kg)		Temperature (°C)	Pressure (kPa)
FEED	h_1	698.5364	165.5	
SUPERHEATER	h_5	3433.3158	534.4	12601
COLD REHEAT	h_6	3166.0	375.2	3398
HOT REHEAT	h_7	3530.0167	534.4	3398

Table 7: Comparison of mean values of decision variables before and after optimization for 2008, 2009, and 2008-2009.

Variables		Before Optimization			After Optimization		
		2008	2009	2008-2009	2008	2009	2008-2009
x(1)	$\dot{m}_{sh}$ (kg/s)	174.3	174.3	174.3	174.3	174.3	174.3
x(2)	h_5 (kJ/kg)	3423.81	3436.951	3430.389	3433.13	3453.1151	3433.3158
x(3)	h_1 (kJ/kg)	966.37	749.3159	857.9285	559.20	657.7572	698.5364
x(4)	$\dot{m}_r$ (kg/s)	157.7	157.7	157.7	157.7	157.7	157.7
x(5)	h_7 (kJ/kg)	3522.15	3512.742	3517.4548	3533.018	3552.9351	3530.0167
x(6)	h_6 (kJ/kg)	3166.0	3166	3166	3166.0	3166.0	3166.0
x(7)	$\dot{m}_f$ (kg/s)	12.7	12.7	12.7	12.1	11.9400	11.9400
x(8)	CV_f (kJ/kg)	48851.036	48851.036	48851.036	48851.036	48851.036	48851.036
E	H	0.78	0.843213	0.812053	0.944148	0.939843	0.915634

Table 8: Comparison of Optimum Boiler Parameters

Variables	Pressure (kPa)	Temperature (°C)					
		Before Optimization			After Optimization		
		2008	2009	2008-2009	2008	2009	2008-2009
FEED		224.67	176.74	201.2	133	156	165.5
SUPERHEATER	12601	531.05	541.20	533.3	534.3	541.8	534.4
COLD REHEAT	3398	375.20	375.20	375.2	375.2	375.2	375.2
HOT REHEAT	3398	531.50	541.20	528.8	535.7	544.4	534.4

3.2 DISCUSSION

Before GA is used as an optimizing tool, the problem above has to be modeled in MATLAB and a script (M-file) is written to represent the objective function of the problem together with all other governing equations. Once this is done, it is a matter of calling up the M-file with GA to begin the optimization.

In the optimization plots for 2009, the algorithm generates the best individual that it can, using the genes at generation number 50, where the best fitness plot becomes level. After this, it creates new copies of the best individual, which are then are selected for the next generation. By generation number 170, all individuals in the population are the same, namely; the best and mean individual. When this occurs, the average distance between individuals is 0. Since the algorithm cannot improve the best fitness value after generation 170, it stalls after 30 more generations, because generation is set to 200.

From the curve of Best Fitness and Mean Fitness, as the number of generations increase, the mean fitness converges to the best fitness, this shows that optimization is actually taking place. It could also be seen that the best fitness is also reduced.

From the plot of average distance between individuals, it is obvious that the population converges, since the average distance between individuals in terms of the fitness is reduced, as the generations pass. This is a measure of the diversity of a population. With the average distance between individuals much lower in 2008, gotten with a reduced elite count and increased mutation in the GA options as compared with those of 2009, it is evident that the results of optimization for 2008 is better than that obtained for 2009.

From table 1, the thermal efficiency at optimum condition is 94.54% indicating a 16.54% improvement, compared to the existing mean operating value 78%%.

From table 3, the thermal efficiency at optimum condition is 93.98% indicating a 9.66% improvement, compared to the existing mean operating value 84.32%.

Combining the data for 2008 and 2009 provides a larger initial population, its effect is seen as the optimization plots for 2009-2009 is analyzed and compared with the previous plots.

From table 5, the thermal efficiency at optimum condition is 91.56% indicating a 10.31% improvement, compared to the existing mean operating value 81.21%, and a 3.7% increase, compared to the existing maximum operating value of 87.67%.

From table 8, the superheat temperature and hot reheat temperature are equal (534.4^{O}C) only for 2008-2009 optimized data, this can also be seen in the raw data for 2009 and 2009 as it is the design specification for the boiler. With these analysis and comparisons, it is evident that the optimization for 2008-2009 is the best of the three optimized data (i.e. 2008, 2009, and 2008-2009).

GA can work in many ways depending on how the objective function, constraints and GA options are defined in the program. In the thermodynamic optimization of steam boiler, the objective function is defined in equation (21), the constraints are defined in equations (22-24), while Genetic Algorithm options as set in GA toolbox in MATLAB for the results obtained are detailed below.

GA OPTIONS

The optimization of the steam boiler with GA was done with the following GA options:

For 2009 data:

Population size: 200; Initial range: [0.82;0.92]; Scaling function : Rank;

Selection function: Uniform; Elite count: 5; Crossover fraction: 0.5;

Mutation function: Constraint dependent; Crossover function: Scattered

Generations: 200; Stall generation: 200.

For 2008 and 2008-2009 data:

Same as those for 2009 data with the following changes:

Elite count: 2; Crossover fraction: 0.8.

4.0 CONCLUSION

Efficiency increase and pollutant emission control are the most significant projects of the world. In the present investigation, an optimization has been done to one of the boilers in Egbin steam power plant to increase boiler efficiency. Ensuring that the operation of a steam turbine power plant is at an optimum level is rather complicated. There are too many factors to be considered and a wrong decision might increase the cost of operation. It has been demonstrated that genetic algorithm (GA) can be successfully implemented as an optimization tool for a boiler unit in a steam turbine power plant.

For 2008 and 2009 the average thermal efficiency of the boiler has been determined to be 78% and 84.32% respectively, while the maximum thermal efficiency was calculated to be 86.8% and 87.67% respectively as shown in the plot of Variation of Thermal Efficiency with Days (figures 1 and 2).

It has been established that increasing the initial population, reducing the number of elite children and increasing the crossover fraction increases the probability of getting a more accurate result of optimization using genetic algorithm.

After optimization with genetic algorithm, the mean fitness value obtained for 2008-2009 was 91.56%. The individual with this mean fitness value, whose chromosomes are $(\dot{m}_{sh}, h_5, h_1, \dot{m}_r, h_7, h_6, \dot{m}_f, CV_f)$, has genes (174.3, 3433.3158, 698.5364, 157.7, 3530.0167, 3166.0, 11.94, 48851.04).

From the above it is evident that if the boiler is operated at $\dot{m}_{sh}$ = 174.3kg/s, feed temperature = 165.5^{O}C, superheat temperature/pressure = 534.4^{O}C/12601kPa, cold reheat temperature/pressure = 375.2^{O}C/3398kPa, and hot reheat temperature/pressure = 534.4^{O}C/3398kPa, $\dot{m}_r$ = 157.7kg/s, $\dot{m}_f$ = 11.94kg/s, CV_f = 48851.04kJ/kg, its thermal efficiency would be 91.56% which amounts to 4.76% and 3.89% increase in boiler thermal efficiency compared to maximum thermal efficiency obtained in 2008 and 2009 respectively.

It is recommended that future research should use hybrid models to optimize power plants. Genetic algorithm together with artificial neural network should be used in power plant modeling and optimization.

REFERENCES

Astrom, K.J. and Bell, R. D. (2000) Drum-Boiler Dynamics, *Journal of Automatica. vol. 36 (3), pp.363-378.*

Borsi, L. (1974) Extended Linear Mathematical Model of a Power Station Unit with a Once-Through Boiler, *Siemens Forschungs und Entwicklingsberichte, vol. 3 (5), pp. 274-280.*

Buljubašić, I. and Delalić, S. (2008). Improvement of steam boiler plant efficiency based on results of on-line performance monitoring. *Tehnički vjesnik*, *15*(3), 29-33.

De Mello, F. P. (1991) Boiler Models for System Dynamic PerformanceStudies, *IEEE Transaction on Power Systems, vol. 6 (1), pp. 66-74.*

Gen, M. and Cheng, R. (2000). *Genetic algorithms and engineering optimization* (Vol. 7). John Wiley & Sons.

Hassanein, O. I. Aly, A. A. and Abo-Ismail, A. A. (2012). Parameter tuning via genetic algorithm of fuzzy controller for fire tube boiler. *International Journal of Intelligent Systems and Applications (IJISA)*, *4*(4), 9.

Haupt, R. L., & Haupt, S. E. (2004). *Practical genetic algorithms*. John Wiley & Sons.

Horst, R., Pardalos, P. and Thoai, N. (2000) Introduction to Global Optimization, Second Edition, *Kluwer Academic Publishers, Dordrech, pp. 34-36.*

Lu, S. and Hogg, B. W. (2000) Dynamic Nonlinear Modelling of Power Plant by Physical Principles and Neural Networks, *Journal of Electrical Power and Energy Systems, vol. 22, pp. 67-78.*

Maffezzoni, C. (1997) Boiler-Turbine Dynamics in Power Plant Control, *Control Engineering Practice. vol. 5, pp. 301-312.*

Weng, C. K., Ray A. and Dai, X. (1996) Modeling of Power Plant Dynamics and Uncertainties for Robust Control Synthesis, *Application of Mathematical Modeling, vol. 20, pp. 501-512.*