Comparative Analysis of Heuristic Optimization for Achieving Maximum Efficiency of Multi-Fuel Boiler

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Abstract*: In, this paper, we propose operator point of view of optimizing combustion efficiency of steam boiler maintaining targeted superheat temperature and pressure. For this purpose, the data from actual running steam boiler has been noted from Bhilai Steel Plant (Steel Authority of India). We adopted data-mining approach to model boiler and its process variables. The variables selected play vital role in control of combustion efficiency for multi-fuel boiler with operating constraints and variables. These variables are divided into two categories: controllable and non-controllable. Controllable variables are those which can be adjusted by operator easily like air flow, feed water temperature, mass flow rate of fuel etc. Non-controllable variables are those that are not affected by changes of controllable variables, e.g. the boiler's room temperature, humidity, quality of fuel etc. This paper illustrates the implementation of heuristic approach to control boiler and industrial case study has also developed.*

Keywords: Artificial Neural Network**,** Data Mining, Efficiency, Genetic Algorithm, Process Control, Regression Tree.

1. Introduction

Increase in population, its huge power demand and depletion of non-renewable fuels across the world makes the mankind to find optimum solution for power generation and energy management. The optimization of power generating organization has become one of the most important fields in engineering since last decade. In last decade numerous of thermo-economic and multi-objective models have been presented: providing better optimum solutions and systems [1]. Recently, applications of soft computing techniques such as artificial neural network, fuzzy logic, genetic algorithm etc have become more popular than conventional thermodynamics analysis [2]. Because of complex, non-stationary and non-linear combustion process conventional approach of thermodynamics was very tedious and prone to calculation errors. With advancement of intelligent control theory (like artificial neural network, fuzzy logic, evolutionary computing) one can easily model complex problem, and also get acceptable results which shows great possibility of growth.

To optimize the combustion efficiency of boiler with prediction of performance index and non-linear constraints S.S Shieh *et al.*[3] applied neural network and hence successfully replace trial and error method of finding optimum solution. Evolutionary computational algorithm was used by P. Stoll *et al.*[4] to design system with minimum NOx emission as well as minimum pressure fluctuation. Hybrid algorithm (evolutionary computational techniques and neural network) was used by B. Radl *et al.*[5] to find optimal fuel/air ratio. Fuzzy logic was implemented appreciably by S. Tanaka *et al.*[6] to control combustion process in coal fired power plant. Farzanels *et al.*[7] proposed NSGA-II and ANN techniques to optimize steam cycle power plant (maximize efficiency subject to minimize the cost of operation). Dincer *et al.* [8] use multi-objective approach for optimization for gas turbine and combined cycle power plant. They indeed energy efficiency and total cost as its objective function. Zhe *et al.* [9] used K-means clustering data mining algorithm to control boiler efficiency.

Heuristic approaches are mainly classified into three major categories. Rule based expert systems are fall under this category, in this knowledge base of domain is coded in form of rules. Soft computing techniques e.g. neural network, evolutionary techniques, fuzzy logic etc, contributes to second category. Among all soft-computing techniques neural network, fuzzy logic and genetic algorithm are popular in optimization of power plants. The third category normally called as hybrid systems which include both first and second categories.

In this paper we presented a data driven computational approach to find optimum mass flow rate of fuel for targeted efficiency, superheat temperature and boiler pressure for different boiler load of Bhilai Steel Plant. To find optimum value we used three heuristic techniques: Neural Network, Genetic algorithm and Regression tree.
This paper is designed in four sections: Section I contributed to the introduction. Section II includes the thermal modeling of boiler and formulation problem statement. Section III includes introduction about heuristic techniques. Finally last

section IV includes result and conclusion part of the paper.

2. Thermal Modeling of Boiler

In order to model thermal efficiency of boiler we must be familiar with controllable and non-controllable variables. Feed water temperature, superheated water temperature, pressure in boiler drum, boiler load, water consumption, flue gasses concentration rate, mass of fuel low rate are taken as controllable variables. Whereas boiler constraints like drum radius, boiler's surface etc, and fuels properties, boiler room temperature and humidity etc are taken as non-controllable variables.

According to first law of thermodynamics mass balance equation as follows

$$\Sigma\ \dot{m}_i = \Sigma\ \dot{m}_e \quad (1)$$

Energy balance equation

$$\dot{Q} - \dot{w} = \Sigma\ \dot{m}_e h_e - \Sigma \dot{m}_i h_i \quad (2)$$

Subscripts *i and e* stands entering and leaving the control volume respectively.

The performance index of boiler is defined by its evaporation capacity. However equivalent evaporation from feed water at 100°C and converted into dry and saturated steam at 100°C at normal atmospheric pressure.

As the water is already at 100°C, it requires only latent heat at 1.013 bar to convert it into steam at 100°C. The value of latent heat is taken at 2257kJ/kg [10].

Equivalent evaporation "from and at 100°C",

$$E = \frac{Totalheatrequiredtoevaporatedfeedwater}{2257} \quad (3)$$

t_1 = Temperature of feed water in °C

h_{f_1} =Enthalpy or sensible heat of feed water in kJ/kg of steam corresponding to t_1 °C.

h = Enthalpy or total heat of steam kJ/kg of steam corresponding to a given working pressure (from steam table)

$$h = h_f + x\ h_{fg} \text{ ….. (For wet steam)} \quad (4)$$

$$h = h_f + h_{fg} \text{ ….. (For dry steam)} \quad (5)$$

$$= h_g + c_p\ (\ t_{sup} - t\ ) \quad (6)$$

Boiler efficiency may be defined as the ratio of heat actually used in producing steam to the heat librated in the furnace. It can be shown as follows:

$$\eta = \frac{\text{Heat actually used in producing steam}}{\text{Heat labirated in the furnace}}$$

m_e = mass of water actually evaporated kg/kg of fuel

m_s = Total mass of water evaporated into steam in kg

C =Calorific value of fuel in kJ/kg of fuel.

m_f =Mass of fuel in kg.

So,

$$\eta = \frac{m_s(h - h_{f1})}{m_f \times C} \quad (7)$$

The efficiency of boiler is defined in equation no. 7 is taken as first objective function for genetic algorithm and cost of fuel i.e. wealth cost of fuel per standard quantity as second objective function.

Problem statement from running boiler of Bhilai Steel Plant at 630 hrs-730hrs :

Feed water temp=109°C
Temperature of super-steam=450°C
Pressure in Boiler Drum=40 kgms/cm^2
Boiler load =140Ton/hr
Feed Water Pressure=53kgms/cm^2
Water Consumption=24(L) 115 (R) Ton/hr
No's of coal dust burner=6 of (6Ton/hr)
No's of oil burner=2 of (2 kiloliter/hr)
Blast Furnace gas=60000 M^3/hr
CO gas=8000 M^3/hr

Fuel	Calorific Value
Blast Furnace Gas (BFG)	900 to 1100 cal per NM^3
Coke Oven Gas (COG)	400 to 4500 cal per NM^3
Basic Oxygen Furnace Gas (BOFG)	2,000 kcal per Nm^3
PCM Oil	8500 Kcal per Kg

Till now we restricted our research only to BFG and COG. For calculation c_p (specific heat of superheated steam) is taken as 2.1. kJ/kg K.:
Mass of water evaporated m_s = 140 Ton or 140000 kg.
Mass of fuel used m_f = (60000 M^3/hr (BFG) and 8000 M^3/hr (COG).
From steam table, corresponding to a feed water temperature of 100°C:
h_{f_1} = 419.1 kJ/kg.
At corresponding to a steam pressure of 39.2266bar
h_g =2800.4 kJ/kg at 250°C
So, total heat required:

$$h_{sup} = h_g + c_p\ (\ t_{sup} - t\ ) = 2800.4 + 2.1x(450-250)$$
$$= 3220.4 \text{ kJ/kg}$$

3. Heuristic Techniques

3.1 Genetic Algorithm

Multi-objective optimization problem consists of optimizing more than one objective function with equality, non-equality constraints simultaneously. The solution of multi-objective problem requires satisfactory solution of number of objective function and often conflicting objectives. It is point to note that no combination of variables can optimize all objectives simultaneously. Moreover it provides best trade-off between all the objectives.
The problem can be expressed as :

Find

$$x = (x_i) \forall i = 1, 2, 3 \ldots\ldots\ldots. N_{param} \text{ such as}$$

$$f_i \text{ is minimum (respectively maximum)}$$

$$\forall i = 1, 2, 3 \ldots\ldots\ldots\ldots N_{obj}$$

subjected to:

.

$$g_j(x) = 0 \forall j = 1, 2, \ldots\ldots\ldots\ldots\ldots M$$

$$h_k \leq 0 \forall k = 1, 2, \ldots\ldots\ldots\ldots\ldots\ldots\ldots K$$

Where x is vector containing the N_{parm} design parameters, $(f_i)_{i=1,\ldots\ldots N_{obj}}$ the objective function and N_{obj} the number of objectives. The objective function $(f_i)_{i=1,\ldots\ldots N_{obj}}$ returns the vector containing the set of N_{obj} values associated with the elementary objective to be optimized simultaneously.

As defined by Deb and Goel [10], an individual X(a) is said to constrain-dominate an individual X(b), if any of the following conditions are true:

(1) X(a) and X(b) are feasible, with

(a) X(a) is no worse than X(b) in all objective, and

(b) X(a) is strictly better than X(b) in at least one objective.

(2) X(a) is feasible while individual X(b) is not.

(3) X(a) and X(b) are both infeasible, but X(a) has a smaller constraint violation.

Here, the constraint violation l(X) of an individual X is defined to be equal to the sum of the violated constraint function values

$$l(X) = \sum_{j=1}^{B} \gamma(g_j(X)) g_j(X)$$

where γ is the Heaviside step function. A set of non-dominated individuals is used to form a Pareto-optimal fronts.

Tournament selection

Each individual competes in exactly two tournaments with randomly selected individuals, a procedure which imitates survival of the fittest in nature.

Controlled elitism sorting

To preserve diversity, the influence of elitism is controlled by choosing the number of individuals from each subpopulation, according to the geometric distribution.

To form a parent search population, P(t+1)(t denote the generation), of size S, where 0 < c < 1 and w is the total number of ranked non-dominated.

Crowding distance

The crowding distance metric proposed by Deb and Goel [10] is utilized, where the crowding distance of an individual is the perimeter of the rectangle with its nearest neighbors at diagonally opposite corners. So, if individual X(a) and individual X(b) have same rank, each one has a larger crowding distance is better.

Crossover and mutation

Uniform crossover and random uniform mutation are employed to obtain the offspring population, Qt+1.The integer-based uniform crossover operator takes two distinct parent individuals and interchanges each corresponding binary bits with a probability, 0 < pc ≤ 1. Following crossover, the mutation operator changes each of the binary bits with a mutation probability, 0 < pm < 0.5.

3.2 Artificial Neural Networks

The feed-forward neural networks are the most popular architectures due to their structural flexibility, good representational capabilities and availability of a large number of training algorithms. Here the individual element inputs are $I_1, I_2, \ldots\ldots\ldots\ldots I_R$ multiplied by weights w_{11}, $w_{12}, \ldots.. w_{1R}$ and the weighted values are fed the summing junction. The neuron has a bias b, which is summed with the weighted inputs to form the net input n. This sum, n, is the argument of the transfer function F:

$$a = F(n) = F(w_{11}l_1 + w_{12}l_2 + \ldots\ldots\ldots\ldots\ldots. + w_{1R}l_R + b)$$

This network consists of neurons arranged in layers in which every neuron is connected to all neurons of the next layer.

3.3 Regression Tress

Multivariate regression analysis is widely accepted tool according to Drapper and Smith [11] traces back to back work of SIR Francis Galton a British anthropologist and meteorologist. Regression analysis can be loosely defined as application of methods that investigate the relationship between a dependent (or response) variable and set of independent variable (or predictor) variables.

Linear regression is a global model, where there is a single predictive formula holding over the entire data-space. When the data has lots of features which interact in complicated, nonlinear ways, assembling a single global model can be very difficult and hopelessly confusing when you do succeed. An alternative approach to nonlinear regression is to sub-divide, or partition, the space into smaller regions, where the interactions are more manageable.

4. Result & Conclusion

Optimization:

In this paper total boiler efficiency and fuel cost has taken as two objective functions. The efficiency is defined by equation (7). And cost of fuels is modeled by equation as

$$\cos t_{fu\ l} = c_1 m_{f1} + c_2 m_{f2} + c_3 m_{f3} + c_4 m_{f4} \qquad (8)$$

Where c_1, c_2, c_3, c_4 is the cost of fuels and $m_{f1}, m_{f2}, m_{f3}, m_{f4}$ is the mass flow rate of fuel.

Defining multi-objective problem as Pareto problem we minimize the cost of fuel and maximize the efficiency subjected to:

Super-heat temperature=450°C.

Boiler pressure =40kgms/cm^2.

Boiler load =140 Ton/hr.

Artificial Neural Network:

In this paper data mining prediction approach is utilized to model the boiler combustion cycle. Time invariant combustion process is expressed as input-output model Y=f(X), where X is the vector of controllable and non-controllable variables and Y is the output of plant.

Controllable variables include feed water temperature, water consumption, and fuel consumption. Non-controllable variables include boiler room temperature, humidity, and calorific value of fuel. Thus Y=f(feed water temperature, water consumption, and fuel consumption, boiler room temperature, humidity, boiler load and calorific value of fuel). And Y= super-heat temperature, constant boiler pressure, and maximum efficiency.

Efficiency is set to 87.5% to 90%, super-heat temperature at 450℃ and boiler pressure at 40kgms/cm^2

We first train feed forward 20 neurons neural network with thousand data, after training the neural network we test our neural network with 100 test data.

Conclusion:

We have compared the multi-objective optimization problem with three heuristic approaches Genetic algorithm, artificial neural network and regression tree. We have considered feed water temperature, feed water pressure, boiler pressure, boiler load, water consumption, fuel consumption as design variable to achieve targeted super-heat steam temperature and pressure. It should be noted that the data mining approach using ANN produce minimum mean square error.

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