Multilevel Optimization of Boiler Performance using Genetic Modeling

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Abstract: The complexity exists almost in all the industrial applications to determine the optimal solution and predict how the solution behaves for the changes in the operational parameters. The engineering process problem will have a large no. of solutions out of which some are feasible and some are infeasible solutions. The aim of optimizing task is to get the best solution out of the feasible solutions set. The solution space contains the complete set of feasible solutions and optimization involves some kind of search with in the space. In both the cases of stochastic and deterministic searching methods it is possible to enhance the performance by judicious operating procedure. In this paper, first section represents the implementation of K-means clustering method by considering hydrogen, ratio of hydrogen and gross calorific value along with its corresponding loss. The resultant clustering patterns were analysed with the objective of achieving linearity. The second section demonstrates implementation of genetic algorithm to perform multilevel optimization and results that overcome the intricacy produced by K-Means over boiler samples.

Keywords: *K –Means, Boiler, Efficiency, Optimization ,Loss , optimal solution*

I. Introduction

The optimization of the boiler process is multi objective in nature, since it has several objectives that must be satisfied at the same time. The performance of the system depends on large number of different criteria, which are often conflicting. So solving such kind of problem is accompanied with difficulties starting with the way of formulating the objective function and continuing with the choice of working procedure and selection of the results from more possible options.

Process optimization is the discipline of adjusting a process so as to optimize some specific set of parameters without violating some constraint. The most common revised goals are minimizing cost, maximizing throughput, and efficiency. This is one of the major quantitative tools in industrial decision making.

When optimizing a process, the goal of the process is to maximize one or more of the process specifications while keeping all others within their constraints. Operating procedure vary widely from person to person or from shift to shift. Automation of the plant will help significantly. But automation will be of no help if the operators take control and run the plant in manual.

In a power plant, the overall performance depends on the efficiency of various components, in that the boiler efficiency plays vital role because its process execute with the constituents present in the fuel. The need arises to enhance boiler efficiency when there is an increase in the demand [1].

The primary objective of most boiler operations is maintaining availability or uptime. Many facilities have more than one boiler on site running parallel. It is essential to maintain and upgrade the boiler control systems to assure steam availability. Modern control strategies are reliable more and can readily adjust to load swings caused by varying overall plant operations.

The need for optimization is to improve combustion efficiency to reduce fuel consumption by reducing excess air, reducing engineering, installation and start up costs, reduce maintenance cost associated with older, less reliable equipment, reduce manpower requirements by automatically responding to load changes, provide flexible control strategy to reduce or eliminate process upsets and to make data available for remote monitoring to determine process unit optimization, boiler efficiency and load allocation.

The optimization of boiler process needs detailed information and data about the actual operating conditions. Modern process control systems utilize computers to collect and store data as well as to control the actual process conditions. These control systems report the actually measured process values in the plant as well as time behaviour of these values.

It is essential to monitor the efficiency periodically especially in large power plants. Boiler Efficiency is affected by various factors such as poor water treatment, high flue gas temperature, low quality fuel, too much excess air, low feed water supply temperature, low combustion- air supply temperature, radiant heat loss, conduction heat loss, poor combustion,operation at low or cyclic loads and poor controls. Because of this various complex factors, it is highly difficult for the operators to identify the root cause of deviation in boiler efficiency.

Data mining has been used as essential approach to performance monitoring and fault diagnosis of power plant components. Various mining techniques accuracy were compared and highlighted the best one suited for industrial applications [2] [4].

Clustering methods were suitable for any application for decomposing the large dataset into manageable parts that contain similar group of instance in which each cluster is dominated by different clusters [3].Most of the Researchers those who are interested in clustering are implementing the clustering method based on the steps associated with it. They are visualizing the resultant cluster and concluding any one category to be the best among others simply by taking the minimum of some mathematical criteria.

Here the significance of the clustering was not clear. If we considered that best cluster and implement variable scaling it shows that the expected output of the particular application was not an expected one and it deviates some where. So it is not possible to consider the parameter values in the selected best cluster for doing optimization. It is highly tedious to apply such kind of implemented methodology for power plant efficiency optimization process.

Effectiveness of neural network model with evolutionary computation for performance optimization which includes parameter selection , model building and evaluation are demonstrated [5].

Genetic algorithms are being computerized search and optimization technique based on the principles of natural genetics and natural selection. Genetic algorithm (GA) proves its success in many fields like computer science, image processing, physical science, neural networks etc.The aim of GA is make the objective function either maximum or minimum that is required to find an element E_0 if it exist s such as

$F(E_0) <= F(E)$ for minimization.

$F(E) <= F(E_0)$ for maximization

II. Application Background

The problem defined in this paper is to provide guidelines to the operator by calculating various losses and possible deviations to improve boiler efficiency. The process values are decomposed between controllable, non-controllable and response variables. The guidelines helps the operator to predict the response variables such as load, efficiency, heat rate etc., with the help of controllable and non-controllable parameters.

The non-controllable parameters such as carbon, hydrogen, sulphur, nitrogen, ash etc., are fuel dependent. The operator cannot have the control over the losses generated because of the above specified parameters. Operator can control only the controllable parameters such as air, temperature etc., with the help of the interface.

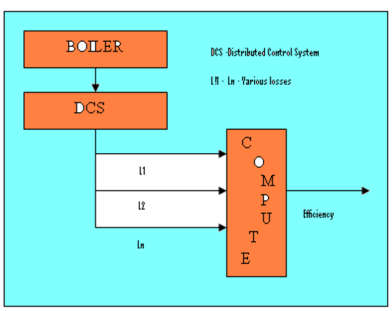


Fig. 1 Efficiency calculation process

In a power plant the boiler run time data was collected periodically at specific interval using various sensor devices. The large volume of data was recorded in DCS for future analysis. The data from DCS are fetched and used by various data mining techniques and algorithms in order to perform analysis on optimization of boiler process and also to identify the root cause which act as an important factor resulting in reducing the efficiency. Data Mining techniques provide various advantages in optimizing boiler efficiency by considering multiple parameters and generating accurate results. With the help of fetched historical data from DCS the specified losses (such as L1. L2 - - - - Ln) are calculated by using appropriate formulas. The total losses are identified by the summation of all the losses.

$$L = \sum_{i=1}^{n} L_i$$

The efficiency is calculated as

$$\text{Efficiency } (\eta) = 100 - L$$

The losses occurred due to fuel dependent parameters are not under the control of humans. When attempting to perform optimization, it is understood some losses cannot be controllable, but it is possible to generate an algorithm which provides the online help to the operator by representing the reason for the loss and deviation. By that the operator can understand the causes instead of evaluating the output.

Boiler efficiency evaluation using direct method needs to analyse few parameters and essential components. The speed of computation is high but does not give deviation alert information during boiler execution results in low efficiency. It does not calculate various losses accountable for various efficiency levels. The indirect method requires the in depth knowledge about more parameters which have more impact on effecting efficiency level due to its loss value [1].

The minimum error rate in indirect method cannot affect the output efficiency. But in direct method the minimum error rate can also affect the overall output efficiency. When performing comparative study on both methods we select the indirect method is best in terms of accuracy by gaining knowledge about the deviation in efficiency.

III K-Means Clustering method

The formatted dataset that consist of selected variables with appropriate values are passed to clustering algorithm. The K-means clustering algorithm learns the input values, process required computation and generates new knowledge or patterns

The cluster analysis is to decompose or partition the dataset into groups so that the data points in one group are similar to each other and are as different as possible from the data points in other groups. The K-Means clustering algorithm is categorized under partitioned clustering method and well suited for large amount of numeric data and easy to implement. We have n data points D={ x1,x2……xn} and the problem is to find k clusters { c1,c2….ck}.The basic idea is to begin with randomly chosen n data points as centroids and k number of clusters. Assigning each point to the cluster whose mean is closest in a Euclidean distance, then computing the mean vectors of the points assigned to each cluster and using the new centroids in an iterative approach.

Steps in K-means

1. Consider the training data set with n data points, select initial centroids and number of clusters.
2. Form k clusters by assigning each data point to its closest centroid.
3. After all data points are assigned, recompute each centroid based on the instances appeared in the clusters.
4. Perform step2and 3 iteratively until the centroids remains same.
5. Visualize the final centroid and the resultant cluster.

IV. RESULTS AND DISCUSSION

The process of selecting the suitable variable is the primary task when dealing with high dimensional problems. Consider for example the problem of predicting the response variable A using multiple input variables like {B1,B2,……Bn}.some b variables may be completely unessential to the response variable A (i.e) denoted as If P(A|B1,B2) =P(B2) then A is independent of B1 if the value of B2 is already known. It is highly difficult to identify from a finite sample which variables are independent and which are not, we must estimate the effect. It is not most important to identify the degree of dependence instead of specify dependency or independency.

Consider hydrogen and its loss alone for obtaining meaningful patterns as a result of implementing K-means clustering.

A. Implementation of K-means Clustering using Hydrogen and its loss:

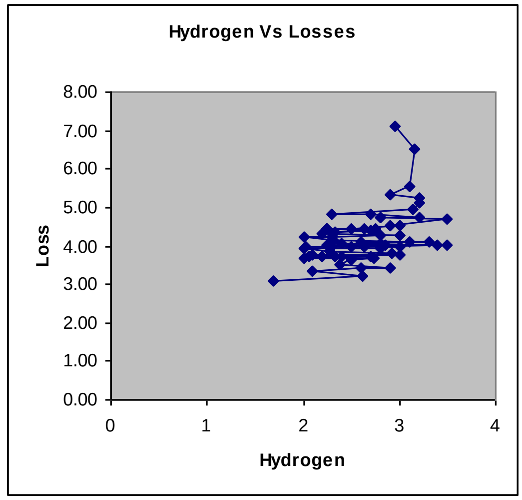
Clusters are formed with all the losses along with its associated efficiency. The useful information is not obtained in the resultant pattern. With the aim of identifying meaningful information for enhancing boiler efficiency the K-means clustering method was implemented with different fuel dependent parameters with its corresponding losses. The different cluster pairs are denoted as

i) Hydrogen with its loss.
ii) Carbon with its loss.
iii) Moisture in fuel with its loss.
iv) Moisture in air with its loss.
v) Bottom ash with its loss.
vi) Fly ash with its loss.

When analysing the resultant patterns of all the cluster pairs it shows the non linear relationship. hydrogen and its loss is described below.

In the first iteration, among 67 instances only six points{ D6, D9, D40 ,D43, D64, D67}were considered as centroids randomly, using Euclidean distance ,the distance between each centroids with all other instances were calculated and each instances are partitioned among various destination cluster based on the The steps followed to form clusters with minimum distance. Then, calculate the mean value based on the instances in each cluster in order to update the centroids.

After seventh iteration, the centroids in the resultant cluster remains constant and all the data points were fall into six clusters. when analyzing the patterns obtained in each cluster it was understood that the non linear relationship exist between hydrogen and its loss. Clusters 1,3,4 contains few instances that will not result in any inference .so the clusters were neglected from analysis. Clusters 2,5,6 more or less equal number of instances. When performing ultimate analysis on the patterns in different clusters , it was clearly understood that only 25% of difference exist between them and results in non linear relationship. The non linear relationship was shown below:



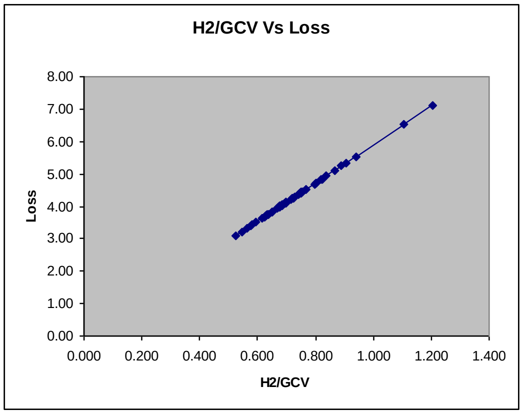
b. Implementation of K-means clustering using the ratio of Hydrogen and GCV with its loss:

With the aim of achieving linearity between fuel dependent parameters with its loss the ratio between individual parameter and GCV was calculated and considered that as an major input along with their losses for clustering. The new cluster pair is obtained after calculating the ratio are represented below:

i) Hydrogen and GCV with its loss.
ii) Carbon and GCV with its loss.
iii) Moisture in fuel and GCV with its loss.
iv) Moisture in air and GCVwith its loss.
v) Bottom ash and GCV with its loss.
vi) Fly ash and GCV with its loss.

After completing the analysis of resultant patterns of different cluster pairs, it clearly shows the existence of linear relationship. The steps followed to form clusters with the ratio of hydrogen and GCV along with its loss is described below. The same procedure as in Implementation I , the clustering was done.

After ninth iteration, the centroids in the resultant cluster remains constant and all the data points were fall into six clusters. when analyzing the final result it was understood that the linear relationship exist between the ratio of hydrogen and GCV with its loss. Clusters 1,3,4 contains few instances that will not result in any inference .so the clusters were neglected from analysis. Clusters 2,5,6 more or less equal number of instances. When performing ultimate analysis on the patterns in different clusters , it was clearly understood that only 5% of difference exist between them and result in linear relationship. The linear relationship was shown below:



This analysis shows that the ratio of hydrogen and GCV becomes constant and this act as a cause for linearity. Various losses were calculated in order to compute efficiency of the boiler by using indirect method. After analysing the patterns obtained in clustering method, it is possible to state that non linear relationship exist between the fuel dependent losses(hydrogen) and linear relationship exist only if we make the value of the fuel dependent variable to be a constant one. The significance of the cluster instance with linear relations was not clear in taking operational decision to generate new set points for various loss attributes with the intent of minimising losses and maximising boiler efficiency.

III. IMPLEMENTATION OF GENETIC INHERITANCE OPERATOR

Genetic algorithms are well suited for maximization problems. In case of minimization problem there is a need of converting that to maximization is essential. The important aspect of GA is as follows:

- Determining objective function
- Defining genetic representation
- Selecting genetic inheritance operator

Among various genetic inheritance operator selection, crossover and mutation are responsible for performing meaningful transformation to reach optimal solution. Selection operator is the one that ensures survival of the fittest chromosomes. Crossover generates new offspring by inheriting the features from each pair of parents. Mutation is an continuous change made to each individual of the member or new feature added into the population.

Genetic algorithm started with a set of solutions represented by chromosomes called populations. Each individual in the populations represent some potential solutions. Fitness value for each population is calculated and based on the maximum fittest criteria, that population is selected to form a new population that is also called as creation of offspring. The selected population is having the capability to reproduce better solutions after some suitable transformations. The iteration terminates when suitable condition for obtaining best solutions are reached [7].

The aim of optimizing boiler process is to minimize the possible losses with the intent of maximizing efficiency. Sequential execution of each process (reproduction, crossover and mutation) is must to achieve the objective of finding best optimal solutions.

The boiler dataset with sample instances were referred from [2].

The implementation steps in each level are clearly specified as follows:

- Reproduction of best individual
- Cross over between reproduced parents
- Select best offspring after cross over
- Mutated with minimum attribute value
- Repeat until termination criteria arise.

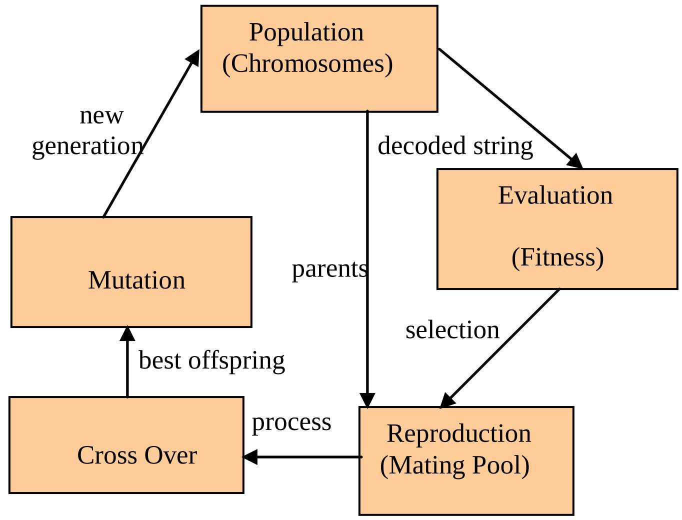


Fig : Implementation task in each levels.

Consider the population of n size with losses and its efficiency (here n=10).

- Reproduction or selection operator is initially applied on the population. Chromosomes are selected from the population to be parents to cross over and produce offspring. Based on the principle stated on steady state method five different pairs of populations like { set1,set2,set3,set4,set5 } were selected.
- Uniform cross over operation was permed on each set of selected populations independently. Cross over process is termed as higher order transformation creates new individuals by combining parts of several individuals.

$$C_j = s * \ldots..*s \;\text{->}\; S$$

- Boundary type of mutation operation was applied on the result obtained during cross over to find out optimized solutions on independent pair. Mutation process creates new individuals by a small change in a single individual and termed as unary transformation.

$$M_i = S \text{->} s$$

- Generate new population set by combining all the optimized solutions {1, 2, 3, and 4}.
- Perform cross over and mutation on the newly generated sets until iteration reaches unique feasible solution.
- Display the obtained optimal solution.
- Generate new control settings with obtained set points to enhance performance of boiler process.

IV. MULTILEVEL OPTIMIZATION

Parent 1						Off Spring 1					
6.75	6.25	2.34	0.21	0.64	2.01	6.75	6.39	2.34	1.65	0.64	1.5
Parent 2						**Off Spring 2**					
8.19	6.39	4.17	1.65	0.76	1.5	8.19	6.25	4.17	0.21	0.76	2.01

The dataset contains various losses as attributes. Initially maximum and minimum possible values among the samples are identified for each attributes. In order to reach the objective, the minimum value will be considered as best mutants in each iteration and replace the largest value. The aim of proposed genetic model is to generate new set points with optimized solution. The multilevel optimization is specified below as:

Level 1: With the initial reproduced sets(s1,s2,s3,s4,s5) with efficiency of (81.8, 77.32 , 72.78 .71.68 .70.74) and genetic model obtains four set of possible optimized solutions.

The minimum and maximum value for each attribute from the obtained samples are denoted as, A(5.72,19.88), B(5.12,6.88), C(2.34,14.78), D(0,4.34), E(0.9.89), F(1.5,3.08) and for efficiency (61,81.8). The ultimate aim is to minimize the losses and maximize the boiler process efficiency as much as possible. The minimal value of the parameters is considered as constrained mutants to perform mutation operation. In each levels of optimization cross over and mutation was implemented according to the processing procedure.

The selected parents are capable of producing new offspring, after crossover the best offspring is selected and evaluated with its parents. It is not possible to assure that the generated offspring results in optimal solution in some occasion it deviates. In order to attain optimized solution the parameter value that causes deviation should be identified and apply mutation over that. Mutants are considered depending upon the objective function either to be maximized or minimized. In each level of optimization after crossover is over apply mutation over deviated parameter value. In boiler process optimization the objective is to minimize the losses.

Level 2: Genetic model performs optimization process on the (best offspring) result generated in level 1 (81.76, 77.64, 77.12 .78.37) and produced three set of optimized solutions.

Level 3: Process continues over the resultant set obtained in level 2 (81.06, 79.93 .80.33) and generates two set of optimized solutions.

Level 4: The unique optimized solution is obtained with the results retrieved from level 3 (82.89, 83.54).

Level 5: Unique solution (84.54) is analyzed and the largest attribute value (L6) 2.5 is replaced with its minimum mutant value 1.5 and proves the efficiency maximized to 85.32%.

In each level of optimization the best selected offspring is evaluated against its source parents (chromosomes) to ensure its optimality. If the response attribute of the offspring is lower than its parents the process terminates and selected offspring is ignored by stating as not capable for new generation and parents will remove from the pool. If the response attribute of the offspring is greater its optimality is proved and new generation proceeds with other offspring.

Optimization of any application comprising of numerous attributes is a challenging problem due to its huge size of search space. Multilevel optimization is implemented and proved to eliminate the effect of the above specified draw back. This proposed approach reducing the size of the search space for individual attributes in each successive level of the optimization process.

In this approach an initial optimization is carried out with an original set used by all the selected attributes. Then the optimizing technique automatically divides the original set into several subsets. Next level optimization begins on more restricted regions of the search space. The process continues in the similar manner by dividing the considered subset into new subsets and directing the specific attribute to the most appropriate search space. The new set points for attributes { L1, L2 , L3 ,L4 ,L5 , L6} are { 5.72 , 5.12 , 2.34 , 0 , 0 ,1.5 } from the initial boiler samples.

Among the selected attribute here L1 is identified as loss with maximum value with in the samples. Offspring 1 is selected as best with respect to the boiler efficiency and 6.75 is mutated with 5.72.

Parent 1						Off Spring 1					
9.2	5.12	4.1	4.34	2.23	2.23	9.2	6.55	4.1	1.78	2.23	2.25
Parent 2						**Off Spring 2**					
10.34	6.55	6.25	1.78	0.9	2.5	10.34	5.12	6.25	4.34	0.9	2.23

Offspring 2 is selected as best with respect to the boiler efficiency and 9.2 is mutated with 5.72.

Parent 1						Off Spring 1					
8.19	6.39	4.17	1.65	0.78	1.5	8.19	5.12	4.17	4.34	0.78	2.23
Parent 2						**Off Spring 2**					
9.2	5.12	4.1	4.34	2.23	2.23	9.2	6.39	4.1	1.65	2.23	1.5

Offspring 1 is selected as best with respect to the boiler efficiency and 9.2 is mutated with 5.72.

Parent 1						Off Spring 1					
10.34	6.55	6.25	1.78	0.9	2.25	10.34	6.26	6.25	0	0.9	2.5
Parent 2						**Off Spring 2**					
5.72	6.26	14.78	0	0	2.5	5.72	6.55	14.78	1.78	0	2.25

Offspring 1 is selected as best with respect to the boiler efficiency and 10.34 is mutated with 5.72.

Computation Level 1

Parent 1						Off Spring 1					
5.72	6.39	2.34	1.65	0.64	1.5	5.72	5.12	2.34	4.34	0.64	2.23
Parent 2						**Off Spring 2**					
5.72	5.12	4.17	4.34	0.78	2.23	5.72	6.39	4.17	1.65	0.78	1.5

Among the selected attribute here L2 is identified as loss with maximum value with in the samples. Offspring 2 is selected as best with respect to the boiler efficiency and 6.39 is mutated with 5.12.

Parent 1						Off Spring 1					
5.72	5.12	4.17	4.34	0.78	2.23	5.72	6.55	4.17	1.78	0.78	2.5
Parent 2						**Off Spring 2**					
5.72	6.55	4.1	1.78	2.23	2.5	5.72	5.12	4.1	4.34	2.23	2.23

Offspring 1 is selected as best with respect to the boiler efficiency and 6.55 is mutated with 5.12.

Parent 1						Off Spring 1					
5.72	6.55	4.1	1.78	2.23	2.5	5.72	6.26	4.1	0	2.23	2.5
Parent 2						**Off Spring 2**					
5.72	6.26	6.25	0	0.9	2.5	5.72	6.55	6.25	1.78	0.9	2.5

Offspring 1 is selected as best with respect to the boiler efficiency and 6.26 is mutated with 5.12.

Computation Level 2

Parent 1						Off Spring 1					
5.72	5.12	4.17	1.65	0.78	1.5	5.72	5.12	4.17	1.78	0.78	2.5
Parent 2						**Off Spring 2**					
5.72	5.12	4.17	1.78	0.78	2.5	5.72	5.12	4.17	1.65	0.78	1.5

Among the selected attribute here L3 is identified as loss with maximum value with in the samples. Offspring 2 is selected as best with respect to the boiler efficiency and 4.17 is mutated with 2.34.

Parent 1						Off Spring 1					
5.72	5.12	4.17	1.78	0.78	2.5	5.72	5.12	4.17	0	0.78	2.5
Parent 2						**Off Spring 2**					
5.72	5.12	4.1	0	2.23	2.5	5.72	5.12	4.1	1.78	2.23	2.5

Offspring 1 is selected as best with respect to the boiler efficiency and 4.17 is mutated with 2.34.

Computation Level 3

Parent 1						Off Spring 1					
5.72	5.12	2.34	1.65	0.78	1.5	5.72	5.12	2.34	0	0.78	2.5
Parent 2						**Off Spring 2**					
5.72	5.12	2.34	0	0.78	2.5	5.72	5.12	2.34	1.65	0.78	1.5

Among the selected attribute here L5 is identified as loss with maximum value with in the samples. Offspring 1 is selected as best with respect to the boiler efficiency and 0.78 is mutated with 0.

Computation Level 4

V. RESULTS AND DISCUSSIONS

The below table representation shows the result obtained in multilevel optimization includes cross over and mutation operation.

81.8	77.32	72.78	71.68	70.74
Level 1	81.76	77.64	77.12	78.37
After Cross Over& Mutation	Level2	81.06	79.93	80.33
		Level 3	82.89	83.54
			Level 4	84.32
			Level 5	85.32

Fig : Multilevel optimization solutions

When examining the independent losses it shows that it occurs due to the fuel constituents and intermediate process. The fuel dependent operational parameters make the losses unpredictable and uncontrollable. It is highly tedious to compute and identify the set points with the combination of all the losses. Thus the resultant optimal solution proves that newly obtained loss values can be considered as standard set points for future process. The new set point arises as a result of multilevel optimization can be considered as a base to evaluate the actual.

Genetic algorithm has sustainable history and range of use. It is inherently parallel and easily distributed. It is modular, separate from application and easy to understand. It is suitable for the situation that needs an exploratory tool to examine new approaches.

CONCLUSION

The K-Means clustering method has been implemented with fuel dependent parameters such as carbon, hydrogen, sulphur etc and its constant values obtained using gross calorific values. The resultant patterns of two categories were analyzed to measure the consequences. The objective of maximizing boiler efficiency and minimizing various indirect losses were achieved by implementing genetic inheritance operators. Explicitly the mutant selection criterion was specified based on the requirement expected for performance enhancement of the application. The resultant optimal solution obtained after several levels of optimization performed on identified population set. The optimized solutions shows minimal value of each losses that can be defined as new set points for boiler process.

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