Asian Journal of Information Technology 15 (21): 4165-4173, 2016
ISSN: 1682-3915
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Multiple Regression Analysis on Thermal Power Plant Components Leading to Estimation of Heat Absorption

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Abstract: The objective of the proposed work is topredict the heat absorption pattern of boiler elements through multiple linear regression analysis. This regression analysis determines the correlation exist between the operational parameters such as coal flow and burner tilt with related to heat absorption. The different regression co efficient were derived and used for prediction. Through regression model, the heat absorption for all thermal components is predicted. The prediction was performed for three different grades of coal with varying loads. The predicted values are evaluated by comparing it with optimal values for determining its accuracy. The regression results that representing the predicted value, targeted value and error rate are visualized independently for all coal fired boiler components.

Key words: Multiple regression, heat Absorption, boiler elements, regression model, regression analysis

INTRODUCTION

Thermal power sectors are demanded to perform boiler combustion optimization to improve power plant efficiency and fuel consumption. Infinite numbers of optimizing methods are emerging but the analytical models are proven as a powerful methodology. An analytical model provides meaningful information that guides to support in decision making process. An analytical model helps to define performance metric of a complex systems.

Boiler combustion process needs to be optimized with appropriate technique frequently with suitable operational parameters (Wu *et al.*, 2014). Data drivenmethods are stated as the process of extracting hidden patterns as well as predicting trends from large volume of data by generating repeated queries. Visualization techniques makes visual understanding of data, patterns and trends from the emission of leading thermal power plant (MdFazullulas and Ready, 2014).

The various factors result in producing disturbances, that affects the performance improvement of power generation sector are listed as technical change, technical efficiency change in-stability in manpower, political intervention, unplanned operation, scale change and the process result in major errors (Fatima and Barik, 2012). All the evolutionary computing techniques are having capability to optimize complex systems with selected variables and exhibit similarities and difference with each other based on the application domain (Kachitvichyanukul, 2012). The general objective of evolutionary methods is defined in terms of common characteristics and its differences are summarized based on computational procedures with respect to independent algorithms (Malhotra *et al.*, 2011).

Data extracting algorithms are employed to construct predictive models suitable to perform fault diagnosis prediction, specific fault prediction and identification on unseen faults. Robustness of the model is validated for faults that have occurred on turbines with hidden data (Kusiak and Verma, 2012). The relationship between energy consumption and power plant process procedures are measured with some crucial operational parameters. Standard control settings derived from optimization of the model that minimizes the consumption at an accepted level. Optimization approach provides feasible solutions with different preferences (Kusiak and Verma, 2011, 2012).

The applications of datamining techniques for identification and prediction of status patterns in wind turbines are confidently presented. A prediction model was built using operational and status data collected at working environment and different analyzing technique were applied to derive required patterns (Kusaik and Varma, 2011). Power optimization objective is accomplished by computing optimal control settings of wind turbines using data mining and evolutionary algorithm strategies. Computational study included major operational parameter needed to perform optimization (Kusiak *et al.*, 2010a, b). Power system state monitoring

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and fault diagnosis application with high volume of operational data through data mining analysis and reasoning algorithms proved with method fitness to help and improve decision support process in all power plant aspects (YueShun and QiuLin, 2009).

Hybrid combination of evolutionary computation, data mining and model predictive control forms a new framework to provide more exact dynamic information about operational process. Research suggested focusing on multi objective optimization where more performance related variables to be considered. Data mining approach is highly suitable for predicting best patterns applied to execute optimization of boiler process. Analysis reported that the importance of a particular operational variable is not stable. The value of each variable depends on number of factors in different period of times (Kusiak and Song, 2008; Song and Kusiak, 2007; Kusiak and Zhe, 2006).

Data mining clustering algorithm were applied to generate control signatures from the sample instances to improve combustion efficiency. Neural network model were used to validate the boiler efficiency by using control signatures. Virtual testing procedure overcomes the complexities such as cost and time exist in real time testing (Kusiak and Song, 2008; Kusiak *et al*., 2010a, b, 2011). The role of evolutionary computing technologies in parameter selection provides guidelines to take well-formed decisions according to the target specified (Trelea, 2003).

The boiler operational variables are categorized into three groups such as controllable, non-controllable and response variable. Always the response variables are correlated with controllable or non-controllable variables. The plant efficiency is defined through response variables. It is essential to identify the relationship exist between operational variables. Only through the ratio of correlated relationship between boiler operational parameters of all thermal components, an attempt can made to enhance plant efficiency. Efficiency are defined through boiler elements.

MATERIALS AND METHODS

Multiple regressions: Regression analysis is a powerful method to perform prediction of unknown value of the variable from the known value of one or more variables. Regression method is classified into various types to solve the difficulties exist in complex systems. The effectiveness of each regression categories are based on the decision made by the user in selecting dependent and independent variables. Multiple regressions is also stated as multiple linear regressions and defined as a mechanism to exhibit the relationships existed between the domain variables.

Let, Y be the dependent variable that need to be predicted from two or more correlated variables, i.e., X_1, X_2, ..., X_n. Here , X_1, X_2,..., X_n are used as predictors and each of its individual impact over the operations are observed by means of regression analysis. In general, the multiple regression model was framed based on the below specified equation structure:

$$Y = po + p1x1 + p2x2 + \dots pnxn$$

Whre:

Y	=	Predicted vriable
$x_1, x_2, \dots x_n$	=	Predictors
P0	=	Intercept (Constant)
$p_1, p_2, \dots pn$	=	Regression cefficients

The general inference derived from the behavior or value of regression coefficients are stated as when there is an increase in the independent variable X_i that cause to have increases in the value of target variable Y also.

Multiple regression method follows certain assumptions, first, it never bothers or examines to determine whether the sampled data is linear or not. It always assumes that relationship exists between Y and X is linear. Second, that Y can predict from multiple independent variables and it is not required that independent variable must relate with each other. This can be evaluated by determining correlation coefficients between each possible pair of independent variables. The basicrepresentation of Y and X is:

$$Y = (y1, y2, \dots \dots \dots, yn)$$
$$X = (x11, x12, \dots x1i)(x21, x22, \dots x2i)$$

Though the multiple regressionsis a powerful methodology, the complexity arises to select the dependent variable among huge collection of variables in a dataset. The decision is purely based on certain conditional assumptions needed to derive a model and select other influenced variables as predictors.The non-optimal combinations of predictors will not result in accurate prediction. If the chosen predictors are really optimal to the operation, then the prediction of actual target variable using multiple regression method is accurate. The prediction outcome of multiple regression analysis supports to design effective model that involves the process of complex systems. The model computes the error rate ε by measuring the difference between predicted variable a (k) and target variable t (k).

$$\varepsilon = t(k) - \alpha(k)$$

Application background: The thermal power plant mainly focuses on the boiler combustion process in defining the

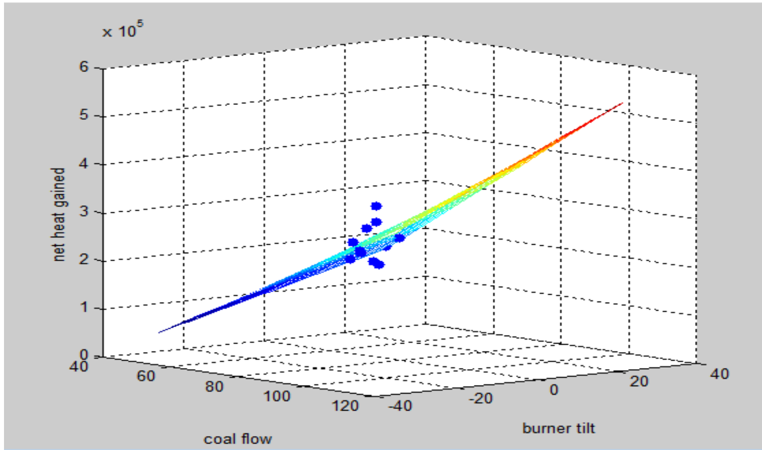

Fig. 1: NHI-correlated relationship

expected outcome of the plant. The overall plant efficiency depends on the efficient contribution of boiler elements. Effective monitoring and enrichment in sub units helps to attain performance improvement. The boiler process unit is comprised intovarious elements based on its functionality. They are integrated with each other through logical process strategies. The boiler components are Water Wall (WW). platen, panel and divisional Super-Heaters (SH), Re-Heater (RH), Primary Air Heater (PAH), Secondary Air Heater (SAH) and Economizer (ECO).

The combustion process is the chemical reaction between coal and oxygen which results in producing heat in the form of steam. Carbon (C) and Hydrogen (H_2) in the coal are burnt with Oxygen (O_2) from the air is expressed in the following equations:

$$\text{Carbon} + \text{Oxygen} = \text{CarbonDioxide} + \text{Heat}$$
$$\text{Hydrogen} + \text{Oxygen} = \text{Water vapour} + \text{Heat}$$

Basically, it is not possible to distribute fixed ratio of fuel and air. This difficulty leads to have an analysis of correlation exist between operational parameters. The boiler elements are functionally depends on each other in the form of input and output flow. The output of one element can become an input to another element. The deviation occurs in the process or outcome of one element will affect the outcome of overall plant.

The combustion process can be graded as perfect, complete and incomplete combustion. The most important reason for incomplete combustion is inadequate coal flow, improper coal sizing inadequate fuel velocity, lack of air leakage control and improper temperature control.

In this proposed work, three different grades of coal (Grade 1-3) with five different levels of load (250, 300, 400, 500 and 550 mW) were used for performing regression analysis and results are visualized. The two most important operational parameters coal flow and burner tilt were considered as independent variables and used to predict the heat absorption pattern of all the boiler elements:

$$X_1 = \text{Coal flow}$$

$$X_2 = \text{Burner tilt}$$

$$Y = \text{Heat absorption}$$

The Y dependent variable is predicted by using two independent variables by deriving appropriate regression coefficients:

$$Y = p0 + (p1 \times x1) + (p2 \times x2) + p4$$

Where:

x_1 and x_2 = Predictors
p_0 = Intercept
p_4 = The negligible error

The Net Heat Input (NHI) is the ratio of total energy input to the unit of the net electrical generation.The unit thermal efficiency is termed as the ratio of the net generator output to the total heat input of the boiler. The optimal values derived for all the boiler units based on the NHI. The derived regression coefficients for all grades of coal for each boiler elements were estimated. Estimated coefficients are used to predict the heat absorption of all boiler elements.

Figure 1 shows the correlated relationship of NHI with coal flow and burner tilt. Table 1 shows the derived regression co-efficient needed to predict heat absorption

Table 1: Regression co-efficient

C_i	P_0	P_1	P_2	P_3
NHI	1.4154	-0.0045	0.0169	-0.0001
WW	5.0503	-0.0175	0.0332	-0.0003
ECO	1.06	-0.0012	0.0247	-0.0002
SH1	1.8053	-0.0127	0.0107	-0.0002
SH23	2.7236	-0.0059	0.0296	0.0000
RH	1.4604	-0.0133	0.026	0.0001
PAH	-1.3153	0.0462	0.1275	-0.0006
SAH	6.5279	-0.0722	0.1028	-0.0006

Table 2: Error rate of heat absorption -250 mw

C_i	T(k)	A(k)	Err
NHI	1.8616	2.2435	-0.3819
WW	5.4245	6.5903	-1.1659
ECO	1.8799	2.3240	-0.4440
SH1	1.7112	2.2309	-0.5197
SH23	3.7859	4.1939	-0.4080
RH	2.2574	2.6708	-0.4135
PAH	5.3117	5.7336	-0.4219
SAH	7.3563	11.1166	-3.7603

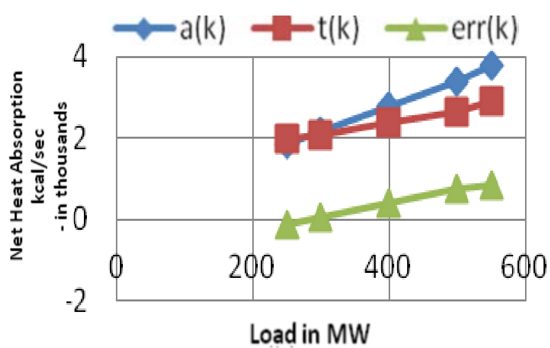

Fig. 2: NHI regression-grade

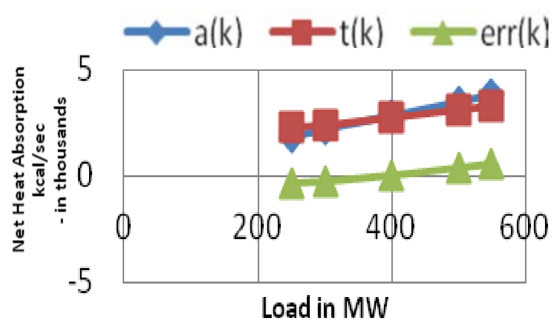

Fig. 3: NHI regression-grade: 2

for all thermal components. Table 2-6 shows the error rate exist between actual and target values of heat absorption.The error rate is negligible based on its impact over normal operations.

Regression analysis on net heat input: The regression analysis on net heat inputare given in Fig 2-5.

Table 3: Error rate of heat absorption-300 mw

C_i	T(k)	A(k)	Err
NHI	2.1728	2.3742	-0.2014
WW	6.2083	6.8384	-0.6301
ECO	2.2488	2.5204	-0.2715
SH1	2.0985	2.3038	-0.2053
SH23	4.2288	4.4248	-0.196
RH	2.7158	2.8655	-0.1497
PAH	6.3523	6.7998	-0.4475
SAH	9.9907	11.8668	-1.8762

Table 4: Error rate of heat absorption-400 mw

C_i	T(k)	A(k)	Err
NHI	2.8193	2.7395	0.0798
WW	7.9784	7.7062	0.2722
ECO	3.0416	2.9611	0.0805
SH1	2.8325	2.7059	0.1266
SH23	5.063	5.0303	0.0327
RH	3.513	3.5381	-0.0251
PAH	8.5313	8.1665	0.3648
SAH	15.3343	14.8659	0.4684

Table 5: Error rate of heat absorption -500 mw

C_i	T(k)	A(k)	Err
NHI	3.4532	3.059	0.3942
WW	9.7051	8.4176	1.2875
ECO	3.9371	3.3761	0.5610
SH12	3.538	3.0034	0.5346
SH3	5.7279	5.5708	0.1571
RH	4.3009	4.0913	0.2096
PAH	11.0063	9.8024	1.2039
SAH	20.8887	19.2429	0.6458

Table. 6: Error rate of heat absorption-500mw

C_i	T(k)	A(k)	Err
NHI	3.8413	3.2966	0.5446
WW	10.6523	9.0057	1.6467
ECO	4.4873	3.6481	0.8392
SH12	4.2168	3.2918	0.9251
ssSH3	6.1627	5.9593	0.2034
RH	4.5207	4.5462	-0.0255
PAH	12.3447	10.4731	1.8716
SAH	23.6997	22.316	1.3837

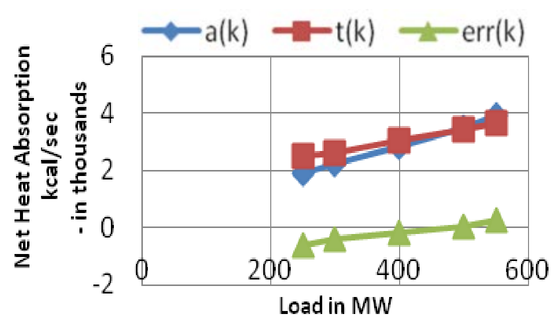

Fig. 4: NHI regression-grade: 3

Regression analysis on re-heater heat absorption: The regression analysis on re-heater heat absorption are given in Fig. 6-9.

Regression analysis on economizer heat absorption: The regression analysis on economizer heat absorption are given in Fig. 10-13.

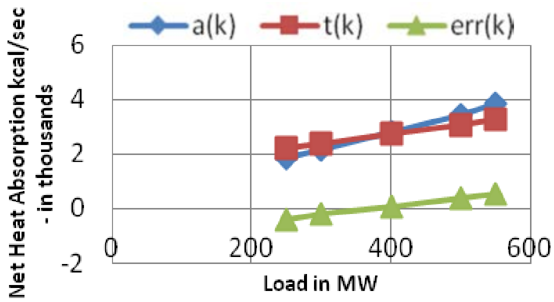

Fig. 5: NHI regression-grade average

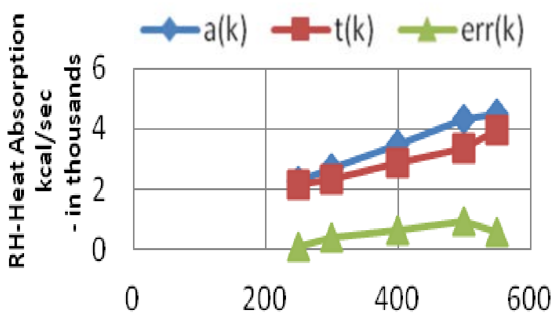

Fig. 6: RH regression-grade 1

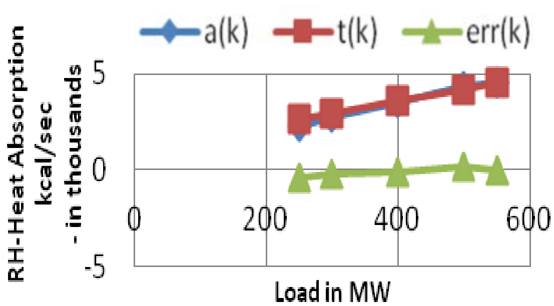

Fig. 7: RH regression-grade 2

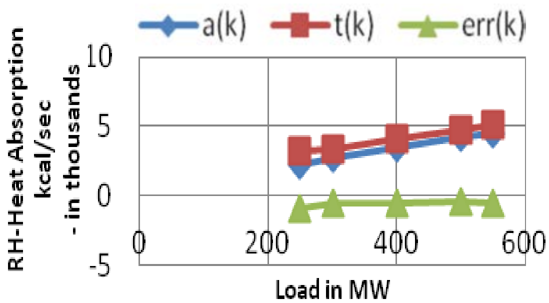

Fig. 8: RH regression-grade 3

Regression analysis on water wall heat absorption: The regression analysis on water wall heat absorptionare given in Fig. 14-17.

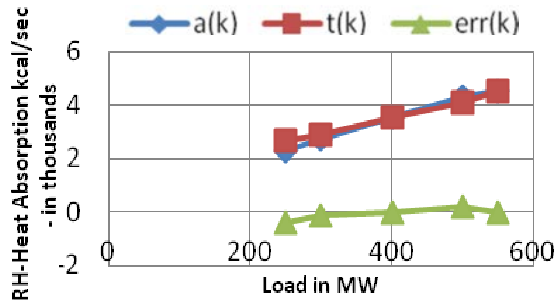

Fig. 9: RH regression-grade average

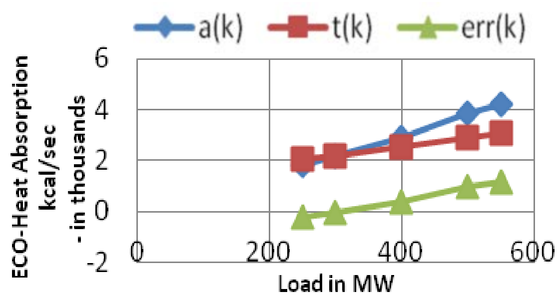

Fig. 10: ECO regression-grade: 1

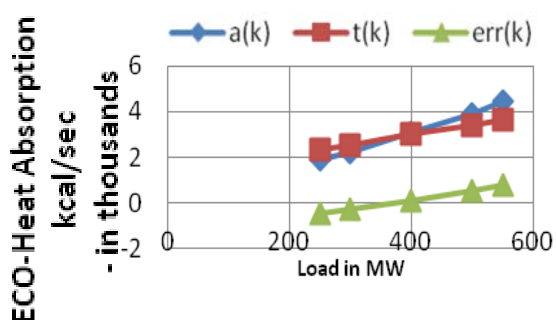

Fig. 11: ECO regression-grade: 2

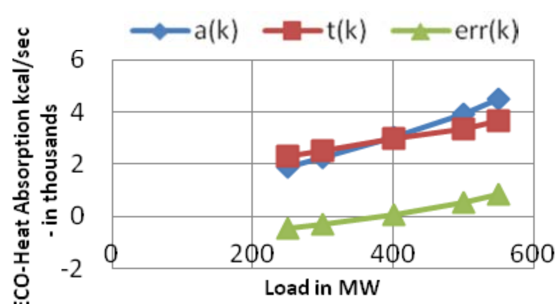

Fig. 12: ECO regression-grade: 3

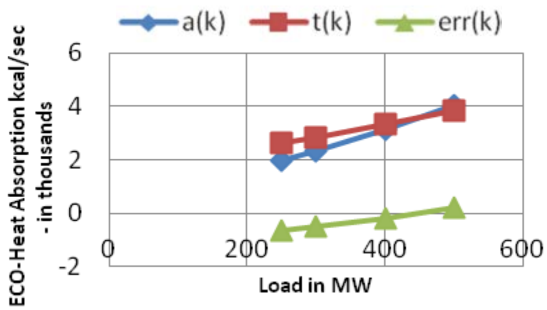

Fig. 13: ECO regression-grade average

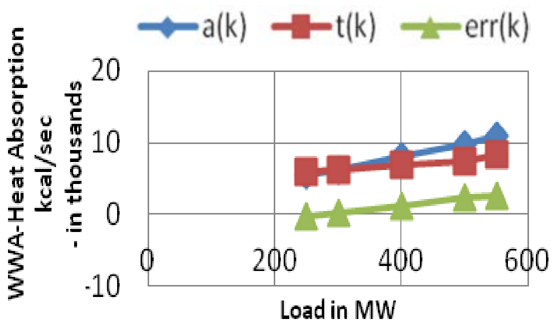

Fig 14: WWA regression-grade:1

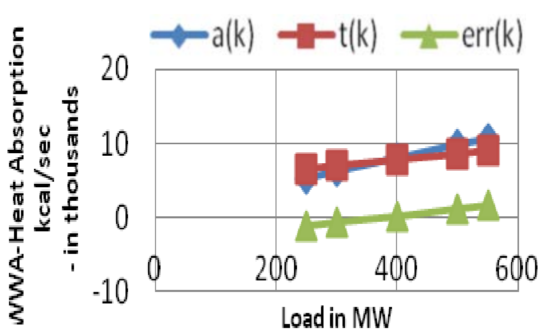

Fig 15: WWA regression-grade:2

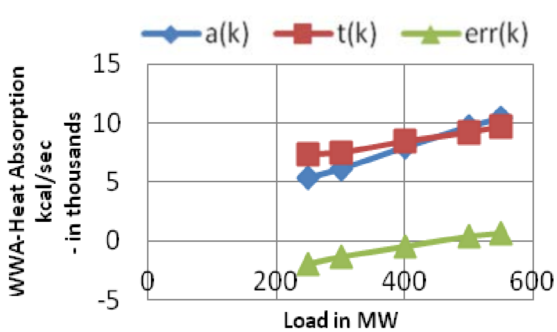

Fig. 16: WWA regression-grade:3

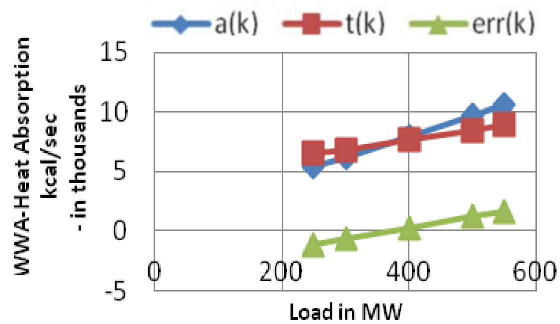

Fig. 17:WWA regression-grade average

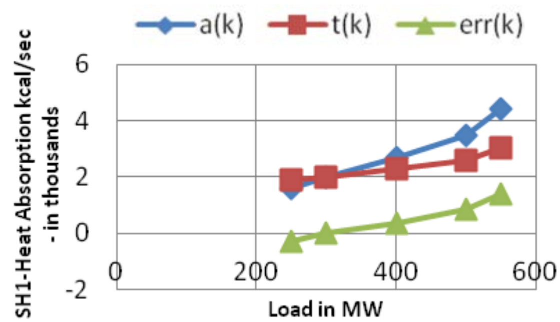

Fig. 18: SH1egression-grade: 1

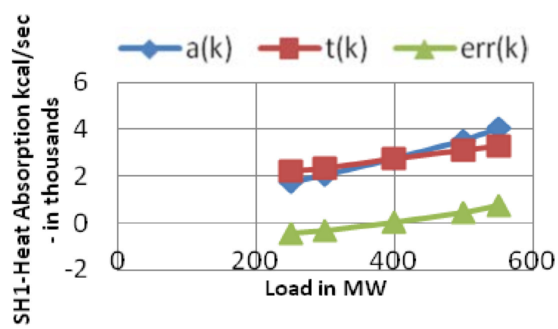

Fig. 19: SH1regression-grade: 2

Regression analysis on superheater1 heat absorption: The regression analysis on superheater 1 heat absorptionare given in Fig. 18-21.

Regression analysis on superheater23 heat absorption: The regression analysis on superheater23 heat absorption are given in Fig. 22-25.

Regression analysis on primary air heater-heat absorption: The regression analysis on primary air heater-heat absorption are given in Fig. 26-29.

Regression analysis onsecondary air heater-heat absorption: The regression analysis onsecondary air heater-heat absorption are given in Fig. 30-33.

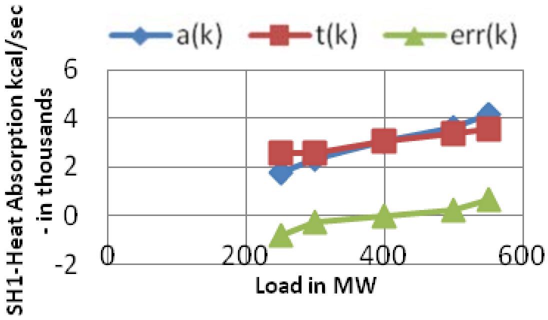

Fig. 20: SH1regression-grade: 3

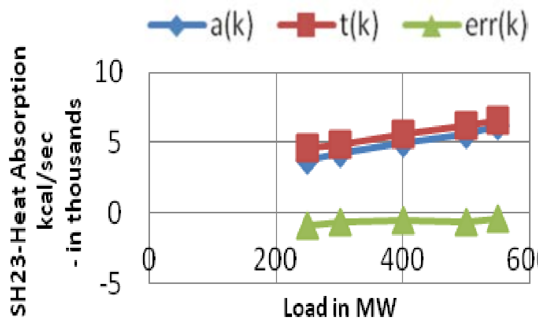

Fig. 24: SH23 regression-grade:3

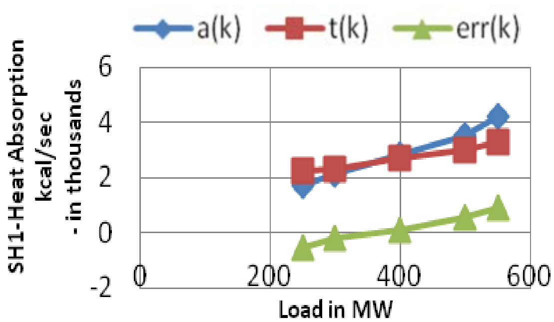

Fig. 21: SHI regression-gradeaverage

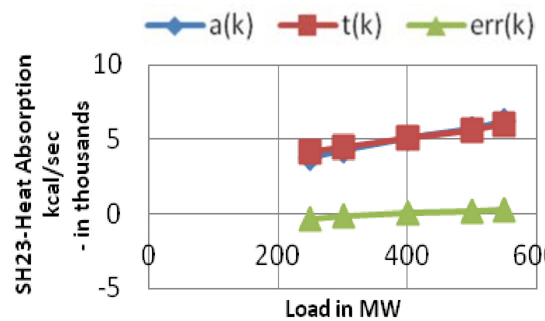

Fig. 25: SH23 regression-grade average

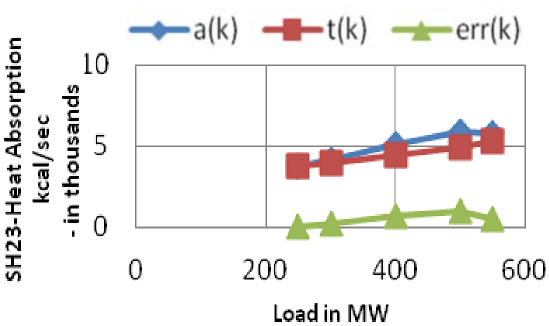

Fig. 22: SH23 regression-grade:1

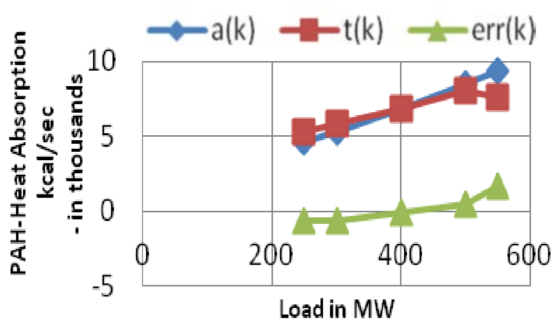

Fig. 26: PAH regression-grade: 1

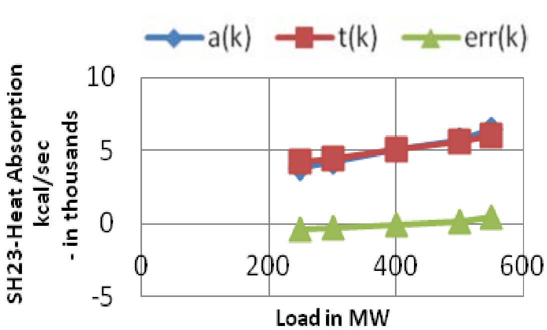

Fig. 23: SH23 regression-grade:2

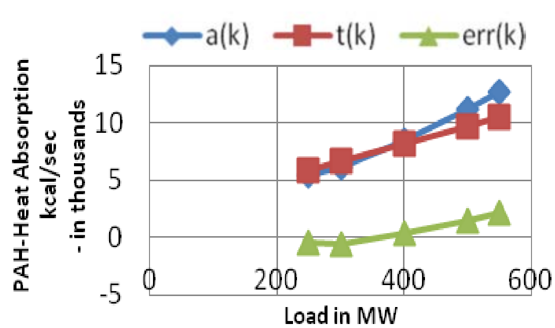

Fig. 27: PAH regression-grade: 2

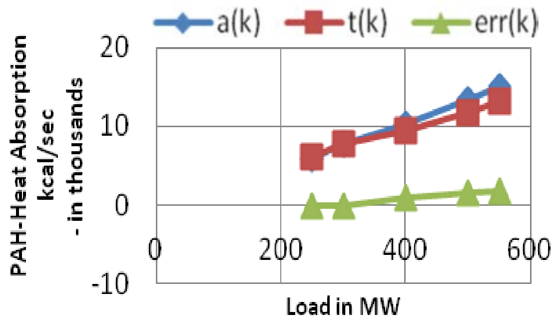

Fig. 28: PAH regression-grade: 3

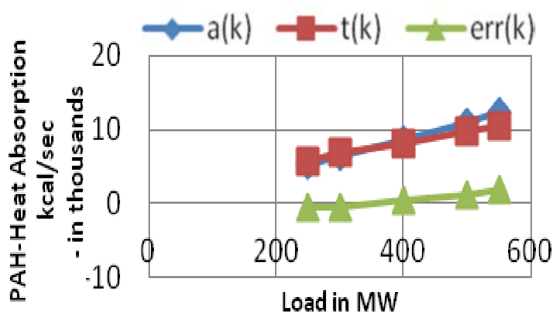

Fig. 29: PAH regression-grade average

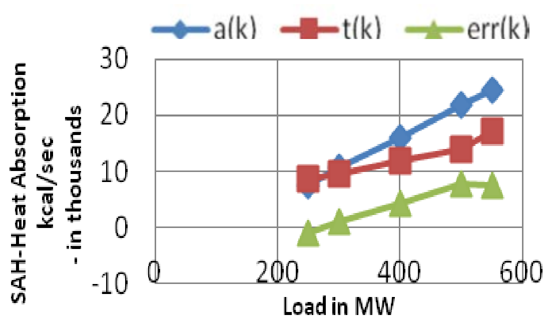

Fig. 30: PAH regression-grade: 1

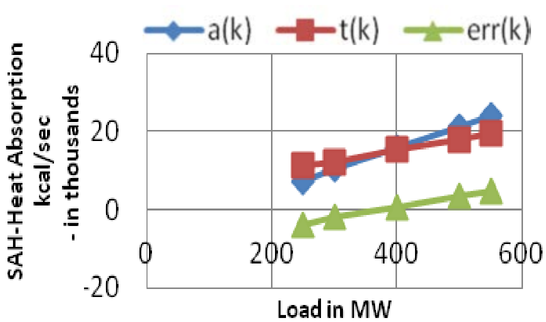

Fig. 31: SAH regression-gerade: 2

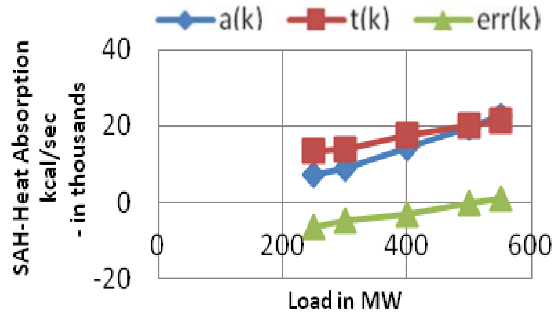

Fig. 32: SAH regression-gerade: 3

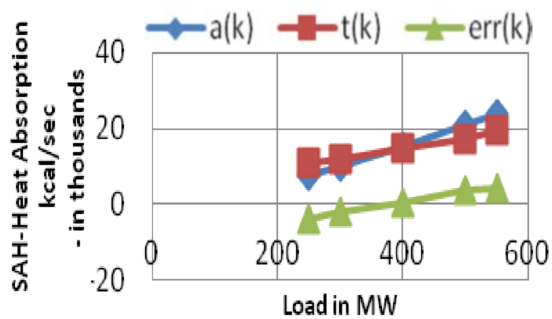

Fig. 33: SAH regression-gerade-average

CONCLUSION

The proposed work clearly indicates that the known vales of coal flow and burner tilt contribution to the variance of energy outcome of each boiler components. Individual influence of those parameters over the plant performance is visualized. Expected results are derived from small datasets. These estimated values under usual assumptions can be used to design system model.The practical investigation makes to have clear understandability of the correlated relationship existed between the operational parameters of the thermal power plant.

ACKNOWLEDGEMENTS

The researchers would like to express thanks to the management of sri krishna Institutions and BHEL for giving continuous guidelines, support and encouragement for the success of the research.

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