REAL TIME PULVERISED COAL FLOW SOFT SENSOR FOR THERMAL POWER PLANTS USING EVOLUTIONARY COMPUTATION TECHNIQUES

B. Raja Singh[1], S. Rominus Valsalam[2], H. Pratheesh[3], K.T. Sujimon[4] and C. Aditi[5]

Control and Instrumentation Group, Centre for Development of Advanced Computing, India
E-mail: [1]rajasingh@cdac.in, [2]rominus@cdac.in, [3]pratheesh@cdac.in, [4]sujimon@cdac.in, [5]aditi@cdac.in

Abstract

Pulverised coal preparation system (Coal mills) is the heart of coal-fired power plants. The complex nature of a milling process, together with the complex interactions between coal quality and mill conditions, would lead to immense difficulties for obtaining an effective mathematical model of the milling process. In this paper, vertical spindle coal mills (bowl mill) that are widely used in coal-fired power plants, is considered for the model development and its pulverised fuel flow rate is computed using the model. For the steady state coal mill model development, plant measurements such as air-flow rate, differential pressure across mill etc., are considered as inputs/outputs. The mathematical model is derived from analysis of energy, heat and mass balances. An Evolutionary computation technique is adopted to identify the unknown model parameters using on-line plant data. Validation results indicate that this model is accurate enough to represent the whole process of steady state coal mill dynamics. This coal mill model is being implemented on-line in a 210 MW thermal power plant and the results obtained are compared with plant data. The model is found accurate and robust that will work better in power plants for system monitoring. Therefore, the model can be used for online monitoring, fault detection, and control to improve the efficiency of combustion.

Keywords:

Pulverised Coal, Primary Air, Mill Differential Pressure, Fitness Function, Raw Coal

1. INTRODUCTION

In coal fired power plants, pulverised coal (PF) flow from coal mills is to be measured accurately for maximising combustion efficiency and improved dynamic response to load changes. However, realization of this is difficult due to the non-availability of accurate measurement of on-line pulverised coal flow. The function of coal mills in power generation station is to grind the large raw coal feed and to supply dry and finely pulverised coal to the furnace for faster combustion and energy release. In addition to the precise fuel supply, the mill-control system has to control primary air flow in a certain ratio to the PF flow, thereby maintaining the efficiency of unit energy release and absorption thereby reducing environment emissions. An area of power plant control that has received much less attention from modelling and control specialists is the coal mill. It is now accepted that the coal mills and their poor dynamic response are major factors in the slow load take-up rate and plant shut-down. A Coal mill model using Evolutionary computation technique reported in [1]. Expertise in mill modelling has been developed over many years which are mainly empirical. Although some progress has been made in the development of mill models, it is still very difficult to obtain exact analytical results because of the intrinsic complexity of coal pulverising process which comprises of two-phase flow and heat-transfer process. Using conventional methods, many results are reported in the form of transfer functions which are not derived from physical principles [2]. However with the advance in modern computer control systems, all measured signals can be stored in data bases covering long periods of time. These data can be used for modelling without additional field tests, but require suitable modelling techniques which are to be identified properly. A novel coal mill modelling technique for E-type coal mill and dynamic behaviour are developed using genetic algorithms [3].

Genetic Algorithms (GAs) have been successfully applied to problems in business, engineering, and science. GAs are stochastic, population-based search and optimization algorithms inspired by the process of natural selection and genetics [4]. A major characteristic of GA is that, it works with a population, unlike other classical approaches which operate on a single solution at a time. A fitness function is needed for differentiating between good and bad solutions. Unlike classical optimization techniques, the fitness function of GAs may be presented in mathematical terms, or as a complex computer simulation, or even in terms of subjective human evaluation. Fitness function generates a differential signal in accordance with which GAs guide the evolution of solutions to the problem [5]. Selection chooses the individuals with higher fitness as parents of the next generation. In other words, selection operator is intended to improve average quality of the population by giving superior individuals a better chance to get copied into the next generation [6] [7]. GA is tried in some of the thermal power plant modelling and estimation problems [8] - [10].

Coal mill model development is based on measurable variables from physical analysis and real time plant data. Since a coal mill is a multi-input-multi-output nonlinear system with a coefficient group to be determined, conventional identification methods tend to diverge due to the multivariable characteristics, strong coupling, time delays, as well as to the pollution of onsite data by noise. In this paper, GA is applied to develop the coal mill model and to estimate the pulverised coal flow using real time on-site plant data.

2. COAL MILL MODELLING

In thermal power plant, pulverization of coal is carried out by coal mill. Raw coal is moved from the storage to the mill by conveyor mechanism. The type of coal mill envisaged for our model is bowl mill which is shown in Fig.1. Raw coal is introduced near the centre of the grinding table through the coal feed pipe. The coal moves outward on the rotating table and it is ground under the roller.

The primary air is generated by mixing hot and cold air, and it is introduced through an opening near the base of the coal mill. The primary air flows upward at the grinding table

periphery and the air is mixed with the pulverised coal. Some of the larger particles fall back on the table and they are ground again. Finer particles of the pulverised coal pass into a classifier. In the classifier, the oversized coal particles fall back to the grinding table and the finer particles are carried through the outlet of the coal mill to the burner of the boiler.
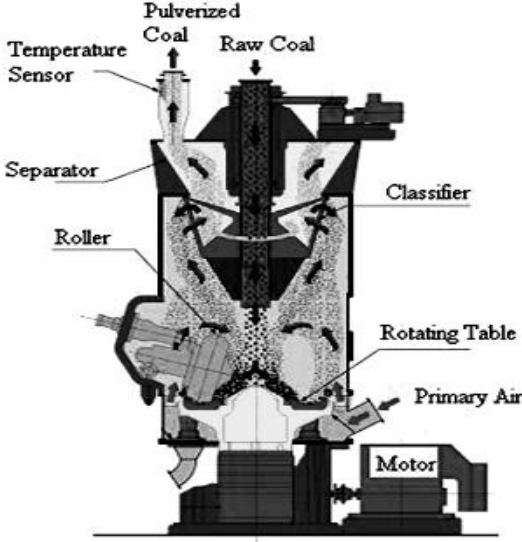

Fig.1. Sectional View of Bowl Mill

Coal mill model development involves a mathematical model with sixteen unknown mill specific parameters and estimation of these model parameters using Genetic Algorithm. The coal mill model is derived from physical mass and heat balance. In order to obtain the simple model for control purpose, it is assumed that the pulverizing mechanism in the mill is simplified, i.e., classification operation is not included. Coal is grouped into two categories only; that are Pulverised coal and Raw coal. The conceptual mass and heat balance models of the coal mill are shown in Fig.2 and Fig.3 respectively. In Fig.2, the raw coal flow (W_c) is introduced into the mill and pulverised coal (W_{pf}) comes out. The coal mass is converted into pulverised mass through grinding. According to the assumption, at a particular instant there will be certain amounts of raw coal (M_c) and pulverised coal (M_{pf}) in the mill. The raw coal is fed into the mill by raw coal feeders for pulverizing at a mass flow rate of W_c. By grinding the raw coal M_c in the mill, the pulverized coal M_{pf} is produced and carried out by the warm air flow at the mill outlet with a pulverised coal mass flow rate of W_{pf}. From the mass balance point of view, the total mass of the pulverized coal output from the mill at the flow rate W^{pf} should be equal to the total mass of the raw coal flowing into the mill at the flow rate W_c eventually.
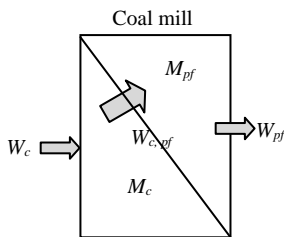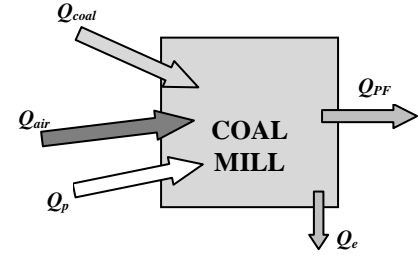

Fig.2. Mass Balance Model of Coal Mill

Fig.3. Heat Balance Model of Coal Mill

In Fig.3, the changes in mill outlet temperature are considered as the result of heat balance. The temperature increases with the heat contributed by hot primary air entering the mill and the heat generated by grinding. It decreases by the heat energy lost due to coal and moisture entering the mill and to the hot primary air, pulverised fuel leaving the mill. From the above given Mass and Heat balance, the model is derived. So the mill outlet temperature can be written as,

$$T_{out} = Q_{coal} + Q_{air} + Q_p + Q_e - Q_{pf} + k_{17}T_{out} \qquad (1)$$

where,

Q_{coal} - Heat of coal inlet flow

Q_{air} - Heat of primary air inlet

Q_p - Heat generated due to grinding

Q_e - Heat emitted from mill body to environment

Q_{pf} - Heat of pulverised coal outlet from mill

The variables used for the Coal mill model is as follows: Input variables are W_c, T_{in}, Δ_{pf} and W_{air}; Intermediate variables are M_c, M_{pf}, ΔP_{mpd} and W_{pf}; Output variables are Tout, ΔP_{mill} and P.

2.1 MATHEMATICAL MODEL

The Model consists of four Differential Equations and three algebraic equations.

2.1.1 Differential Equations:

$$\frac{dM_c}{dt} = W_c - k_{15}M_c \qquad (2)$$

$$\frac{dM_{pf}}{dt} = k_{15}M_c - k_{16}\Delta P_{pa}M_{pf} \qquad (3)$$

$$\frac{d\Delta P_{mpd}}{dt} = k_{11}M_{pf} + k_{12}M_c - k_{13}\Delta P_{mpd} \qquad (4)$$

$$\frac{dT_{out}}{dt} = (k_1 T_{in} + k_2)W_{air} - k_3 W_c - [(k_4 T_{out} + k_5)$$
$$(W_{air} + W_c)] + k_{14}(k_6 M_{pf} + k_7 M_c + k_8) \qquad (5)$$
$$+ k_{17}T_{out}$$

2.1.2 Algebraic Equations:

$$P = k_6 M_{pf} + k_7 M_c + k_8 \qquad (6)$$

$$\Delta P_{mill} = k_9 \Delta P_{pa} + \Delta P_{mpd} \qquad (7)$$

$$W_{pf} = k_{16}\Delta P_{pa}M_{pf} \qquad (8)$$

2.2 DISCRETISED MODEL

In order to calculate the on-line Pulverised Coal flow in real time, the model needs to be discretised with a suitable numerical

ISSN: 2229-6956(ONLINE)

ICTACT JOURNAL ON SOFT COMPUTING:
SPECIAL ISSUE ON SOFT – COMPUTING THEORY, APPLICATION AND IMPLICATIONS IN ENGINEERING AND TECHNOLOGY,
JANUARY 2015, VOLUME: 05, ISSUE: 02

technique, so the difference equation model is used. Using standard Euler's method, we solve the differential Eq.(9) to Eq.(12).

$$M_c(k+1) = \{[W_c(k) - k_{15}M_c(k)]T\} + M_c(k) \qquad (9)$$

$$M_{pf}(k+1) = \{[k_{15}M_c(k) - k_{16}\Delta P_{pa}(k)M_{pf}(k)]T\} + M_{pf}(k) \qquad (10)$$

$$\Delta P_{mpd}(k+1) = \{[k_{11}M_{pf}(k) + k_{12}M_c(k) - k_{13}\Delta P_{mpd}(k)]T\} + \Delta P_{mpd}(k) \qquad (11)$$

$$\begin{aligned} T_{out}(k+1) = \{&[k_1 T_{in}(k) + k_2]W_{air}(k) - k_3 W_c(k) \\ &- \{(k_4 T_{out}(k) + k_5)[W_{air}(k) + W_c(k)]\} \\ &+ k_{14}[k_6 M_{pf}(k) + k_7 M_c(k) + k_8(k)] \\ &+ k_{17}T_{out}(k)]T\} + T_{out}(k) \end{aligned} \qquad (12)$$

$$P(k+1) = k_6 M_{pf}(k+1) + k_7 M_c(k+1) + k_8 \qquad (13)$$

$$\Delta P_{mill}(k+1) = k_9 \Delta P_{pa}(k+1) + \Delta P_{mpd}(k+1) \qquad (14)$$

$$W_{pf}(k+1) = k_{16}\Delta P_{pa}(k+1)M_{pf}(k+1) \qquad (15)$$

where, 'T' is the sampling time

3. PARAMETER ESTIMATION USING GENETIC ALGORITHM

3.1 GENETIC ALGORITHM

GA belongs to the class of probabilistic search procedure known as evolutionary algorithms that use computational models resembling natural evolutionary processes to develop computer-based problem solving technique. It provides a robust way of exploring virtually any solution space where an objective function is defined, in pursuit of its global optimum and it manipulates a population of solutions in parallel. Each trial solution in the population is coded as a single vector, is termed as chromosome. A shared environment determines the objective value or raw performance of each individual in the population. These objective values are, in turn transformed into fitness values for the requirements associated with the subsequent statistical selection. The GA is typically composed of three fundamental operator's viz., Selection, Crossover and Mutation. Selection is a process in which each chromosome is reproduced in proportion to its own fitness relative to the other chromosomes in the population. Following the selection process, other genetic operators crossover and mutation are performed to generate the offspring of the selected chromosomes.

3.2 OPTIMIZATION OF COAL MILL MODEL WITH GA

The coal mill mathematical model equations given in Eq.(9) to Eq.(15) contain 16 unknown coefficients which are to be determined. It should be noted that in this model, some model variables are non-measurable. For such an intrinsically complex dynamic milling process, the analytical solution cannot be obtained easily with noise-contained plant data. The conventional gradient-based optimization techniques, such as least-squares and steepest-descent methods apply to local optimization problems, not taking into account of the fact that there may be many local minima of the merit function in the space of all variables. They are not suitable for this underlying modelling issue, arisen from unobservable states involved in the model and a wide range of parameter search domain leads to inadequateness for identifying so many parameters in parallel. In order to identify the 16 unknown parameters k_1, $k_2 \ldots k_{17}$ in the coal mill mathematical model in Eq.(9) to Eq.(15), the Genetic Algorithm (GA) is used since it has been proved that GA is a robust optimization method for the parameter identification problems.

The single-population real-value GA is chosen such that the fitness function compromises the errors between the normalized coal mill measured outputs and the normalized model simulated outputs. Applying the scheme of the parameters identification shown in Fig.5, the 16 unknown parameters are identified. The performance of the GA is influenced strongly by the fitness functions used which is given in Eq.(16) to Eq.(19).

$$e_1(k) = T_{out}^n(k) - \hat{T}_{out}^n(k) = \frac{T_{out}(k) - \hat{T}_{out}(k)}{T_{out}^{ML}} \qquad (16)$$

$$e_2(k) = \Delta P_{mill}^n(k) - \Delta \hat{P}_{mill}^n(k) = \frac{\Delta P_{mill}(k) - \Delta \hat{P}_{mill}(k)}{\Delta P_{out}^{ML}} \qquad (17)$$

$$e_3(k) = P^n(k) - \hat{P}^n(k) = \frac{P(k) - \hat{P}(k)}{P^{ML}} \qquad (18)$$

where, $\hat{T}_{out}(k), \hat{P}(k)$ and $\Delta \hat{P}_{mill}(k)$ are the measured outputs of the mill model at instant 'k'; $\hat{T}_{out}(k), \hat{P}(k)$ and $\Delta \hat{P}_{mill}(k)$ are the simulated outputs of the mill model at instant 'k'. $T_{out}^{ML}, \Delta P_{mill}^{ML}$ and P^{ML} are the maximum limit value of these variables. The sequence of Parameter estimation by GA is shown in Fig.6. The ultimate target of this optimization is to minimize the error between the model output and measured plant data.
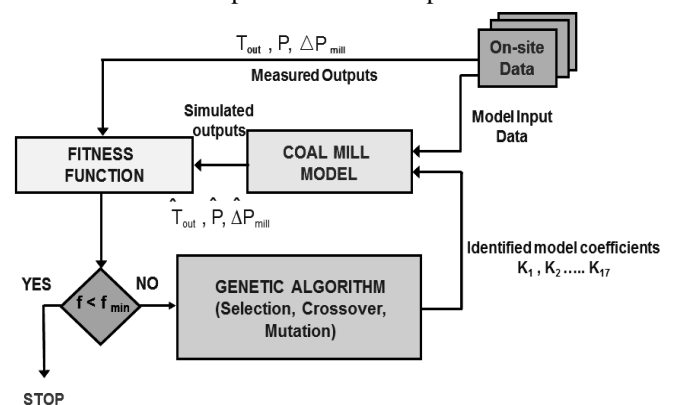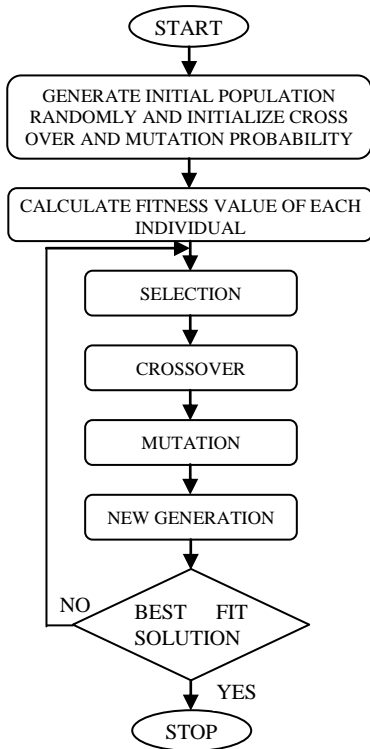

Fig.5. GA Optimization for Coal mill model

Fig.6. Flow chart of Genetic Algorithm

The fitness function used for GA is given below:

$$Fitness = \frac{1}{N} \sum_{t=0}^{N} \left\{ W_1 \left| e_1(k) \right| + W_2 \left| e_2(k) \right| + W_3 \left| e_3(k) \right| \right\} \qquad (19)$$

4. ON-LINE IMPLEMENTATION OF SOFT SENSOR FOR PULVERISED COAL FLOW MEASUREMENT

The configuration diagram for the on-line implementation of Pulverised coal flow soft sensor setup is given in Fig.7. For each mill, seven field signals are identified as the mill model input (4 nos.) and output variables (3 nos.) which are connected to a Remote Terminal Unit with proper field isolation and are then given to CDAC's iCon controller (Industrial Controller). The Genetic Algorithm driven system identification to compute the unknown model parameters runs in the work station and the coal mill model runs in the iCon controller in order to provide real time measurement of pulverised coal flow. Each GA run of a mill requires 1500 data points of the seven signals logged at 1 second interval from the database logger. The scan time for each coal mill model loop is 1 second. Once the unknown parameters are estimated using GA, parameters are downloaded to iCon at a definite time interval to compute the Pulverised coal flow from the model. Every 4 hours, the unknown parameters of the model are identified on-line using the Evolutionary computational technique (Genetic Algorithm) and updated in the model to match the current dynamics of the coal mill process. Similar computations are done for all running mills of a 210 MW boiler and summed up to arrive at the total pulverised coal flow for the boiler.
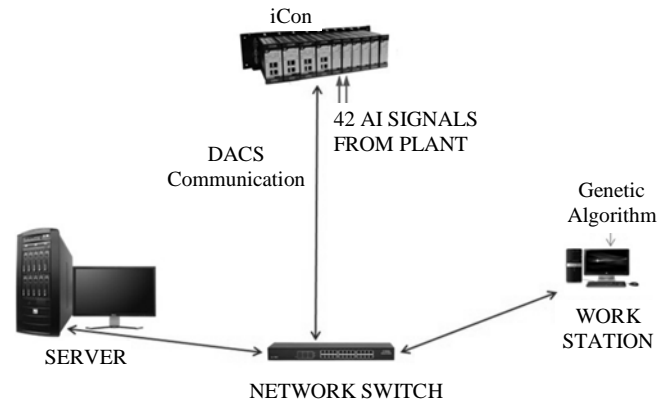

Fig.7. System configuration diagram of the Pulverised coal flow soft sensor

The real time Coal mill model response with respective plant signals is shown in Fig.8 to Fig.11. In Fig.8, the total pulverised coal flow (from all the running coal mills) to the furnace is compared with raw coal flow signal of the plant. The accuracy of the pulverised coal flow soft sensor for the plant steady state condition is $\pm$ 0.05%. Subsequently the soft sensor output for one mill in full load condition is shown in Fig.9. The Fig.10 to Fig.12 show the comparison between model output variables and the respective plant signal for a single mill. From the graph, it is clear that the model is accurate enough and exactly follows the real time dynamics of the mill. Currently in the thermal power plant monitoring scenario, there is no physical measurement technique is readily available to measure the pulverised coal flow. So this on-line pulverised coal flow soft sensor paves a way to get best possible control accuracy on the master pressure control of coal based thermal power plant where one of the input for the steam pressure control is amount of coal flow to the combustion. Also, plant Engineers/Operators will have a better visibility about the exact pulverised coal which actually goes to the furnace for combustion rather than having an approximated approach based on raw coal flow (measurement prior to pulverisation process).
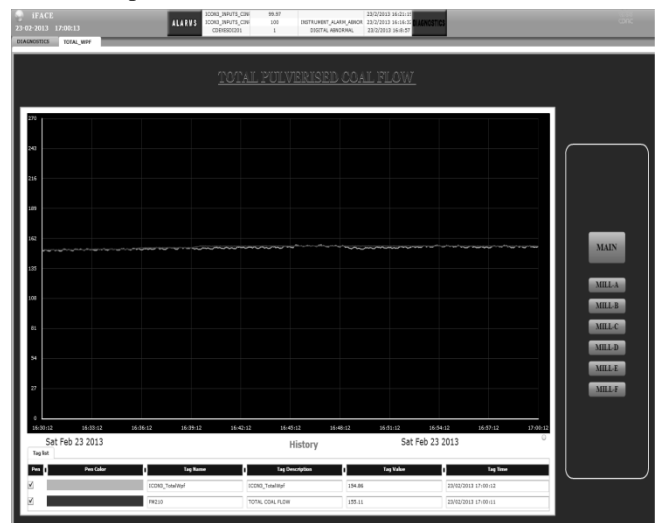

Fig.8. HMI frame of Total Pulversied coal flow (model output) vs Total raw coal flow (plant signal)
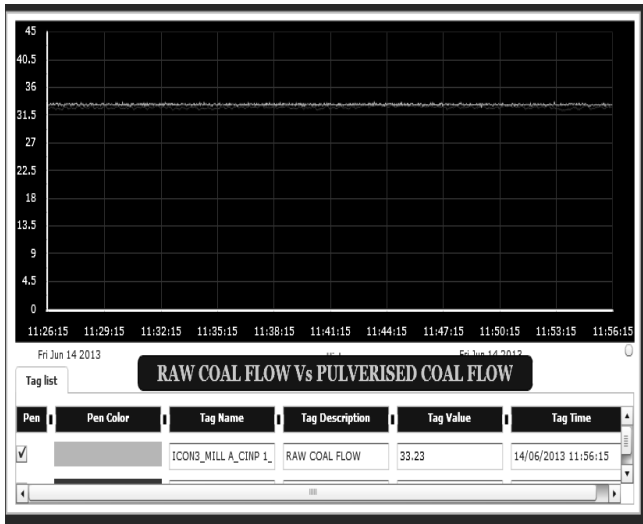
Fig.9. Comparison of Model output and Plant data for Pulverised coal flow (one coal mill)
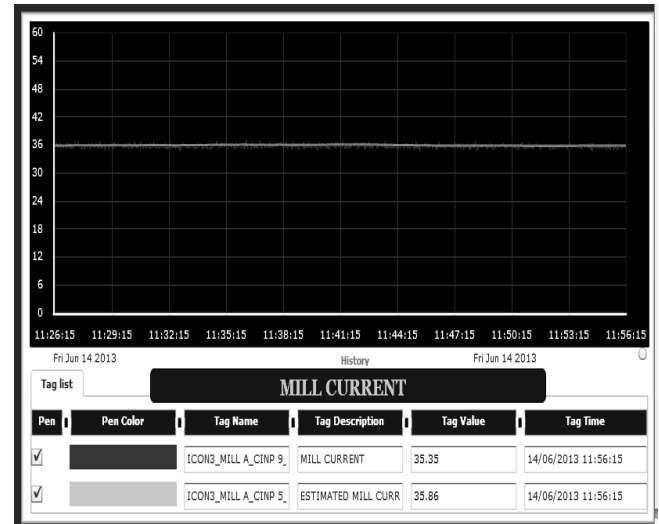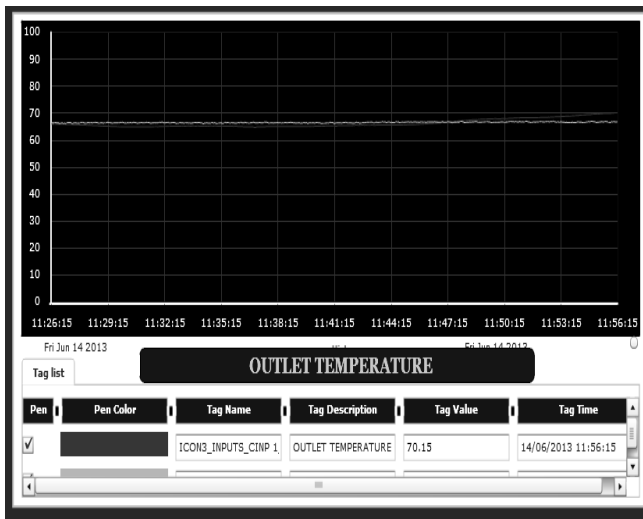

Fig.10. Comparison of Model output and Plant data for Mill Outlet Temperature

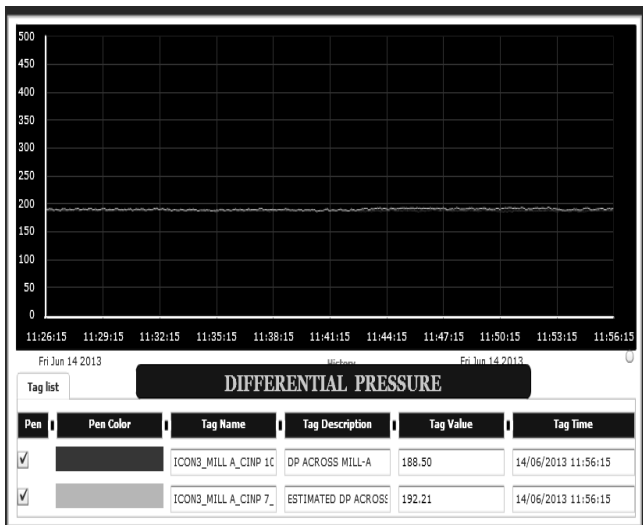Fig.11. Comparison of Model output and Plant data for Mill Differential Pressure

Fig.12. Comparison of Model output and Plant data for Mill Current

5. CONCLUSION

In this paper, a Coal mill model is developed for steady state condition and is used to estimate/predict the internal dynamics of coal mill and to compute the pulverised coal flow measurement of the coal pulverising system. The Genetic Algorithm is used to identify the unknown model parameters of the coal mill. The system is implemented in a 210 MW thermal power plant for a bowl mill type pulverising system and the results are compared and validated with on-site plant data. From the results, it has been observed that the model outputs are matched exactly to the measured plant signals.

The outcome of this work will be useful in assessment and prediction of mill performance and in seeking improvement in design, operating procedures and control strategies for pulverizing process of coal mill. It has opened up a way to implement advanced control algorithms in coal pulverizing process for better control and state diagnosis to improve the pulverising process. The Coal mill model is also a pre-requisite for implementing advanced control algorithms for master pressure control of a thermal power plant. There is enormous scope for applying estimation techniques like Kalman Filter to fine tune the model and novel intelligent hybrid Evolutionary techniques in place of GA to achieve further accuracy in the result.

ACKNOWLEDGEMENT

NOMENCLATURE

W_c : Mass flow rate of Raw coal into mill (kg/s)
T_{in} : Inlet temperature of coal mill (°C)
ΔP_{pa} : Primary air differential pressure (mbar)
W_{air} : Primary air flow rate into coal mill (kg/s)
M_c : Mass of Raw coal in mill (kg)
M_{pf} : Mass of pulverised coal in mill (kg)
ΔP_{mpd} : Mill product differential pressure (mbar)
W_{pf} : Mass flow rate of pulverised coal out of mill (kg/s)
T_{out} : Outlet temperature of coal mill (°C)
ΔP_{mill} : Mill differential pressure (mbar)
P : Mill Current (A)

REFERENCES

[1]   Damian Flynn, "Thermal Power Plant Simulation and control", *The Institution of Electrical Engineers*, 2003.

[2]   K. E. Bollinger and H. R. Snowden, "The Experimental Determination of Coal Mill Models", *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-102, No. 6, pp. 1473-1477, 1983.

[3]   J. L. Wei, J. H. Wang and Q. H. Wu, "Further study of coal mill modeling by machine learning based on on-site measurement", *Proceedings of the 16th International Conference on Systems Engineering*, pp. 741-746, 2003.

[4]   T. Back, D. B. Fogel and Z. Michalewicz, "*Handbook of Evolutionary Computation*", Institution of Physics Publishing and Oxford University Press, 1997.

[5]   Y. P. Chen, "*Extending the Scalability of Linkage Learning Genetic Algorithms*", Springer - Artificial Intelligence, Vol. 190, 2004.

[6]   T. Back, "Selective pressure in evolutionary algorithms: A characterization of selection mechanisms", *Proceedings of the First IEEE Conference on Evolutionary Computation*, Vol. 1, pp. 57-62, 1994.

[7]   Y. G. Zhang, Q. H. Wu, J. Wang, G. Oluwande, D. Matts and X. X. Zhou, "Coal mill modeling by machine learning based on on-site measurement", *IEEE Transactions on Energy Conversion*, Vol. 17, No. 4, pp. 549-555, 2002.

[8]   P. Zachariades, J. L. Wei and J. Wang, "Development of a Tube-ball Coal Mill Mathematical Model Using Particle Swarm Optimization", *Proceedings of the World Congress on Engineering*, Vol. I, 2008.

[9]   Omar Mohamed, Jihong Wang, Shen Guo, Bushra Al-Duri and Jianlin Wei, "Modelling Study of Supercritical Power Plant And Parameter Identification Using Genetic Algorithms", *Proceedings of the World Congress on Engineering*, Vol. II, 2010.

[10] Heng Wang, Min-ping Jia, Peng Huang and Zuo-liang Chen, "A study on a new algorithm to optimize ball mill system based on modeling and GA", *Elsevier Energy Conversion and Management*, Vol. 51, No. 4, pp. 846-850, 2010.