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Thermal Power Plant Real Time Pulverised Coal Flow Soft Sensor Using Evolutionary Computation Techniques

Sai Gani Prasad [1*], P.Paulpandian[2]
[1*]Professor, Department of Mechanical Engineering, Nalanda Institute of Technology, Bhubaneswar, Odisha, India
[2*]Associate Professor, Department of Mechanical Engineering, Nalanda Institute of Technology, Bhubaneswar, Odisha, India

*Corresponding author e-mail: saiganiprasad@thenalanda.com

Abstract

The core of coal-fired power plants is the technology for preparing pulverised coal (coal mills). Finding an accurate mathematical model of the milling process would be extremely challenging due to the complexity of the milling process and the complicated connections between coal quality and mill parameters. The pulverised fuel flow rate of the vertical spindle coal mills (bowl mills), which are frequently used in coal-fired power plants, is estimated using the model in this study. Plant parameters like air flow rate, differential pressure across the mill, etc. are taken into consideration as inputs/outputs for the steady state coal mill model development. The mathematical model was created by analysing the mass, energy, and heat balances. Using online plant data, an evolutionary computation technique is used to determine the model parameters that are unknown. According to the validation results, this model is precise enough to capture the dynamics of a steady state coal mill in its entirety. In a 210 MW thermal power plant, this coal mill model is being deployed online, and the results are being compared to plant data. The model is reliable and accurate, making it more suited for system monitoring in power plants. In order to increase combustion efficiency, the model can be utilised for online monitoring, problem identification, and control.

Keywords:
Pulverised Coal, Primary Air, Mill Differential Pressure, FitnessFunction, Raw Coal

1. INTRODUCTION

Pulverized coal (PF) flow from coal mills needs to be precisely measured in coal-fired power plants in order to maximise combustion efficiency and increase dynamic response to load fluctuations. Due to the lack of precise online pulverised coal flow measurement, it is challenging to realise this. Coal mills are used in power plants to grind large amounts of raw coal and supply the furnace with dry, finely ground coal for quicker combustion and energy release. The mill-control system must also precisely control the fuel supply and the ratio of primary air flow to PF flow in order to maintain the efficiency of unit energy release and absorption and lower emissions. The coal mill is a part of power plant control that modelling and control experts have paid significantly less attention to. It is now well acknowledged that the coal mills' subpar dynamic responsiveness and delayed load take-up rate are key causes of plant shutdown. Using evolutionary computation, a coal mill model was presented in [1]. Throughout many years, expertise in mill modelling has grown, and it is primarily empirical. Due to the inherent complexity of the coal pulverising process, which includes two-phase flow

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and heat-transfer processes, it is still exceedingly difficult to achieve precise analytical data, despite some advances in the creation of mill models. 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].

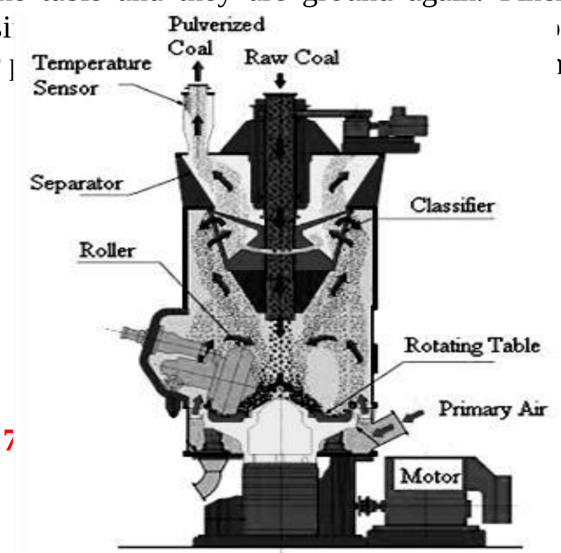
Genetic Algorithms (GAs) have been successfully applied to problems in business, engineering, and science. GAs are stochastic, population-based search and optimization algorithms inspired by the process of natural selection and genetics [4]. A major characteristic of GA is that, it works with a population, 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 classi … articles fall back to the grinding table and the finer … e coal mill to the burner of the boiler.



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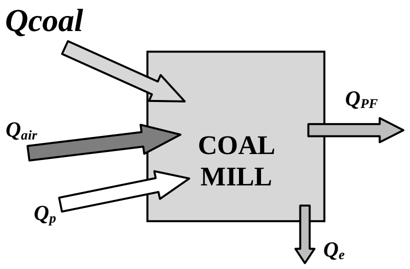


Fig.3. Heat Balance Model of Coal Mill

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,

$Tout = Qcoal + Qair + Qp + Qe - Qpf + k17Tout$ (1)

Fig.1. Sectional View of Bowl Mill

Coal mill model development involves a mathematical model
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
with sixteen unknown mill specific parameters and estimation of these model parameters using Genetic Algorithm. The coal mill
is derived
air *c*
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})
M_{pf}, □P_{mpd} and W_{pf} ; Output variables are Tout, □P_{mill} and P.

MATHEMATICAL MODEL

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

Differential Equations:

comes out. The coal mass is converted into pulverised mass
dM c □ *W* □ *k* *M*

(2)
through grinding. According to the assumption, at a particular
instant there will be certain amounts of raw coal (M_c) and
dt
dM pf

c 15 *c*

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

dt □ *k*15*Mc* □ *k*16□*PpaM pf*

(3)

grinding the raw coal M_c in the mill, the pulverized coal M_{pf} is

d□Pmpd □ *k M*

+ *k M*

– *k* □*P*

(4)

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

dt

dTout □ □*k T*

11 *pf* *dt* 1 *in*

+ *k*2 □*Wair*

12 *c*

– *k*3*Wc*

13 *mpd*

– □ □*k*4*Tout* □ *k*5 □

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.

Coal mill

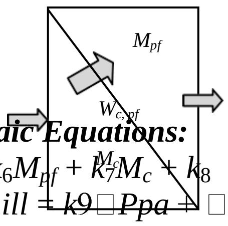
Wair □ *Wc*

+ *k*17*Tout*

+ *k*14 *k*6 *M pf* □ *k*7 *Mc* □ *k*8

(5)

Wpf



Algebraic Equations:

$P = k_6M_{pf} + k_7M_c + k_8$ (6)

□*Pmill* = *k*9□*Ppa* + □*Pmpd* (7)

Wc *W* = *k* □*P M*

(8)

pf 16 *pa pf*

Fig.2. Mass Balance Model of Coal Mill

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

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

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

$M (k+1) = \{[k M (k)-k \square P (k)M (k)]T\}+M (k)$ (10)

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

pf 15 *c*

16 *pa* *pf* *pf*

not suitable for this underlying modelling issue, arisen from

$\square Pmpd \square k \square 1\square \square \{[k11M pf (k) \square k12Mc (k) \square k13\square Pmpd (k)]T\}$

$+ \square Pmpd (k)$

$Tout \square k \square 1\square \square \{[k1Tin \square k \square\square k2]Wair (k) \square k3Wc (k)$

$\square\{(k4Tout (k) \square k5)[Wair (k) \square Wc (k)]\}$

(11)

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

$+ k14[k6 M pf$

$(k) \square k_7 Mc (k) \square k_8 (k)]$

(12)

since it has been proved that GA is a robust optimization method for the parameter identification problems.

$+ k17Tout (k)]T\} \square Tout (k)$

$P(k+1) = k_6M_{pf}(k+1) + k_7M_c(k+1)+k_8$ (13)

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

$W_{pf}(k+1) = k_{16}\square P_{pa}(k+1)M_{pf}(k+1)$ (15) where, „T‟ is the sampling time

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).

3. PARAMETER ESTIMATION USING

$e \square k \square \square T^n \square k \square\square \hat{T}n \square k \square \square Tout\square k \square\square \hat{T}$

$\square k \square$

(16)

GENETIC ALGORITHM

GENETIC ALGORITHM

GA belongs to the class of probabilistic search procedure

1 *out*

$e_2 \square k \square \square \square P^n \square k \square\square \square \hat{P}$ *mill* *mill*

out

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n

□*k* □ □

ML
out
□*Pmill* □*k* □□ □*P*ˆ
ML
out
□*k* □

T *out*

ΔP *mill*

(17)

known as evolutionary algorithms that use computational

e □*k* □ □ P^n □*k* □□ *P*ˆ *n* □*k* □ □ *P*□*k* □□ *P*ˆ□*k* □

(18)

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

where,

ˆ
ut
3

and

ˆ
mill
PML
□*k* □ are the measured outputs of

function is defined, in pursuit of its global optimum and it manipulates a population of solutions in parallel. Each trial

the mill model at instant „*k*‟; *T*ˆ
□*k* □, *P*ˆ□*k* □ and
ˆ
mill
□*k* □ are the

out

solution in the population is coded as a single vector, is termed

simulated outputs of the mill model at instant „*k*‟.

T ML , □*PML*
out *mill*

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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.

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

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.

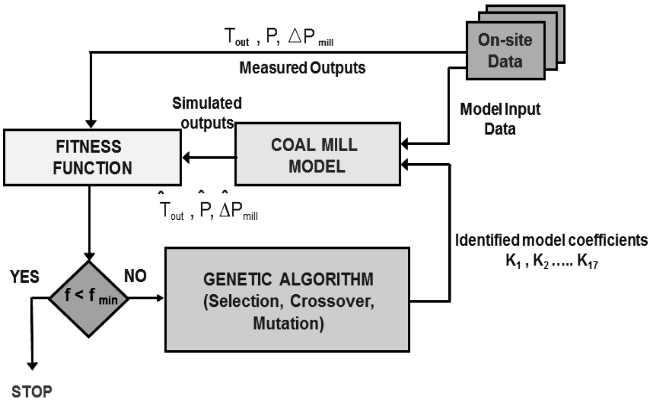

Fig.5. GA Optimization for Coal mill model

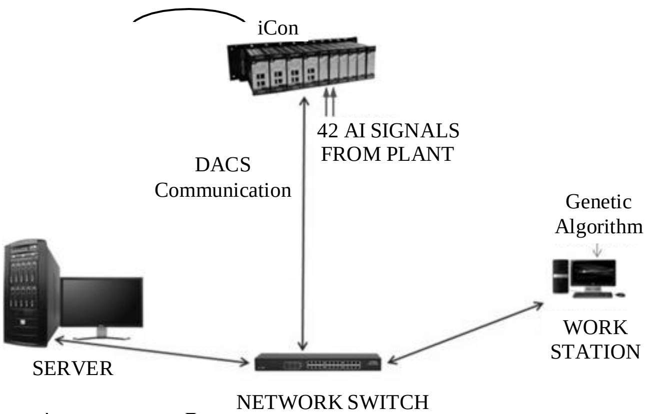

Fig.7. System configuration diagram of the Pulverised coal flow soft sensor

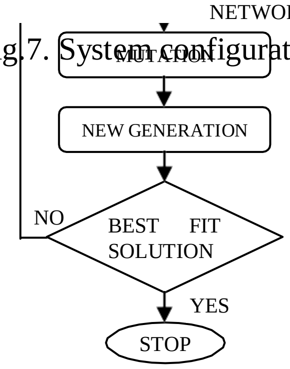

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Fig.6. Flow chart of Genetic Algorithm The fitness function used for GA is given below:

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 ± 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

$$Fitness = \frac{1}{N}\sum_{t=0}^{N}\left(W1\,|e1(k)| + W2\,|e2(k)| + W3\,|e3(k)| \right) \quad (19)$$

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

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.

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).

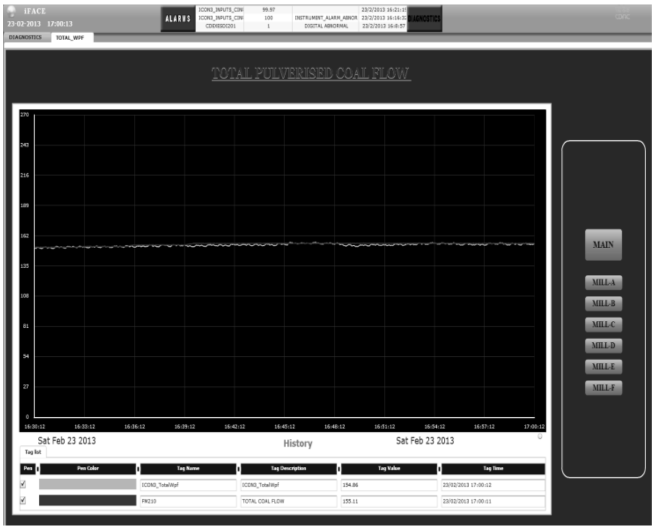
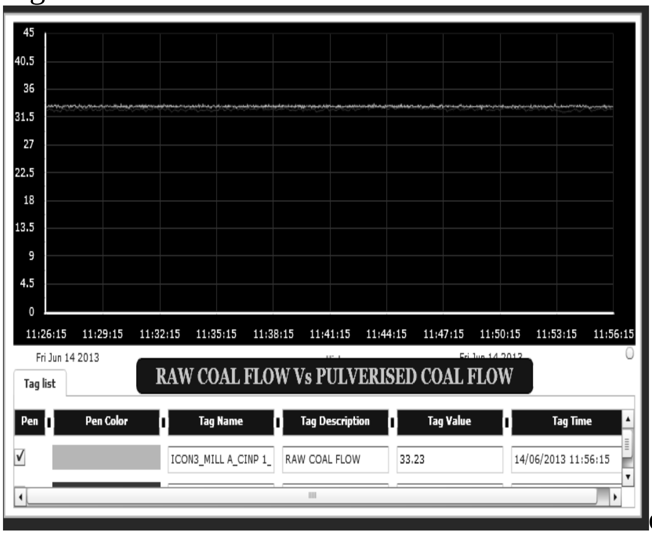


Fig.8. HMI frame of Total Pulversied coal flow (model output) vs Total raw c



oal flow (plant signal)

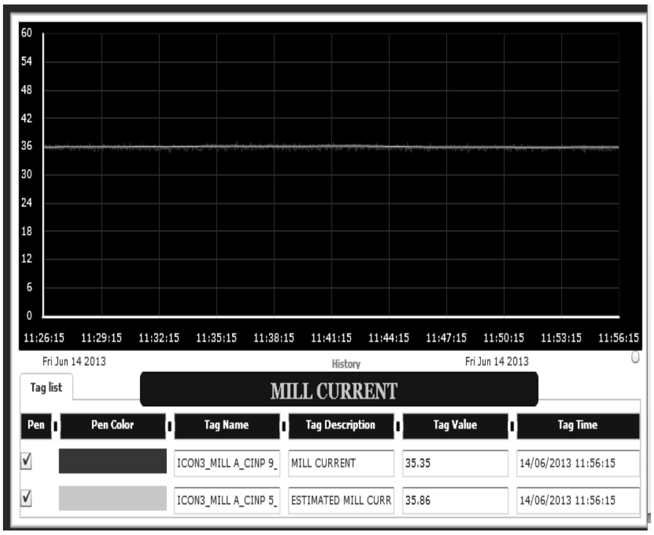


Fig.9. Comparison of Model output and Plant data for Pulverised coal flow (one coal mill)

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

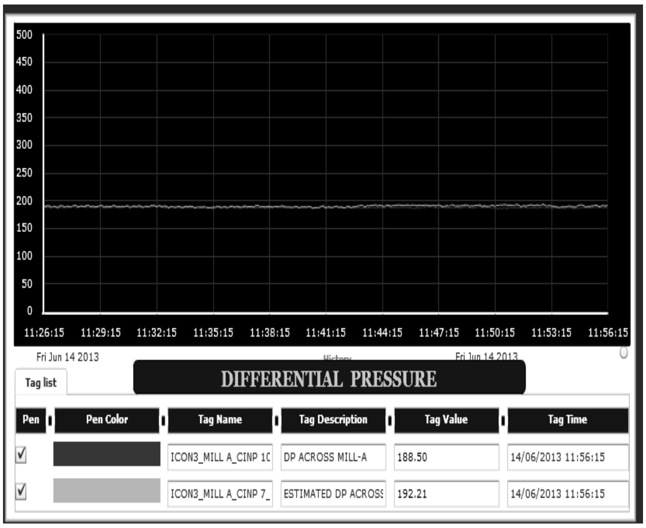


Fig.11. Comparison of Model output and Plant data for Mill Differential Pressure

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

5. CONCLUSION

The internal dynamics of the coal mill are estimated or predicted in this article for steady state conditions, and the pulverised coal flow measurement of the coal pulverising system is computed. The coal mill's unknown model parameters are found using the Genetic Algorithm. The technology is put into use in a 210 MW thermal power plant for a pulverising system that uses a bowl mill, and the outcomes are compared and confirmed using data from the actual plant. From the findings, it has been noted that the model outputs match the measured plant signals completely.

The results of this work will be helpful in assessing and forecasting mill performance as well as in exploring advancements in design, operational practises, and control strategies for the coal mill's pulverising process. It has made it possible to integrate sophisticated control algorithms into the coal pulverising process for improved status diagnosis and control. The Coal Mill Model is also a requirement for putting advanced control algorithms into practise for a thermal power plant's master pressure control. There is a tonne of room for using estimating methods like the Kalman Filter to fine-tune the model and cutting-edge intelligent hybrid evolutionary methods in place of GA to increase the result's accuracy.

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	Primary air flow rate into coal mill

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air	(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)

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