Development of a Tube-ball Coal Mill Mathematical Model Using Particle Swarm Optimization (P.S.O.)

P. Zachariades , J. L. Wei, J. Wang*

Abstract

This paper presents a mathematical model for Tube-ball mills which is developed based on the previous work. The Particle Swarm Optimization (PSO) method is used to identify the unknown parameters of the coal mill model with the on-line measurement data provided by EDF Energy. Simulation studies are carried out and the results are encouraging although it is still in the early stage of the model development.

Keywords: Particle Swarm Optimization (PSO); system identification; system modeling; nonlinear systems; coal mill modeling.

I. INTRODUCTION

Four well known paradigms currently exist in evolutionary computation: Genetic Algorithms, Evolutionary Programming, Evolution strategies and Genetic Programming. Particle Swarm Optimization (PSO) is newly developed evolutionary computation technique that was originally proposed by Eberhant and Kennedy [1]. It is based optimization algorithm motivated from the simulation of the social behaviour of birds within a flock, wherein each particle (individual) adjusts its "flying" according to its own flying experience and its companions flying experience. A traditional PSO can be classified into three different versions, namely, Individual Best, Global Best and the Local Best versions [2, 3]. In the Individual Best PSO, each particle compares its current position to its own best position to tune the velocity of "moving". No information from other particles is used. In the Global Best PSO, the social knowledge used to drive the movement of particles includes not only its own best position thus far but also the position of the best particle from the entire swarm. In the Local Best PSO, the particles are influenced by the best position with their neighbourhood, as well as their own past experience. Similar to other population-based algorithms, such as evolutionary algorithms, PSO can solve a variety of difficult optimization problems with a faster convergence rate than other evolutionary algorithms [4, 5].

Coal-fired stations are now obliged to vary their outputs in response to changing electricity demand (load following operation) and are required to operate more flexibly with more varied coal specifications. Mill controls need to respond effectively to changes in plant load and coal quality [6].

The Tube Ball mill used by EDF is a motor driven tumbling barrel charged with steel grinding balls as shown in Figure 2. The mill drive is via a 1.6MW, 740 RPM, 3.3KV 3ph 50 Hz constant speed electric motor through a reduction gearbox. The speed of the mill barrel is 15 RPM being 75% of the critical speed. Raw coal is delivered to the mill via drag link variable speed coal feeders. The coal feeder outlet chute delivers the coal. Hot air is swept through the mill by two 1.75mtr diameter variable speed exhauster fans. Hot air at 280^{O}C is available to the mills from the main boiler airheaters and facilities for raising this temperature up to 500^{O}C are available by the use of boost gas. Pulverised fuel (p.f.) flows via the discharge end of the mill to two static vane type M.E.L classifiers before being delivered by the variable speed exhausters to the p.f. burners. There are 4 p.f. burners per exhauster and the p.f. is equally distributed by splitter box arrangements at the exhauster discharge [6, 7, 8].

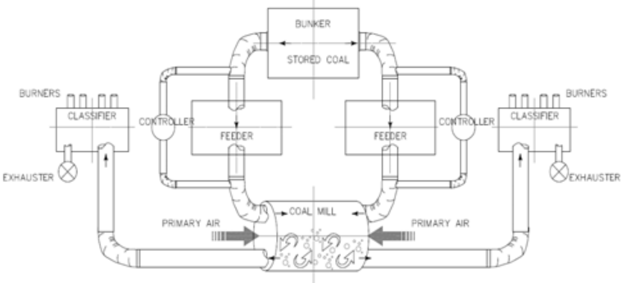

Figure 1 Tube Ball Mill Principle of Operation

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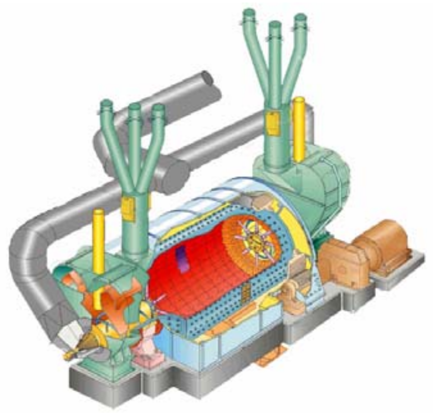

Figure 2 Tube Ball Mill Structure

II. MATHEMATICAL MODEL OF TUBE-BALL MILL

The procedure for coal mill modelling can be broken down into the following steps:

1) To derive the basic mill model dynamic equations through analyzing the milling process, applying physics and engineering principles and integrating the knowledge of experienced engineers
2) To identify unknown parameters using PSO techniques based on-site measurement data
3) To analyze the simulation results and interpret the parameters identified through the discussions between the researchers and experienced engineers
4) To return back to step 2 if any modification is required in order to improve the mill model or to conduct further simulation in order to validate the model.

The variables are divided into three groups, the inputs, intermediates and outputs.
A full list of the variables is shown by Table 1.

Table 1 List with Tube-Ball Mill Variables

Coal mill variables		
Input variables	**Intermediate variables**	**Output variables**
- A1 feeder Actuator Position A_{P1} (%)	- Mass of coal in mill M_c	- Mill inlet pressure ΔP_{In}
- A2 feeder Actuator Position A_{P2} (%)	- Mass of pulverised coal in mill M_{pf}	- Mill outlet temperature T_{out}
- Mill outlet pressure ΔP_{Out}	- Mill product pressure ΔP_{mpd}	- Mill power consumed P
- Primary air temperature inlet the mill T_{in}	- Mass flow rate of pulverized coal out of mill W_{pf}	

With this organization of the data sets, the modelling study for the Tube-Ball mill has been carried out. The initial results are described in the following subsections.

A. Modelling Study of Tube Ball Mills

1. Initial Model of the Tube-Ball Mill

The mathematical model of the Tube-Ball mill was developed based on fluid mechanics; principles electrical engineering, thermodynamics and aerodynamics

$$W_c(t) = K_{f1} \cdot A_{P1}(t) + K_{f2} \cdot A_{P2}(t) \tag{1}$$

As the total mass of coal fed into the mill per hour is given in the manual from EDF [5], these two coefficients can be estimated to be 51.6 kg/s and 25.8kg/s.

$$W_{air}(t) = K \cdot \sqrt{\Delta P_{In}(t) \cdot \rho(t)} \tag{2}$$

Combining with the ideal gas law $\rho(t)$ at the temperature $T_{in}(t)$ can be represented by $\frac{273}{273+T_{in}(t)} \cdot \frac{28.8}{22.4}$.

$$W_{air}(t) = 10 \cdot \sqrt{\Delta P_{In}(t) \cdot \frac{273}{273+T_{in}(t)} \cdot \frac{28.8}{22.4}} \tag{3}$$

$$W_{pf}(t) = K_{16} \cdot \Delta P_{out}(t) \cdot M_{pf}(t) \tag{4}$$

$$\dot{M}_c(t) = W_c(t) - K_{15} \cdot M_c(t) \tag{5}$$

$$\dot{M}_{pf}(t) = K_{15} \cdot M_c(t) - W_{pf}(t) \tag{6}$$

$$\Delta \dot{P}_{mpd}(t) = K_{11} M_{pf}(t) + K_{12} M_c(t) - K_{13} \Delta P_{mpd}(t) \tag{7}$$

$$\Delta P_{In}(t) = K_9 \Delta P_{pa}(t) + \Delta P_{mpd}(t) \tag{8}$$

$$P(t) = K_6 M_{pf}(t) + K_7 M_c(t) + K_8 \tag{9}$$

$$\begin{aligned} Q_{in} &= Q_{air} + Q_p + Q_{coal} \\ &= [K_1 T_{in}(t) + K_2] W_{air}(t) + K_{14} P(t) + K_3 W_c(t) \end{aligned} \tag{10}$$

$$\begin{aligned} Q_{out} &= Q_{P.F.} + Q_e \\ &= K_4 T_{out}(t) \cdot [W_{air}(t) + W_c(t)] + K_5 \cdot [W_{air}(t) + W_c(t)] \end{aligned} \tag{11}$$

$$\dot{T}_{out} \propto K_t T_{out} + Q_{in} - Q_{out} \tag{12}$$

$$\begin{aligned} \dot{T}_{out} = {} & [K_1 T_{in}(t) + K_2] W_{air}(t) + K_{14} P(t) - K_3 W_c(t) - \\ & [K_4 T_{out}(t) + K_5] \cdot [W_{air}(t) + W_c(t)] + K_{17} T_{out} \end{aligned} \tag{13}$$

Following the above analysis, the complete coal mill model can be described as follows, which does not cover the start up and shut down processes, where

A_{P1} : A1 feeder actuator position (%)
A_{P2} : A2 feeder actuator position (%)
ρ : Primary air density (*kg/m³*)
M_c : Mass of coal in mill (*kg*)
M_{pf} : Mass of pulverized coal in mill (*kg*)
T_{out} : Outlet temperature of coal mill (*°C*)
ΔP_{Out} : Mill outlet differential pressure (*mbar*)
ΔP_{mpd} : Mill product differential pressure (*mbar*)
W_{pf} : Mass flow rate of pulverized coal outlet from mill (*kg/s*)
P : Mill current (*Amp*)
ΔP_{In} : Mill inlet differential pressure (*mbar*)
W_c : Mass flow rate of coal into mill (*kg/s*)
T_{in} : Inlet temperature of coal mill (*°C*)
W_{air} : Primary air flow rate into coal mill (*kg/s*)
K_{f1}, K_{f2} : A1 A2 feeder coefficients
$K_1, \ldots K_{17}$: Unknown coefficients to be identified

1. Modification of the Initial Model

Equations (7) & (8) are developed based on the working principle of a vertical spindle mill. There is a rotating mechanism that acts like a paddle spinning inside the mill and the mill product pressure ΔP_{mpd} is generated due to influences of aerodynamics. Equation (8) represents the dynamic characteristic of this mill produced pressure inside the mill, which is similar to a first order linear system and also the pulverised coal in mill and the raw coal fed into the mill contribute to the variation of the pressure.

From the working principle of a Tube-Ball mill [7], it is known that there is actually no rotation mechanism like paddles spinning inside of the mill. The mill outlet pressure is a compromised aerodynamic result among the mill inlet pressure, suction pressures generated by the Exhauster Fan A1 & A2, mass of raw coal inside of the mill, and mass of pulverized coal inside of the mill. So, the mill pressure model is modified and presented in Equation (14).

$$\Delta \dot{P}_{out} = K_9 \cdot P_{E1} + K_{10} \cdot P_{E2} + K_{11} \cdot M_{pf} + K_{12} \cdot M_c + K_{13} \cdot \Delta P_{in} + K_{18} \cdot \Delta P_{out} \quad (14)$$

where P_{E1} is the mill A1 exhauster motor current, P_{E2} is the mill A1 exhauster motor current, $K_9 \sim K_{18}$ are the coefficients to be identified.

III. PARAMETER IDENTIFICATION USING PSO

The particle swarm optimization (PSO) algorithm is a population-based search algorithm based on the simulation of the social behaviour of birds within a flock. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock [5], the aim of discovering patterns that govern the ability of birds to fly synchronously, and to suddenly change direction with a regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm.

Similar to other population-based algorithms such as evolutionary algorithms, PSO can solve a variety of difficulty optimization problems but has shown a faster convergence rate than other evolutionary algorithms on some problems [4]. Another advantage of PSO is that it has very few parameters to adjust which makes it particularly easy to implement.

In the previous project, the genetic algorithm (GA) has been employed for the coefficients identification while modelling the vertical spindle coal mill. As an intelligence search algorithm, the GA was first introduced in 1950s, and it offers fast converge and pretty good results. For the newly born PSO algorithm, it ages younger than 10 years, and has make great influence in the computational intelligence engineering. The motivation for studying and using PSO are as follows:

a. looking for alternative and possible better algorithms that can perform faster and robust

b. it is possible fast alogrithms to be used for on-line update the parameter identification

c. finally using PSO better or more accurate results are expected comparing with GAs

The authors anticipate that this newly algorithm will offer great help to our current project. Theoretical and simulation studies of the PSO algorithm are carried out in this paper. As mentioned in the above section, PSO is a population-based optimization algorithm. The population of PSO is called a *swarm* and individual in the population of PSO is called a *particle*, where each *particle* represents a potential solution.

While applying PSO, the particles are flown through the hyperspace, and the position of each particle changes according to its own experience and that of its neighbours. Let $\vec{x}_i(t)$ denote the position of particle P_i in hyperspace, at time step t. The position of P_i is then changed by adding a velocity $\vec{v}_i(t)$ to the current position, i.e.

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \quad (15)$$

Depend on different velocity updating scheme which reflects how the social information exchange, the PSO can be divided into three different algorithms, which are the Individual Best PSO, Global Best PSO, and the Local Best PSO. Simulation studies show that the Global Best PSO offers the best performance and fastest convergence. The evolutionary process of the Global Best PSO is described below:

1. Initialize the swarm, $P(t)$ of particles such that the position $\vec{x}_i(t)$ of each particle $P_i \in P(t)$ is random within the hyperspace, with $t=0$. Each particle represents a possible solution.
2. Evaluate the objective function *ObjF* of each particle, using its current position $\vec{x}_i(t)$.
3. Compare the performance of each individual to its best performance. If $ObjF(\vec{x}_i(t))$ is less than its own best performance $pbest_i$, then: $pbest_i$ is set to be $ObjF(\vec{x}_i(t))$, and its own best position $\vec{x}_{pbest_i}$ is set to be $\vec{x}_i(t)$.
4. Compare the performance of each particle to the global best particle. If $ObjF(\vec{x}_i(t))$ is less than the global best performance *gbest* then: *gbest* is set to be $ObjF(\vec{x}_i(t))$, and the global best position $\vec{x}_{gbest}$ is set to be $\vec{x}_i(t)$.
5. Change the velocity vector for each particle $\vec{v}_i(t)$ using the formula:

$$\vec{v}_i(t) = \omega * \vec{v}_i(t-1) + \rho_1\left[\vec{x}_{pbest_i} - \vec{x}_i(t)\right] + \rho_2\left[\vec{x}_{gbest} - \vec{x}_i(t)\right] \quad (16)$$

where, the ρ_1 and ρ_2 are random variables defined as $\rho_1 = r_1 c_1$ and $\rho_2 = r_2 c_2$, with $r_1, r_2 \in U(0,1)$, and the cognitive acceleration c_1 and the social acceleration c_2 are positive constants; ω is velocity weight, which is linearly decreased from a relatively large value ω_{start}

to a small value ω_{end} through the course of the PSO run. If the velocity $\vec{v}_i(t)$ is bigger than the upper limit of the velocity $\vec{v}_{\max}$, then $\vec{v}_i(t)$ is set to be $\vec{v}_{\max}$.

6. Move each particle to a new position using the following formulas:

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \quad (17)$$

$$t = t + 1 \quad (18)$$

7. Go to step 2, and repeat until termination criteria reaches.

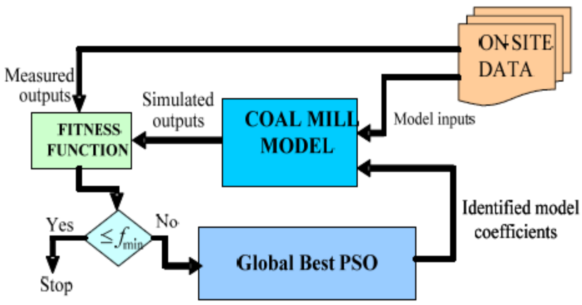

Figure 6 Schematic of the model's coefficients identification

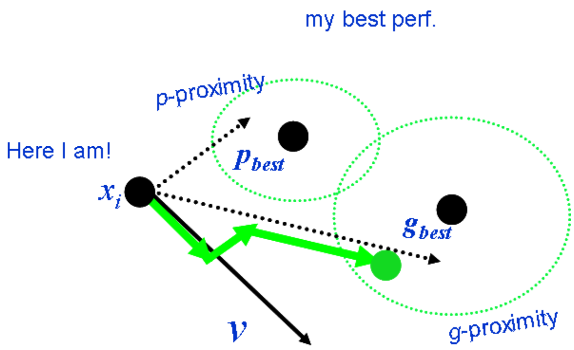

Figure 7 Swarm fly – Psychosocial Compromise

Each particle has 3 tendencies:

a. *Audacious, flows its own way (just using its own velocity)*

b. *Conservative, going back more or less towards its best previous position*

c. *Sheep like, going more or less towards its best neighbour*

What PSO formalizes is how to combine these tendencies in order to be globally efficient.

To achieve faster and robust results as a first step the authors decrease the swarm size from 40 to 30 and later on to 20. The authors believe that more modifications to the PSO algorithms are needed and they are working to improve further the PSO algorithm. The simulation results suing PSO are presented in Figure 8 and Figure 9. Figure 8 shows the variables which can be measured for the current mill system so the estimated values can compare with the measured values. Figure 9 displays the immeasurable variables which are considered as the intermediate variables.

Figure 8 (Top) presents the comparisons between the systems measured mill outlet temperature and the model simulated mill outlet temperature. From the figure, it can be seen that simulated mill outlet temperature can follow the trends of variations in the measured mill outlet temperature well. However, at the middle of the data, the simulated mill outlet temperature vibrates away from the measured mill outlet temperature, and causes errors. Further improvement is required for further work.

Figure 8 (Middle) presents the comparisons between the systems measured mill motor current and the model simulated mill motor current. From the figure, it can be seen that the model simulated mill motor current can follow the general variation trends of the measured mill motor current. Again, some discrepancies can be seen in the diagram although they are in the tolerance range.

Figure 8 (Bottom) presents the comparisons between the systems measured mill inlet pressure and the model simulated mill inlet pressure. From the figure, it can be seen that the model simulated mill inlet pressure approaches to the measured mill inlet pressure until the middle of the data. The main problems observed from the results are that the simulated results are more violent in variations.

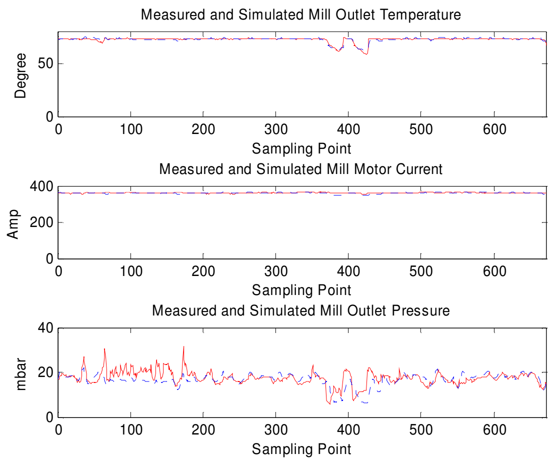

Figure 8 measured (solid lines) and simulated (broken lines) using PSO

In Figure 9, the first row of the figure presents the model simulated raw coal flow rate inlet by feeders and the model simulated pulverised coal flow outlet by exhausters. The inlet raw coal flow rate values at around 18 kg/s (64.8 ton/h) in steady state period, and the outlet pulverised coal flow follows the trends of the inlet raw coal flow very well. The second row of the figure presents the model simulated mass of raw coal and the mass of pulverised coal inside of the mill. In steady state working condition, the model predicts about 18 tons of raw coal and 9 tons of pulverised coal inside of the mill. These have been discussed with the combustion engineers.

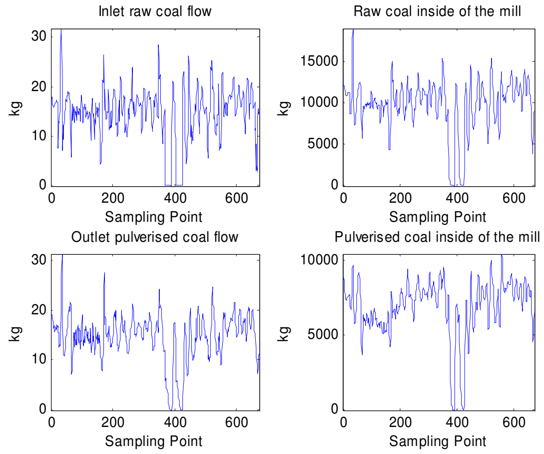

Figure 9: Model simulated

Figure 10 presents the comparisons between the system measured mill outlet temperature and the model simulated mill outlet temperature, the systems measured mill motor current and the model simulated mill motor current, and the system measured mill inlet pressure and the model simulated mill inlet pressure using GA respectively.

Comparing the results between PSO (Figure 8) and GA (Figures 10) we can see that using PSO the model simulated results are better than the GA. In PSO the model simulated results follow the trends of variation of the measured results. In GA the model simulated results follow the general variation of the measured results but at some points there is a striking discrepancy between the measured and simulated results.

Table 2 Unknown Parameter Identification for initial model

$K_1 = 0.00005$	$K_{10} = 0.007966$
$K_2 = 0.008108$	$K_{11} = 0.0001$
$K_3 = 0.0109$	$K_{12} = 0.000007$
$K_4 = 0.00002$	$K_{13} = 0.01$
$K_5 = 0.0015$	$K_{14} = 0.005525$
$K_6 = 0.0001$	$K_{15} = 0.0015$
$K_7 = 0.00001$	$K_{16} = 0.00012$
$K_8 = 343.44$	$K_{17} = -0.03$
$K_9 = 0.005795$	$K_{18} = -0.1$

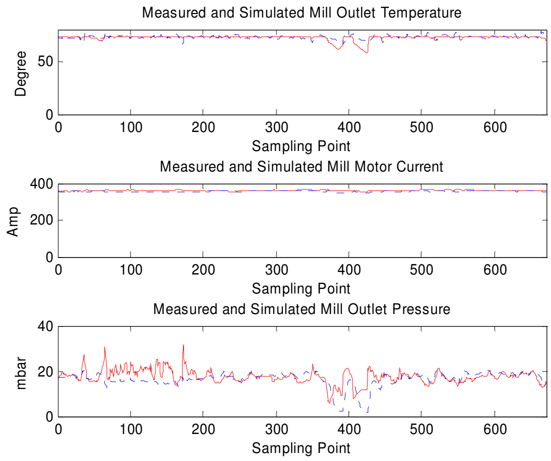

Figure 10 measured (solid lines) and simulated (broken lines) using GA

Table 3 Unknown Parameter Identification after modification

$K_1 = 0.00005$	$K_{10} = 0.007244$
$K_2 = 0.0088$	$K_{11} = 0.0001$
$K_3 = 0.02$	$K_{12} = 0.000007$
$K_4 = 0.00002$	$K_{13} = 0.01$
$K_5 = 0.0015$	$K_{14} = 0.006366$
$K_6 = 0.0001$	$K_{15} = 0.0015$
$K_7 = 0.00001$	$K_{16} = 0.00012$
$K_8 = 345.86$	$K_{17} = -0.03$
$K_9 = 0.00659$	$K_{18} = -0.1$

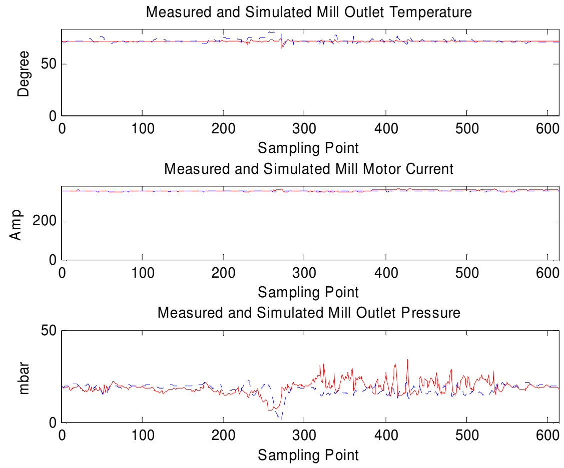

Figure 11 measured and simulated results using the initial model

It can be observed from the results that are shown on figures 11 and 12 after the modification of the tube-ball mill model are better and especially on the mill outlet pressure. Comparing the values of the unknown parameters it can be observe that there differences can be neglected. These changes can not affect the model.

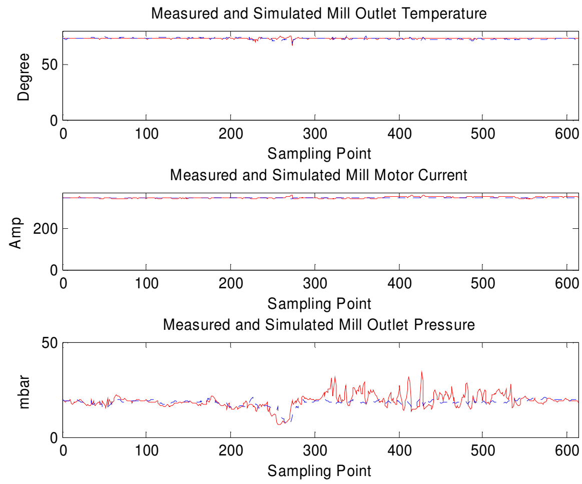

Figure 12 measured and simulated results after the modification

IV. Concluding Remarks

The paper presented the initial - early stage of mathematical model development for a Tube-ball mill. The PSO optimization method is chosen for system parameters identification. Also the PSO method is compared with Gas method. Finally some improvements are included. The results are encouraging although the improvement is required. The project is still on-going in collaboration with EDF Energy and E.ON UK. The results presented in the paper indicated the project methodology is suitable and practical. The future work will focus on improvement of the model and PSO and on-line implementation.

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