Energy Conversion and Management 80 (2014) 10–19

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

A new model-based approach for power plant Tube-ball mill condition monitoring and fault detection ☆

Shen Guo [a], Jihong Wang [a,*], Jianlin Wei [a], Paschalis Zachariades [b]

[a] School of Engineering, University of Warwick, Coventry CV4 7AL, UK
[b] School of Electronic, Electrical and Computer Engineering, University of Birmingham, Birmingham B15 2TT, UK

ARTICLE INFO

Article history:
Received 2 August 2013
Accepted 22 December 2013

Keywords:
System modelling
Genetic Algorithms
Power generation control
Coal fired power plants

ABSTRACT

With the fast growth in intermittent renewable power generation, unprecedented demands for power plant operation flexibility have posed new challenges to the ageing conventional power plants in the UK. Adding biomass to coal for co-fired power generation has become widely implemented practices in order to meet the emission regulation targets. These have impacted the coal mill and power plant operation safety and reliability. The Vertical Spindle mill model was developed through the authors' work before 2007. From then, the new research progress has been made in modelling and condition monitoring for Tube-ball mills and is reported in the paper. A mathematical model for Tube-ball milling process is developed by applying engineering principles combined with model unknown parameter identifications using a computational intelligent algorithm. The model describes the whole milling process from the mill idle status, start-up to normal grinding and shut-down. The model is verified using on-site measurement data and on-line test. The on-line model is used for mill condition monitoring in two ways: (i) to compare the predicted and measured mill output pressure and temperatures and to raise alarms if there are big discrepancies; and (ii) to monitor the mill model parameter variation patterns which detect the potential faults and mill malfunctions.

1. Introduction

Around 40% of electricity in the world is currently generated by coal-fired power plants. The total UK coal-fired power generation capacity is around 28 GW. With recently increased penetration of renewable power generation, coal-fired power stations are required to operate more flexibly to serve as peaking load generation plants, to work with more varied coal specifications and to regularly add biomass materials to coal. In this way, the coal fired power plants are required to vary their output more frequently in response to the electricity load demand changes, which results in more frequent mill start-ups and shut-downs. This greatly increases the risks of explosions or fires in milling processes in associated with the UK aging power stations which were built 30 years ago. On the other hand, as one strategy of achieving green and sustainable energy target, combining bio-mass materials with coal as co-fired fuel is nowadays already a general practice at coal fired power plants in the UK. This, in turn, has a big impact on power plant operation safety ([1–3]). The UK PF Safety Forum recently reported an increase in the frequency of mill incidents in the UK. However, it is difficult to identify the potential incidents of mill fires at the early stage to prevent its happening ([4]). The objective of the paper is to develop a model-based on-line mill condition monitoring method and tool.

The early work on mill modelling has been reviewed and compared by Austin in 1971 ([5]). Austin et al. in their series of papers [6–8], analysed a ball-and-race mill and derived a detailed model based on a scale-up of the Hardgrove mill to an industrial mill. Neal et al. [9] performed a frequency analysis of mill and boiler complex, and analyzed its effects on the steam pressure. This work led to a simple transfer function plant model. Similarly, Bollinger and Snowden [10] performed an experimental study of a mill's transfer function model in order to devise feed forward controllers. An approximated linear transfer function model was reported in [11,12]. Mill modelling using system identification method was reported by Corti et al. in 1984 [13]. With specially designed input signals, a linear discrete time model was obtained by Cheetham et al. in 1990 [14], in which system time-delay was considered. An approximated linear time varying mill model was derived by Fan et al. in 1994 [2]. A polynomial matrix model was reported in [3].

Zhang et al. developed a nonlinear mathematical model for the normal grinding process of Vertical Spindle coal mills using on-site

* Corresponding author. Tel.: +44 (0)2476523780.
E-mail address: Jihong.wang@warwick.ac.uk (J. Wang).

0196-8904/$ - see front matter © 2013 The Authors. Published by Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enconman.2013.12.046

measurement data and an evolutionary computation technique in 2002 [15]. A realistic technique for implementation of the model in real-time was demonstrated in 2006 [4,16]. Niemczyk et al. [17] were inspired by the work reported in [4,15] and improved the work in certain aspects: a rotating classifier is included and the mill temperature equation is based on the first principles. Niemczyk also used an alternative computational algorithm called "differential evolution algorithms" to estimate the model parameters. In 2010, Kamalesh et al. built a mathematical model of Vertical Spindle coal mill by the CFD (computational fluid dynamics) technology that considers exchange of heat, mass and forces between primary air and coal, providing insights into the internal mill aerodynamics [18]. A recent study by Dahl-Soerensen and Solberg [19] shows that it is possible to acquire good estimates of the pulverized fuel flow rate by means of sensor fusion using Kalman filter techniques. Recently, in 2011 and 2013, ABB has reported their work in nonlinear coal mill modelling for vertical roller pressure mills and its application to mill control ([20,21]). In the reported work, mill model parameter sensitivity analysis was performed and the results were used to guide parameter optimisation.

Tube-ball mill is another dominant type of coal mill apart from Vertical Spindle mill in industry. Compared with the Vertical Spindle mills, Tube-ball mills have a much higher grinding capacity. However, there are fewer literatures found in studying Tube-ball mill operation compared with the Vertical Spindle mill. Ma et al. introduced a black box Neural Network model for Tube-ball mills in 2005 [22]. Although the Neural Network can have a good model performance for certain operation status, it provides very little information about the mill physic operation. With the knowledge gained from the study of the Vertical Spindle mill model ([4,16]). The team at Warwick started working on Tube-ball mill modelling with the financial support from British coal utilisation research association. Our initial work for Tube-ball mill normal grinding process modelling was reported in [23,24]. This paper will report the new work on developing a multi-segment Tube-ball mill model for the whole milling process condition monitoring. The main contributions of this paper are: (1) a multi-segment model to represent the starting-up, normal grinding, shutting-down and idle stages which extended the work reported in [23,24]. The test results demonstrated that the model can represent the milling process well, (2) the model is implemented on-line for mill condition monitoring and safe operation. The multi-segment mill models is able to switch from one segment to the next automatically in real-time by capturing the segment change flag/triggering signals, and (3) two particular case studies are reported to demonstrate how the mode-based approach is used for mill fault detection and condition monitoring.

2. Tube-ball mill mathematical model for normal grinding operation process

The working principle of the coal mill is illustrated in Fig. 1 [25]. In normal practice, there are two coal feeders for each mill. Once the raw coal flows into the mill barrel with hot primary air, the iron balls inside the rotating barrel will continuously crash the coal until it is fine enough to be blown out the mill to the furnace. To model the process, the measured input and output variables are identified first. From the study of the plant DCS (distributed control and monitoring systems) data, the feeder actuator positions are considered as one of the input variables, that is, two feeders' (A1 and A2) actuator positions: A_{P1} (%) and A_{P2} (%). The mill inlet pressure ΔP_{In} and primary air inlet temperature T_{in} are also classified as the system input variables. The output variables are mill outlet pressure ΔP_{Out}, outlet temperature T_{Out} and mill power P. Some

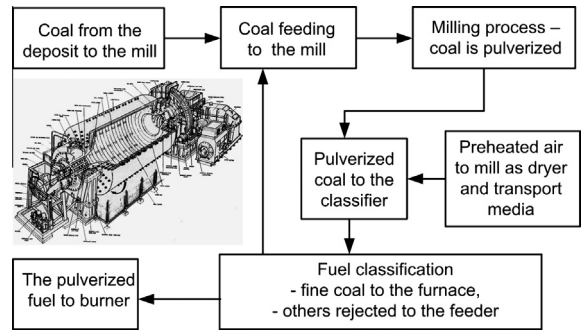

Fig. 1. Working process of a Tube-ball mill.

intermediate variables are also introduced which are not measurable in practice due to lack of suitable sensors or impossible installation of sensors. Those variables are the mass flow rate of pulverized coal output from mill W_{pf}, the mass of un-pulverized coal inside the mill M_c, and the mass of pulverized coal inside the mill M_{pf}. The full list of the variables is given in Table 1. The mill mathematical model is derived through analysis of mass, heat and energy balances.

2.1. Mass flow analysis

In the Tube-ball mill system, each feeder is driven by a variable speed electric motor. Right before the feed hopper, a bunker discharge valve is installed to control the mass flow. In the system, both the feeder motor current and discharge valve actuation position are measured. The mass flow rate varies with the mill current and valve position and is calculated by the following equation:

$$W_c(t) = C_{f1}[K_{f1}A_{P1}(t) + 3.3] + C_{f2}[K_{f2}A_{P2}(t) + 3.3] \quad (1)$$

where A_{P1} and A_{P2} are the feeder actuation positions. The parameters in Eq. (1) were obtained through the on-site power plant test with integration of the knowledge of plant engineers. For the mill discussed in the paper, $K_{f1} = 32.60$; $K_{f2} = 31.64$, which should be re-identified for different mills. When the damper is closed but the feeder is still in operation to feed the raw coal to the mill which is specified in the power plant operation procedure. This has led to the residual value of 3.3 in (1), which is obtained from the test conducted by plant engineers. C_{f1} and C_{f2} are Boolean logical variables to represent which feeder is in operation, that is, $C_{f1} = 1$ or $C_{f2} = 1$ if mill A1 or A1 = 2 feeder is in operation; otherwise, $C_{f1} = 0$ or $C_{f2} = 0$.

The air flow system of a Tube-ball mill can be described by the diagram in Fig. 2, in which 7A, 8A and 14A are inlet air dampers while 12A1 and 12A2 are exhaust outlet dampers. The ΔP_{in} and ΔP_{out} in the figure represents the inlet differential pressure and the outlet pressure of the mill [22]. From the fluid mechanism, the air blowing into the coal mill is governed by:

$$W_{\text{air}}(t) = \kappa_1\sqrt{\Delta P_{\text{in}}(t)} + \kappa_2$$

where ΔP_{in} is the mill inlet differential pressure (mbar); W_{air} is the mass flow rate of the inlet air (kg/s). The two parameters κ_1, κ_2 are obtained from the mill operation data which are 12.42 and 4.01 respectively.

$$W_{\text{air}}(t) = 12.42 \cdot \sqrt{\Delta P_{\text{in}}(t)} + 4.01 \quad (2)$$

To simplify the modelling process, the coal inside the mill barrel is classified into the pulverized and un-pulverized two categories only. The mass flow of the coal during the mill grinding operation can be schematically illustrated by Fig. 3. The raw coal is fed into the mill by the feeders at a mass flow rate of W_c. By tumbling the raw coal M_c with a charge of steel balls, the pulverized coal

Table 1
The list of coal mill inputs and outputs variables.

Input variables	Intermediate variables	Output variables
A_{P1} (%) – A1 feeder actuator position A_{P2} (%) – A2 feeder actuator position	M_c (kg) – mass of coal in mill M_{pf} (kg) – mass of pulverized coal in mill	T_{out} (°C) – mill outlet Temperature
T_{in} (°C) – primary air temperature inlet the mill	W_c (kg/s) – mass flow rate of raw coal into the mill	ΔP_{Out} (mbar) – mill outlet pressure
I^P (Amp) – mill current that is used to indicate the power consumed by the mill so it normally refers as "mill power" by plant engineers ΔP_{In} (mbar) – mill inlet pressure	W_{pf} (kg/s) – mass flow rate of pulverized coal out of mill	

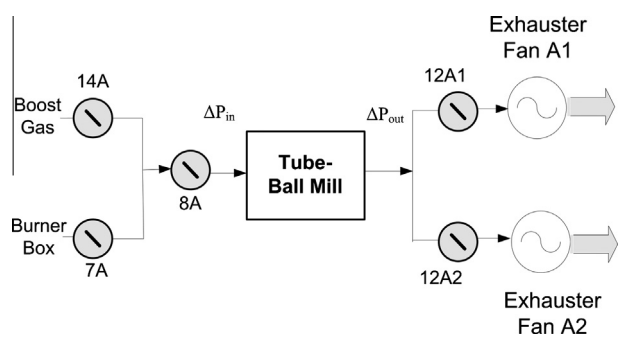

Fig. 2. Sketch of the air flow system of a Tube-ball mill.

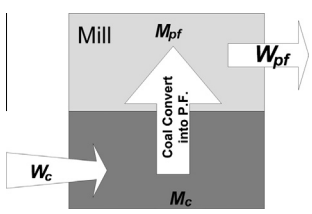

Fig. 3. Illustration of mass flow.

M_{pf} is produced and carried out by the warm air flow to the mill outlet with a mass flow rate of W_{pf}. In order to maintain the coal level inside the mill, the total mass of coal fed into the mill should be close to the total mass flowing out the mill. So the flow rate W_{pf} of the pulverized coal output from the mill will be equal to the flow rate W_c of the raw coal flowing into the mill at the steady state eventually. From the mass flow balance, the coal flow rates are governed by Eqs. (3)–(5).

$$W_{pf}(t) = K_{16}\Delta P_{out}(t)M_{pf}(t) + \left[C_{E1}I^P_{E1} + C_{E2}I^P_{E2}\right] \cdot K_{19} \tag{3}$$

$$\dot{M}_c(t) = W_c(t) - K_{15} \cdot M_c(t) \tag{4}$$

$$\dot{M}_{pf}(t) = K_{15} \cdot M_c(t) - W_{pf}(t) \tag{5}$$

where C_{E1} and C_{E2} are logical control parameters, that is, $C_{E1} = 1$ if mill A1 (Fig. 2) exhauster fan current $I^P_{E1} \gg 22$ A, otherwise $C_{E1} = 0$; $C_{E2} = 1$ if mill A2 exhauster fan current $I^P_{E2} \gg 22$ A, otherwise $C_{E2} = 0$; K_{15}, K_{16} and K_{19} are the unknown parameters to be identified using parameter identification methods described in the late section.

Eq. (3) is derived as the flow rate of PF (pulverized fuel) out of the mill $W_{pf}(t)$ is dependent on how much coal is already pulverized $M_{pf}(t)$ and the mill outlet differential pressure resulted from the power of the two exhauster fans $\Delta P_{Out}(t)$. Eq. (4) shows that the change of mass of coal in the mill $\dot{M}_c(t)$ is controlled by the difference between the coal flow into the mill and the fraction of the coal pulverized. $M_{pf}(t)$ is impossible to be measured in practice so it is treated as an intermediate variable and can only be predicted by the model. From Eq. (5), the changes in mass of the pulverized fuel inside the mill vary with the difference of the fraction of pulverized coal and the pulverized coal flow out from the mill.

2.2. Variations of mill pressure

While pulverizing the coal, the mill barrel rotates at the speed around 15 rpm. The outlet pressure ΔP_{out} is influenced by the coal mass flow and the power of the exhaust fans. The rate of the changes is governed by the following equation:

$$\Delta\dot{P}_{out}(t) = K_9 \cdot I^P_{E1}(t) + K_{10} \cdot I^P_{E2}(t) + K_{11} \cdot M_{pf}(t) + K_{12} \cdot M_c(t) + K_{13} \cdot \Delta P_{in\_diff}(t) + K_{18} \cdot \Delta P_{out}(t) \tag{6}$$

where K_9, K_{10}, K_{11}, K_{12}, K_{13}, K_{18} are the unknown coefficients to be identified.

2.3. Thermal process analysis

Hot air is swept through the mill by two variable speed fans, and the air acts as both the drying and transporting agent for the coal. If the coal mill heating process is treated as it happens in an isolated environment as shown in Fig. 4, the heat input into the coal mill and the heat output from the coal mill complies with the heat balance rule. The heat into the coal mill Q_{in} includes the heat from raw coal Q_{coal} and the heat from the hot air Q_{air}. The heat out from the coal mill Q_{out} includes the heat outlet in the pulverized coal Q_{pf} and the heat emitted from the mill body to the environment Q_e. For heat balance, the change of heat in the mill Q_{mill} can be described as:

$$Q_{mill} = Q_{coal} + Q_{air} - Q_{P.F.} - Q_e.$$

The heat can be obtained through the temperature variations and the quantity of heat brought in from the warm air. Based on the heat balance rule, the mill outlet T_{out} is determined by the following equation:

$$\dot{T}_{out}(t) = K_1 \cdot T_{in}(t) + K_2 \cdot W_{air}(t) - K_3 \cdot W_c(t) + K_{14} \cdot I^P(t) - K_{20} \cdot T_{in}(t) \cdot T_{out}(t) + K_{17} \cdot T_{out}(t) \tag{7}$$

where K_1, K_2, K_3, K_{14}, K_{17} and K_{20} are the unknown coefficients to be identified.

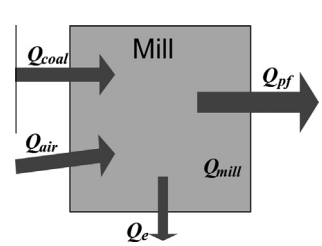

Fig. 4. Mill thermal balance.

In summary, the complete coal mill model for the mill normal grinding process is described by (1)–(7) and all the variables in the equations are defined in Table 1.

3. Multi-segment mill mathematical model

The mathematical model described in the previous section is suitable for the mill operating at the normal grinding process but cannot represent the whole milling process from the mill start-up to shut-down. The mill start-up and the individual operation stages must follow the operation procedures required for power plant safe operation. The operation procedure specifies a pre-defined "on/off" logical sequence that must be followed by different devices and functions while they start or stop.

3.1. Coal mill start-up/shut-down operational sequences

The start-up sequence for a typical coal milling process can be divided into six different operational stages (O1–O6) [25], as shown in Fig. 5. During the typical start-up sequence, one of the two exhausters started at the minimum speed to purge the system (O1). Then the pre-start checking process is initiated and the jacking and lubrication oil start circulating (O2). When the mill oil system is satisfied the lubrication requirement and the inlet and outlet dampers are closed, the mill motor starts (O3) and then the coal feeder is switched on at the minimum speed (O4). The associated outlet damper opens as a following on action and the inlet damper will open after 5 s of O4 (O5). The final step is to shut-down the jacking oil when the mill is running and lubricating oil flow is established (O6) [25].

Similarly, a typical coal mill shut-down sequence can be divided into five different operational stages (O7–O11) [25], as shown in Fig. 6. The first stage is to shut down one of the exhausters if both of them are in operation (O7). The exhauster will purge at the maximum speed for 10 min before it stops. Also, the feeder is switched off, which will prevent continuously feeding more raw coal into the mill (O8). The mill starts shutting-down with the jacking oil pumps start, and the inlet and outlet dampers are closed when the jacking oil pressures are established (O9–O10). Finally, the second exhauster is turned off. Similarly, the exhauster will purge at the maximum speed for 10 min then stops completely (O11).

The operation of a mill from the start-up to shut-down will experience 11 stages. To distinguish the different stages, flag signals are required to indicate which operational stage the system is in. However, there is no direct logical indicator logged into the database at the plant to give the information to the DCS. So the alternative analogue signals of indirect variable values and also the logical values of the plant operations are considered, for example, the analogue signal of A1 feeder motor current and the Boolean signal indicting the mill inlet damper open are chosen to play the role of flag signals. Accordingly, the system's operational stages can be identified and triggered for changes in the simulation program. Detailed descriptions are given in the following subsections.

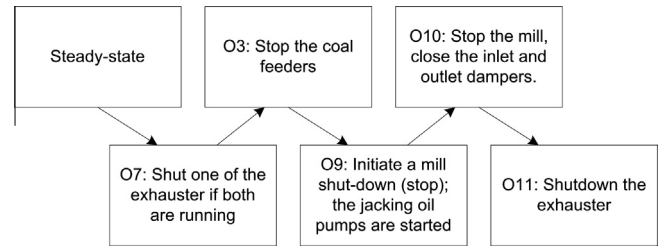

Fig. 6. A typical shut-down sequence.

3.2. Multi-segment coal mill mathematical model

From the analysis of the coal mill start-up and shut-down operation sequence provided in [25], the eleven different operation stages (see Figs. 5 and 6) can be grouped into five working conditions of the coal mill system. A five-segment coal mill model is then developed, and the schematic diagram of which is shown in Fig. 7. The mathematical models for each segment are described in the following subsections.

3.2.1. Mill mathematical model Segment I

The duration of this segment is the "mill preparation" process for start-up, which represents the operational stages O3–O4. During this period, the mill motor starts, but both feeders are still in idle status. The inlet damper is closed. As the coal mill feeders are off, there is no raw coal (W_c) flowing into the coal mill. One or two of the mill exhausters are on, but the outlet dampers remain closed. Therefore there is no pulverized coal outlet (W_{pf}) from the mill to the burner. Similarly, the inlet air damper "8A" is keeping closed at this duration, so there is no hot air (W_{air}) inlet into the coal mill. During this segment, no coal flows into and out of the mill so the mill body can be treated as an isolated volume. The mill outlet pressure becomes the atmosphere pressure and the outlet temperature varies with no heat taken in. The mill motor is on so the grinding process starts. The raw coal (residual coal from the previous operation cycle) inside the coal mill (M_c) reduces due to

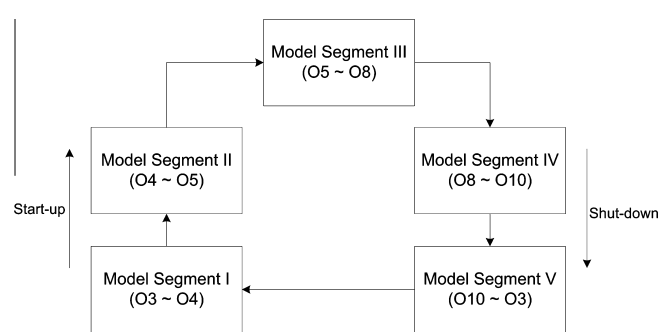

Fig. 7. Five segments for modelling.

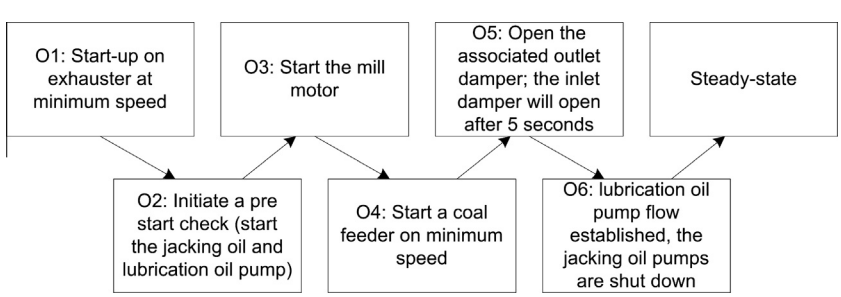

Fig. 5. A typical start-up sequence.

grinding, and the pulverized coal inside the mill (M_{pf}) increases. The Mill Model Segment I are derived as follows:

$$W_{air}(t) = 0 \tag{8}$$

$$W_c(t) = 0 \tag{9}$$

$$W_{pf}(t) = 0 \tag{10}$$

$$\dot{M}_c(t) = -K_{15\_I} \cdot M_c(t) \tag{11}$$

$$\dot{M}_{pf}(t) = K_{15\_I} \cdot M_c(t) - W_{pf}(t) \tag{12}$$

$$\Delta P_{out}(t) = 0 \tag{13}$$

$$\dot{T}_{out}(t) = K_{17\_I} \cdot T_{out}(t) \tag{14}$$

where K_{15_I} and K_{17_I} are unknown coefficients to be identified.

3.2.2. Mill Model Segment II

The segment is for preparation of the coal feeder, which lasts from O4 to O5. In Segment II, the status for the mill motor and inlet damper is the same as Segment I apart from start of one of the feeders. The feeder starts to feed coal into the mill for grinding as described in (16). In this segment, the inlet and outlet air dampers are still closed. Consequently, there is still no W_{air} into the coal mill, likewise there is no W_{pf} outlet from the mill although grinding is kept going. Since there is raw coal fed into the mill, the mass of raw coal (M_c) and mass of pulverized coal (M_{pf}) varies, which are modelled by Eqs. (17 and 18). For this segment, we have:

$$W_{air}(t) = 0 \tag{15}$$

$$W_c(t) = C_{f1}[K_{f1}A_{P1}(t) + 3.3] + C_{f2}[K_{f2}A_{P2}(t) + 3.3] \tag{16}$$

$$W_{pf}(t) = 0 \tag{17}$$

$$\dot{M}_c(t) = W_c(t) - K_{15\_II} \cdot M_c(t) \tag{18}$$

$$\dot{M}_{pf}(t) = K_{15\_II} \cdot M_c(t) \tag{19}$$

$$\Delta P_{out} = 0 \tag{20}$$

$$\dot{T}_{out}(t) = K_{17\_II} \cdot T_{out}(t) \tag{21}$$

where K_{15_I} and K_{17_I} are unknown coefficients to be identified for the segment.

3.2.3. Mill Model Segment III

Model Segment III is the normal grinding segment and the model is described by (1)–(7). The duration of this model segment is valid from O5 to O8.

3.2.4. Mill Model Segment IV

Mill Model Segment IV represents the shutting-down process of a coal mill, which is from O8 to O10 in all the eleven overall operational stages. Studies of coal mill start-up/shut-down operational sequences shows that the mill motor and the inlet damper is on during this period, while the feeders are not feeding raw coals into the mill as all the coal feeders are off in this segment ($W_c = 0$). All the other equipment still operates as the previous segment. The mill motor is kept running and at least one of the exhausters is kept on extracting pulverized fuel out. The model for this segment is shown as follows:

$$W_{air}(t) = 12.42 \cdot \sqrt{\Delta P_{in}(t)} + 4.01 \tag{22}$$

$$W_c(t) = 0 \tag{23}$$

$$W_{pf}(t) = K_{16\_IV}\Delta P_{out}(t)M_{pf}(t) + \left[C_{E1}I^P_{E1}(t) + C_{E2}I^P_{E2}(t)\right] \cdot K_{19} \tag{24}$$

$$\dot{M}_c(t) = -K_{15\_IV} \cdot M_c(t) \tag{25}$$

$$\dot{M}_{pf}(t) = K_{15\_IV} \cdot M_c(t) - W_{pf}(t) \tag{26}$$

$$\begin{aligned}\Delta\dot{P}_{out}(t) = {} & K_{9\_IV} \cdot I^P_{E1}(t) + K_{10\_IV} \cdot I^P_{E2}(t) + K_{11\_IV} \cdot M_{pf}(t) \\ & + K_{12\_IV} \cdot M_c(t) + K_{13\_IV} \cdot \Delta P_{in\_diff}(t) + K_{18\_IV} \\ & \cdot \Delta P_{out}(t)\end{aligned} \tag{27}$$

$$\begin{aligned}\dot{T}_{out}(t) = {} & K_{1\_IV} \cdot T_{in}(t) + K_{2\_IV} \cdot W_{air}(t) - K_{3\_IV} \cdot W_c(t) + K_{14\_IV} \\ & \cdot I^P(t) - K_{20\_IV} \cdot T_{in}(t) \cdot T_{out}(t) + K_{17\_IV} \cdot T_{out}(t)\end{aligned} \tag{28}$$

where $K_{1\_IV}, \ldots, K_{20\_IV}$ are unknown coefficients to be identified in Segment IV.

3.2.5. Mill Model Segment V

Model Segment V stands for the duration while the coal mill is idle, valid between O10 and O3. This is the only segment while mill motor is off. The coal mill system situates in the idle stage. As the inlet and outlet dampers are all closed, the mill can be treated as an isolated object, the mill outlet pressure will take the atmosphere pressure and the mill outlet temperature decreases gradually. The mill model equations for this segment are described by:

$$W_{air}(t) = 0 \tag{29}$$

$$W_c(t) = 0 \tag{30}$$

$$W_{pf}(t) = 0 \tag{31}$$

$$\dot{M}_c(t) = 0 \tag{32}$$

$$\dot{M}_{pf}(t) = 0 \tag{33}$$

$$\Delta P_{out} = 0 \tag{34}$$

$$\dot{T}_{out}(t) = K_{17\_V} \cdot T_{out}(t) \tag{35}$$

where K_{17_V} is an unknown coefficient to be identified for this segment. Analysing the characteristics of different mill operation segments, the triggers are implemented that enable the model to switch from one segment to another. A Boolean variable D53 from the data that indicates the status of the air inlet damper is introduced to this trigger algorithm. D53 = 1 when the damper is on, while D53 = 0 when it is off. The logic behind the model segment switches are illustrated in Fig. 8 and this diagram of logic is implemented in the mill condition monitoring software.

4. Model parameter identification using intelligent Computational algorithms

An intelligent computational algorithm is adopted to identify the unknown parameters or coefficients of the mill model. After reviewing the multiple available methods for parameter identifications, two intelligent computational algorithms are highlighted for further investigation, which are Genetic Algorithms (GAs) and Particle Swarm Optimisation (PSO). From the study, it is found that Genetic Algorithms is more robust than PSO although PSO is faster than GAs for this mill dynamic process parameter identification [4]. So GAs is chosen as a more stable algorithm for parameter identification, real-time and on-line implementation.

The parameter identification process using GAs is illustrated by the block diagram shown in Fig. 9. In this project, twelve sets of

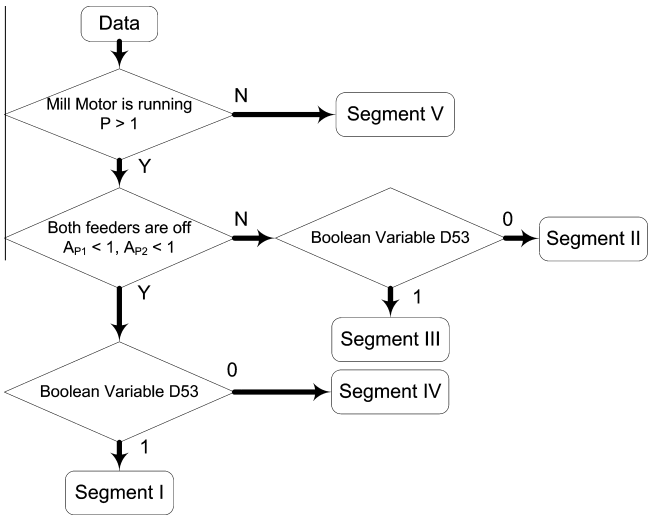

Fig. 8. The algorithm of the segment trigger algorithm.

on-site process data with sampling interval of 5 s have been collected from the power station of the industrial partner, which represent the milling processes at different operation conditions. These on-site measurement data are organized into two groups: one group for identification of the model unknown parameters while the other for verifying the identification results. Genetic Algorithm software tool provided by the "global optimization toolbox" in the Matlab environment from Mathworks Inc is adopted for implementation of the whole parameter identification process. The parameter initial values are chosen to be within the parameter boundaries derived from the real plant operation process, which are coded specified by GAs. The settings for the Genetic Algorithm optimization are given as Table 2.

The fitness function is shown in (36), which compromises the sum of the weighted errors between the normalized outputs measured from the coal mill and the normalized outputs from the estimation using the mill model.

$$\text{fitness} = \sum_{t=0}^{n} (W_1 \cdot |T_{\text{out}} - T_{\text{out\_s}}| + W_2 \cdot |\Delta P_{\text{out}} - \Delta P_{\text{out\_s}}|) \tag{36}$$

where T_{out} and ΔP_{out} are the measured model outputs and $T_{\text{out\_s}}$ and $\Delta P_{\text{out\_s}}$ are the model outputs estimated by the simulation. W_1 and W_2 are the weighting coefficients of the outputs. Following the model parameter identification scheme described above, the model parameters of each model segment are identified with the data sets used, which are listed in Table 3.

With the parameters identified, the model validation results are shown in Figs. 10 and 11, in which the dotted lines are the measured data while the solid lines represent the simulated results. In which, Figs. 10(a) and 11(a) show the on-line measured output comparing with the predicted/simulated output. Figs. 10(b) and 11(b) give the intermediate variables which are not measurable in real power plants. The calculated/estimated intermediate variables provide extra information which indicates what is happening inside the mill. This has been proved very valuable in condition monitoring and fault detection.

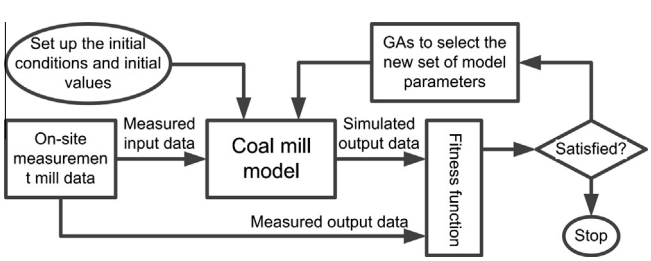

Fig. 9. Schematic of the model's coefficients identification.

Table 2
The property settings for the Genetic Algorithms.

Name of the GA properties	Value of the GA properties
Maximum generations	100
Population size	50
Generation gap	90%
Crossover ratio	70%
Mutation ratio	5%

The simulation results for validation indicated that the multi-segment mill model can capture the segment change flag/triggering signals and transfer the model from one segment to the next automatically. The simulated dynamic responses can follow the measured real mill output data well. The model can represent the mill main characteristics and features well. Finally, the on-line model is installed at the industrial partner's power station for test and the mill model parameters will be re-identified when the coal specifications changed.

5. Model based on-line condition monitoring

The mathematical model is implemented on-line for model validation. After three months on-line test, the mill model demonstrated to have robust performance. As described in the section of Introduction, combining bio-mass materials with coal as co-fired fuel is nowadays already a general practice at coal fired power plants in the UK. This has caused notable serious problems to mill safe operation because biomass materials presented different characteristics of hardness and burning points and also coal and biomass materials are unlikely mixed in a uniform manner inside the mill. This has caused more incidents at power plants so the mill modelling project is extended to develop a model based on-line condition monitoring algorithm and software for Tube-ball mills. The block diagram for on-line mill condition monitoring system is shown in Fig. 12. The mill model is running in parallel with the power plant coal mill operation; the measured and predicted outputs are displayed on the computer screens in the power plant control room. When the measured and predicted mill outputs are over the pre-set threshold values, the system will raise alarm reports to give warning signals. This model based monitoring system has a function for on-line estimation of the total quantity of the residual coal inside the mill (or mill level) which is normally not measurable. This estimation for "coal inside the mill" is very valuable for maintaining mill operation safety. Excessive accumulation of coal inside the mill will increase the mill drive system power and cause mill damages; the excessive coal will also accumulate heat inside the mill to trigger potential fires. The coal inside the mill provides extra information to plant operators to identify mill faults at its earliest possible stage.

With the on-line mill mathematical model, a new parameter signature identification method is further developed to strengthen the condition monitoring performance. The key idea of the new method is: in addition to observing the mill outputs alone, the mill key parameter variations will be used for potential mill fault detections.

A number of tests have been conducted in the following ways: the mill model parameters will be re-identified on-line in every minute. With the updated parameter values, if there is a big gap in between the measured and predicted mill outputs, it is very

Table 3
The identified model parameters of the model Segment I–V.

Parameters	Segment I	Segment II	Segment III	Segment IV	Segment V
K_{1_i}	N/A	0.014483	0.629170	0.179836	N/A
K_{2_i}	N/A	N/A	0.003472	0.003250	N/A
K_{3_i}	N/A	N/A	0.264450	N/A	N/A
K_{9_i}	N/A	N/A	0.022766	0.010173	N/A
K_{11_i}	N/A	N/A	5.84E−05	4.02E−06	N/A
K_{12_i}	N/A	N/A	0.000144	0.000419	N/A
K_{13_i}	N/A	N/A	4.622867	5.166732	N/A
K_{14_i}	N/A	N/A	0.013445	0.007214	N/A
K_{15_i}	0.000311	0.000301	0.001102	0.001133	N/A
K_{16_i}	N/A	N/A	4.60E−05	4.50E−05	N/A
K_{17_i}	−0.000233	−0.01	−0.021802	−0.028476	−0.000026
K_{18_i}	N/A	N/A	−0.684027	−0.998763	N/A
K_{19_i}	N/A	N/A	0.010012	0.010017	N/A
K_{20_i}	N/A	N/A	0.008609	0.003019	N/A

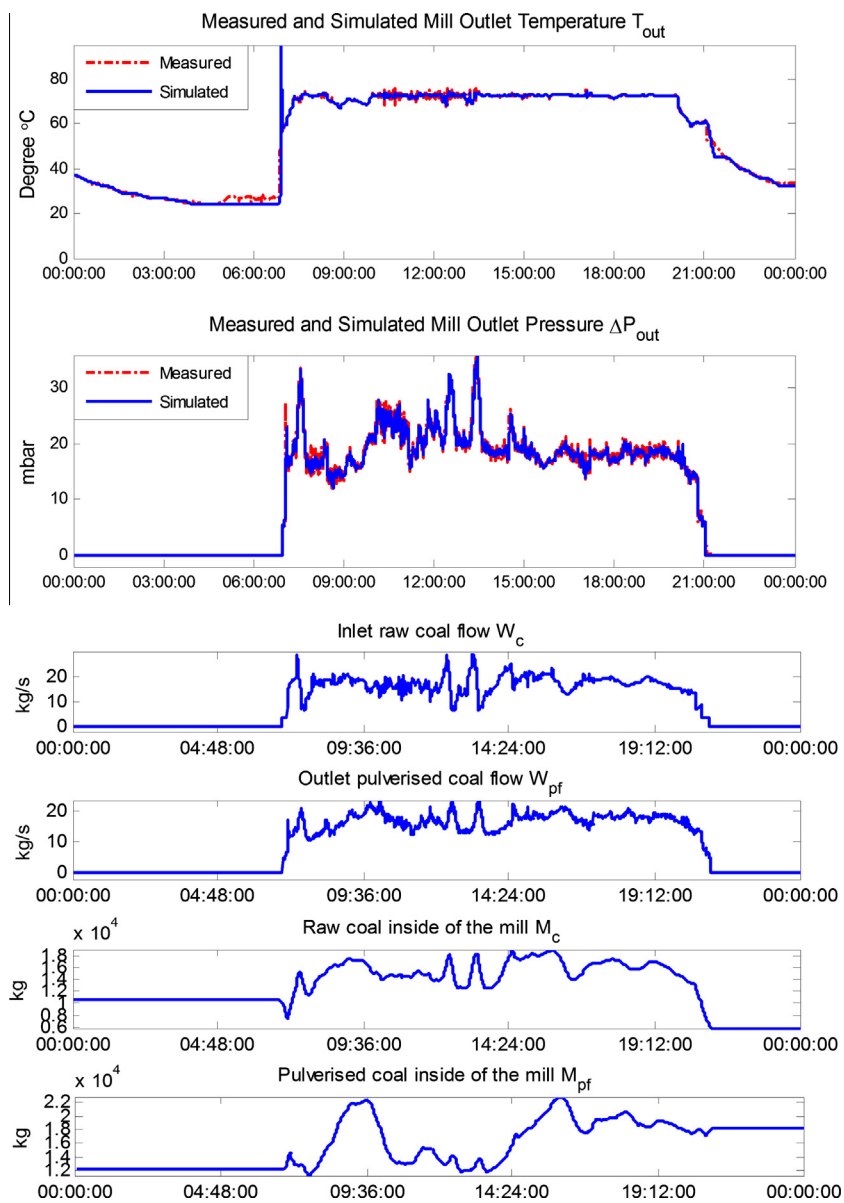

Fig. 10. (a) Model simulated and measured outputs with data set 1 and (b) model intermediate variables with data set 1.

likely that faults exist and an alarm should be raised. From the variation trends of the re-identified model parameters, it is noticed that one particular parameter, K_{17}, is more sensitive to irregular performance variations so the further study has been conducted to locate the relationships between parameter variations and malfunctions.

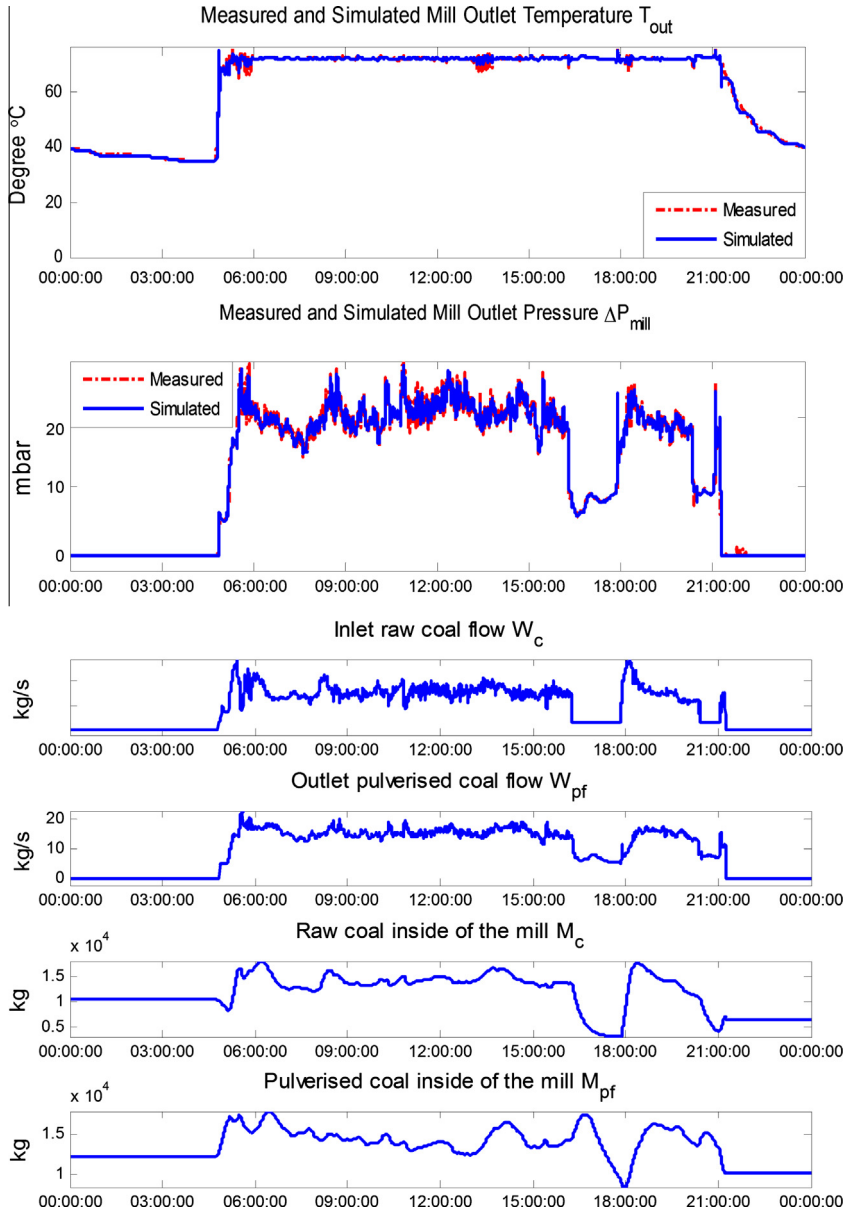

Fig. 11. (a) Model simulated and measured outputs with data set 2 and (b) model intermediate variables with data set 2.

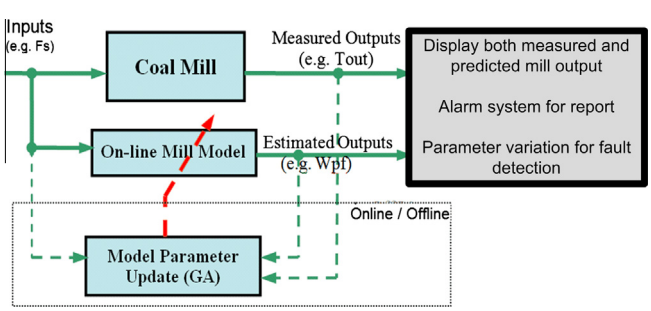

Fig. 12. Block diagram of the on-line mill condition monitoring system.

If the value of K_{17} changes dramatically within a very short time period or drifted away from the initial value significantly, this indicates that there may be some unwanted changes in the coal mill system. One successful case is to identify the biomass fuel choking incidents through observing K_{17} variation patterns. Biomass material pieces are bigger in size and more volatile compared with the pulverized coal so it often leads to fuel choking or fires. With implemented model-based on-line condition monitoring software, the plant operation engineers are able to identify the potential risks in advance to leave sufficient time for taking actions of preventing the damages to the mill. For example, in Fig. 13, the values of K_{17} fluctuated around −0.14 for the whole first 18 h period as normal, and the model output temperature T_{out} matches the measured T_{out} very well. However, the value of K_{17} suddenly changed with a sharp spike. From the on-line test and history record provided by our industrial partner, this sharp change is caused by a biomass injection experiment that took place in the Cottam power station and a big chunk of biomass materials was fed into the mill and was not blended properly. This would embed a potential cause to a fire incident so it should be reported and alarmed. From the figure, the alarm can be raised based on the report of the parameter sharp change at the beginning of the biomass fuel chocking to the control room.

Further analysis has been conducted by examining the parameter variation patterns and the links with the incidents happened in

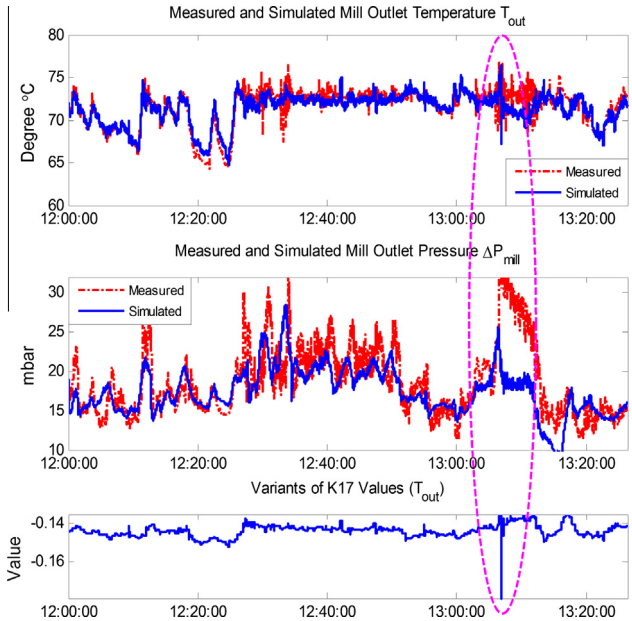

Fig. 13. Model simulated outputs, with K_{17} re-identified in every minute and sharp change observation.

history. Fig. 14 is the data history taken during the period of a fire incident at the power plant for research collaboration. The variations of the parameters K_{17} and K_{18} are monitored closely and it can be seen that the values of K_{17} and K_{18} move away from the average value for a "thinkable" time period and K_{17} even crossed the zero line to become positive. These large offset of K_{17} and K_{18} become the featured patterns to indicate that mill operation condition is severely altered and an incident is very likely to happen soon. It is also noticed that the intermediate variable of coal inside the mill increased greatly, which indicated that excessive coal has been accumulated inside the mill. The two parameters were gradually drifted away from their nominal values for over 1.5 h.

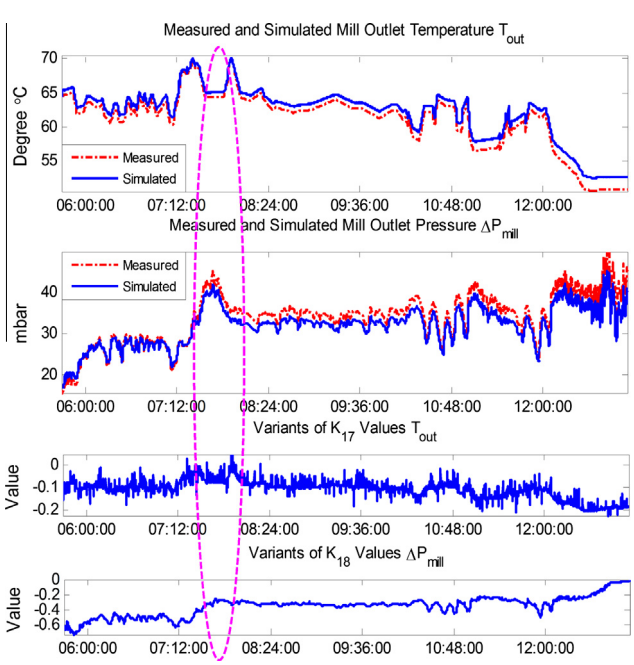

Fig. 14. The simulation results for data obtained on the day of the incident happening.

Therefore, after the parameter draft trend is observed for over 30 min, the serious alarm can be raised to prevent the fire at the possible earliest stage.

5. Conclusion

A multi-segment power plant Tube-ball mill mathematical model is developed, which can represent the whole milling process from the mill start to shut down. The model segments are defined according to the different operational status of the mill, and the operational measurements from the mill auxiliary components including the analogue signals and also some on/off Boolean signals are adopted as triggers to switch the Mill Model Segments. Genetic Algorithm is applied for the parameter identification using on-site measurement. The simulations studies and on-line test show that the model fits to on-site measured outputs well for the whole milling process. The model can estimate some immeasurable variables (e.g. amount of raw coal inside of the mill barrel); this gives extra valuable information for mill operation status. The model is implemented on-line for mill condition monitoring and fault detection. The key model parameter patterns are successfully used to detect biomass chocking for co-fired power generation and potential fires. The on-line condition monitoring software has been successfully implemented onto two mills at the collaboration power plant.

Acknowledgments

The authors would like to give their grateful thanks to Dave Williamsons, Lee Taylor and Piero Maggio, from EDF Energy and Mike Garwood, Will Quick from E.ON UK for their great support and advices; the authors also thank BCURA (85A/B) and EPSRC (EP/G062889) for their research funding support.

References

[1] Scott DH. Coal pulverises – performance and safety, IEA Coal Research: London, ISBN: 92-9029-254-7, 1995.
[2] Fan GQ, Rees NW. Modelling of vertical spindle mills in coal fired power plants. In: National conference publication – institution of engineers, Australia, 1994. pp. 235–40.
[3] Hamiane M. Identification of a pulverized fuel mill from normal operating records using a multivariable polynomial matrix model. Int J Model Simul 2000;20:227–35.
[4] Wei JL, Wang J, Wu QH. Development of a multi-segment coal mill model using an evolutionary computation technique. IEEE Trans Energy Convers 2007;22:718–27.
[5] Austin LG. Introduction to the mathematical description of grinding as a rate process. Powder Technol 1971;5:1–17.
[6] Austin L, Luckie P, Shoji K. An analysis of ball-and-race milling, Part II: the Babcock E-1.7 Mill. Powder Technol 1982;33:113–25.
[7] Austin L, Luckie P, Shoji K. An analysis of ball-and-race milling, Part III: scale-up to industrial mills. Powder Technol 1982;33:127–34.
[8] Austin L, Shah J, Wang J, Gallagher E, Luckie P. An analysis of ball-and-race milling, Part I: the Hardgrove Mill. Powder Technol 1981;29:263–75.
[9] Neal PW, Waddington J, Wilson R. Determination of mill and 33 boiler characteristics and their effect on steam pressure control. Chem Eng Sci 1980;35:2107–14.
[10] Dahl-Soerensen M, Solberg B. Pulverized fuel control using biased flow measurements. In: Proceedings of the IFAC symposium on power plants and power systems control, Tampere, Finland, July 2009, 2009.
[11] Bollinger KE, Snowden HR. The experimental-determination of coal mill models. IEEE Trans Power Apparatus Syst 1983;102:1473–7.
[12] Bollinger KE, Snowden HR. Field test results for multi-variable control of a coal-mill. IEEE Trans Power Syst, PWRS-1, 1986. pp. 96–100.
[13] Corti L, de Marco A, Zizzo A. Mathematical model of a coal mill. In: International conference on power plant simulation, Cuernavaca, Morelos (Mexico DF), 1984. pp. 206–11.
[14] Cheetham RG, Billings SA, Bransby ML. Multivariable modelling of pulverised fuel mills from experimental PRBS data. In: Report Part I and II, U.K.: Central electrical generating board, London, 1990.
[15] Zhang YG, Wu QH, Wang J, Zhou XX. Coal mill modeling by machine learning based on onsite measurements. IEEE Trans Energy Convers 2002;17:549–55.

[16] Wei JL, Wang J, Wu QH. Multi-segment pulverised coal mill model and on-line implementation for condition monitoring. Int J Model Ident Control 2006;1:206–13.
[17] Niemczyk P, Bendtsen JD, Ravn AD. Derivation and validation of a coal mill model for control. Control Eng Pract 2012;20:519–30.
[18] Bhambare KS, Ma Z, Lu P. CFD modeling of MPS coal mill with moisture evaporation. Fuel Process Technol 2010;91:566–71.
[19] Dahl-Sorensen MJ, Solberg B. Pulverized fuel control using biased flow measurements. In: Proceedings of the IFAC symposium on power plants and power systems control, Tampere, Finland, July 2009, 2009.
[20] Mercangoez M, Poland J. Coal mill modeling for monitoring and control. In: Proceedings of the 18th IFAC world congress, Milano (Italy) August 28 – September 2, 2011.
[21] Cortinovis A, Mercang M, Mathur T, Poland J, Blaumann M. Nonlinear coal mill modeling and its application to model predictive control. Control Eng Pract 2013;21:308–20.
[22] Ma P, Du HL, Lv F. Coal mass estimation of the coal mill based on two-step multi-sensor fusion. In: Proceedings of the fourth international conference on machine learning and cybernetics, Guangzhou, August 18–21, 2005.
[23] Wei JL, Wang J, Guo S. Mathematic modelling and condition monitoring of power station Tube-ball mill systems. In: American control conference, St. Louis, MO, USA June 10–12, 2009.
[24] Wang J, Wei JL, Guo S. Condition monitoring of power plant milling process using intelligent optimization and model based techniques, a chapter in the book of fault detection. In-Tech 2010:405–24.
[25] EDF Plc. Pulverised Fuel System (operational manual), 1981. pp. 10–3.