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

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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

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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

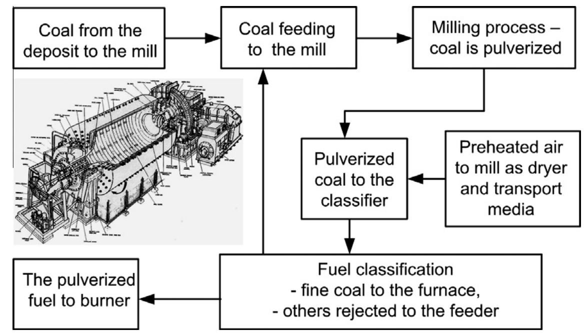

Fig. 1. Working process of a Tube-ball mill.

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:

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

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.

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

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