

Optimization Control for Coal Mill Fault Diagnosis in Coal-Fired Steam Power Plant

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Abstract— Coal pulverizer mill at PLTU Rembang is the main equipment in the boiler that supports the reliability of the generating unit. They serve to supply coal fuel in the furnace to get perfect combustion. In the operation of coal mills, the pattern of operations carried out such as setting flow rate raw coal and primary air to avoid the occurrence of delay combustion and self combustion. The operating parameters change, and their values are often outside standard limits. In this study, a simulation of the correct operation pattern of the coal pulverizer mill was carried out to avoid failure of the coal excessive mill with ANFIS system. By knowing characteristics of the coal mill operating parameters and the probability of the root cause of failure, the operating pattern can be determined in several steps by changing the input settings in the modelling. The operating pattern of the coal pulverizer mill with dynamic modelling is carried out using Matlab software by varying the three inputs are percentage openings of coal flow, hot air and coal air. This modelling can be used to monitor, diagnose disturbances in the plant and optimize control, so that operators can recognize early detection and can assist the proper operation pattern of the coal mill.

Index Terms— Dynamic model, adaptive neuro-fuzzy inference system (ANFIS), fault detection and diagnosis, operation pattern.

1 NOMENCLATURE

U_H	= valve opening of hot air, %
U_L	= valve opening of cold air, %
W_c	= coal feed flow, kg/s
W_{air}	= primary air flow, kg/s
θ_{in}	= primary air temperature, °C
I	= ampere
AFR	= Air Fuel Ratio
θ_{out}	= coal mill outlet temperature, °C
M_c	= raw coal content in coal mill, kg
M_{pt}	= coal powder content in coal mill, kg
M_{pc}	= Moisture content in coal powder, %
M_{ar}	= Coal moisture, %

2 INTRODUCTION

Coal pulverizer mill PLTU Rembang, located in Central Java Province, Indonesia, is a coal-fired steam power plant. Coal pulverizer mill at PLTU (coal-fired steam power plant) Rembang is essential equipment in the boiler which functions to refine coal raw materials into fine coal powder to get perfect combustion in the furnace. In the operation of 4 coal mill units, delays and self-combustion often occurred due to using Low-Rank Call (LRC) coal with high moisture and volatile matter content. So in the pattern of operations carried out to avoid the occurrence of delay combustion and self-combustion, a primary air supply with a sufficiently high temperature and a suitable supply of coal for the drying process in the coal pulverizer mill system is provided. Those conditions cause frequent changes in operating patterns such as setting the flow rate of coal and primary air. The operating parameters change, and their values are often outside the

standard limits.

A nonlinear dynamic model of a direct-fired pulverizing system that considers the effect of coal moisture by estimating the signal of the outlet coal powder flow of the coal mill was constructed as a new output control target of the pulverizing system. [1]. To obtain massive fault sample data effectively, based on the analysis of primary air system, grinding mechanism, and energy conversion process, a dynamic model of the coal mill system which can be used for fault simulation is established [2].

A breakdown will occur in the Distributed Control System (DCS) of the coal mill when the parameter reaches its alarm limit. Operators must analyze multiple sensor measurements simultaneously to solve the root cause of the problem. This process can be tedious and time-consuming, resulting in lost time and maintenance costs. There is a need for automated systems to detect and diagnose problems in the mill operation. The automated system can help operators take appropriate remedial/corrective actions timely. It also shall assist in handling the modeling uncertainties of dynamic modeling, providing advanced information about plant conditions, and making informed decisions [3]. Monitoring, optimization control, and diagnosis of coal mill faults can be mathematically modeled from mass flow analysis, heat exchange, energy transfer balance in which all entering or leaving heat in the coal mill is calculated quantitatively to reduce the number of unknown parameters [3].

3 CHARACTERISTIC DYNAMIC MODEL OPERATION MILL

The coal mill under study is a vertical roller type, such as the

one available at the PLTU (coal-fired steam power plant) Rembang unit, which has two boilers with a steam generator capacity of 51.3 t/h. The schematic of a coal pulverizer mill is provided in Fig. 1. Details of these coal mill parameters are presented in Table 1.

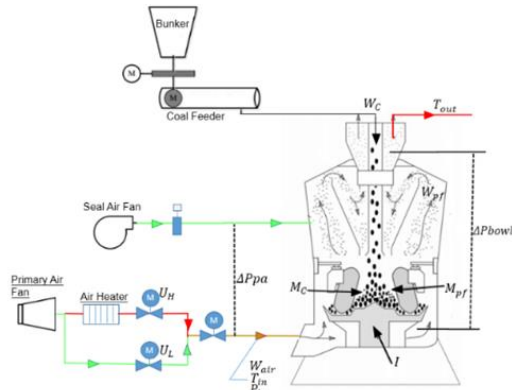


Fig. 1. Schematic of coal pulverizer mill [3]

TABLE I
SPECIFICATION OF COAL PULVERIZER MILL

Item	Specification
Merk/manufaktur	: Dongfang
Type	: HP963
Rated output	: 51.3 t/h
Milling cup speed	: 33 rpm
Finest coal	: 200 mesh
Diameter bowl	: 96"
Quantity of grinding roll	: 3

Coal mill modeling with nonlinear differential equations of coal mill includes primary air, coal quantity, and outlet temperature mill [4].

In this study, the lumped parameter modeling method is adopted with the following assumptions: 1) Low-Rank Call (LRC) coal modeling using coal moisture data parameters; 2) Weather changes are negligible, and the ambient temperature around the coal mill remains constant; 3) all coal passes the classifier; 4) do not consider the coal attached to the inside of the mill body; 5) does not consider coal rejects; 6) model validation by considering the actual values with the model, namely outlet temperature, primary air, amperage, and air-fuel ratio. The identified model parameters are shown in Table 2 and the simulation results for characteristic dynamic coal mill are shown in Table 3.

Based on a medium-speed coal mill model proposed Y.Gao et al. [3].

TABLE 2
IDENTIFIED MODEL PARAMETERS

$W_{Lmax} = 6$	$T_2 = 3.6765$	$K_1 = 0.1799$	$M_{motal} = 4131.7$
$W_{Hmax} = 33$	$K_{conv} = 0.4522$	$K_2 = 0.8496$	$K_3 = 0.8496$
$T_1 = 10.3004$	$K_{pf} = 0.0795$	$K_4 = 14$	

TABLE 3
DATA COMPARISON SIMULATION RESULTS JURNAL Y.GAO ET AL. AND SIMULATION MODEL

VALUE	VARIABLE NAMES	NOTATION	DATA COMPARISON										
			STEP 1		STEP 2		STEP 3		STEP 4		STEP 5		
			INITIAL CONDITION		Input : $U_L \uparrow$		Input : $U_H \uparrow$		Input : $M_{ar} \uparrow$		Input : $W_c \uparrow$		
Item	Unit	Jurnal	Simulasi	Jurnal	Simulasi	Jurnal	Simulasi	Jurnal	Simulasi	Jurnal	Simulasi		
INPUT VALUE	Coal Moisture	Mar	%	19.4	19.4	19.4	19.4	19.4	19.4	21.45	21.45	21.45	21.45
	Coal Flow	Wc	kg/s	9.7	9.7	9.7	9.7	9.7	9.7	9.7	9.7	9.98	9.98
	Valve of Cold Air	U_L	%	33.5	33.5	40	40	40	40	40	40	40	40
	Valve of Hot Air	U_H	%	34	34	34	34	36	36	36	36	36	36
OUTPUT VALUE	Primary Air Flow	Wair	kg/s	24.5	24.87	26	26.06	27.2	27.16	27.2	27.16	27.2	27.16
	Inlet Air Temperature	Tin	°C	271	269.1	259	259	263	262.3	263	262.3	263	262.3
	Raw Coal Content	Mc	kg	21.4	21.45	21.4	21.45	21.45	21.45	21.45	21.45	22	22.07
	Coal Powder Content	Mpf	kg	12.9	12.78	11.8	11.86	10.8	10.85	10.8	10.85	11.1	11.16
	Mill Outlet Temp.	Tout	°C	73	78.98	72	78.02	78	83.65	68.00	75.29	65	72.55
	Amount Coal Powder	Wpf	kg/s	9.65	9.7	9.65	9.7	9.65	9.7	9.65	9.7	9.65	9.97
	Moisture Coal Powder	Mpc	%	3.10	2.75	3.15	2.76	3.00	2.67	3.50	3.10	3.60	3.16
	Current of Coal mill	I	A	40.25	40.3	40.05	40.14	39.9	39.95	39.9	39.95	40.47	40.54

From Table 3 above, it can be seen that the characteristics of changes in the output parameters between the journal Y.Gao et al. and the simulation produce the same changes and the output parameter values are almost the same or the values are not much different.

When a step-increasing signal is applied to U_L , the cold air flow increases while the hot air flow remains constant, thus resulting in an increase in the W_{air} at the inlet of the coal mill and a decrease in θ_{in} , θ_{out} . Then decrease M_{pf} and decreasing the current I required for milling.

When a step-increasing signal is applied to U_H , the hot air flow increases while the cold air flow remains constant, thus resulting in an increase W_{air} at the inlet of the coal mill, and an increase in θ_{out} . The decrease W_{air} resulting in an increase M_{pf} and increase the current I required for milling.

When a step-increasing signal is applied to the raw coal moisture M_{ar} , the energy supplied by W_{air} remains constant while the M_{ar} than needs to be evaporated increases. Then decrease θ_{out} and an increase in M_{pc} .

When a step-increasing signal is applied to coal feed flow, the amount of coal required to be milled increases, resulting in an increase in grinding current I. The increases in W_c increases the amount of coal that needs to be dried, and then decreasing the θ_{out} and increasing M_{pc} .

4 FAULT SIMULATION OF COAL MILL

Case study - Excessive coal in the mill

Mill problems due to all possible causes such as improper air-coal input, change in coal quantity, incorrect settings, aging, problems in reject systems, problems in feeding the coal input system are considered. The list of nodes for excess coal input, error along with state, linked measurements, and threshold values for discretization is illustrated in Table 4.

TABLE 4
LIST OF NODES FOR EXCESSIVE FAULT

No.	Node Name	States	Threshold value for Dizeretization	Unit
1	Coal Flow High	Normal, High [N,H]	> 9 kg/s	kg/s
2	Air Fuel Ratio Low	Normal, Low [N,L]	< 1.8	-
3	Ampere Mil High	Normal, High [N,H]	< 44	Ampere
4	Mill Outlet Temperature Low	Normal, Low [N,L]	< 58	°C

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a common functionally efficient approximator in which the information between the problem input and output variables is interpreted as a set of rules in the form if-then [5]. ANFIS usually includes five layers: fuzzification, product, normalization, defuzzification, and summation. The ANFIS replaces the manual tuning of FIS for the prediction model [6]. Performance of the ANFIS can be improved by increasing the amount of membership functions [7]. Probabilistic methods such as a Bayesian network are adopted for modeling and predicting the probability of fault occurrence [4]. Fault diagnosis is useful in helping technicians detect, isolate, and identify faults and troubleshooting. Bayesian network (BN) is a probabilistic graphical model that effectively deals with various uncertainty problems [8].

Using the mill trending data at the time of the incident on May 21, 2021, it can be concluded that the leading causes were the low Air Fuel Ratio (AFR) and the failure to achieve Mill Outlet Temperature (MOT).

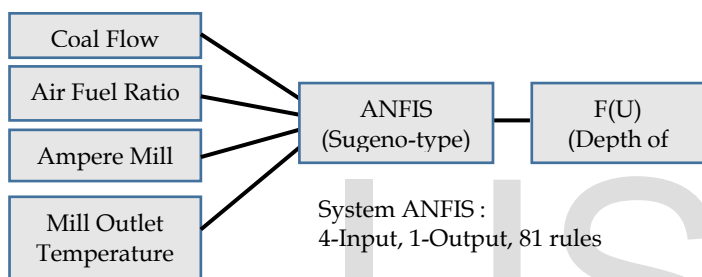


Fig. 2. Fuzzy logic approach for mill fault

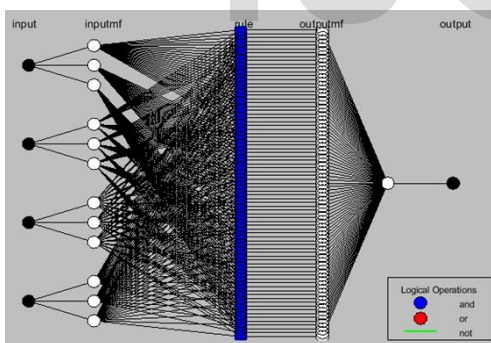


Fig. 3. ANFIS model structure

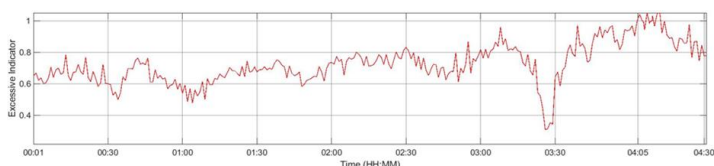


Fig. 4. Fault indicator excessive coal mill

The graphical analysis results in Fig. 4 indicate that excess coal is seen during the operation, and the plugging indicator occurs after 4.5 hours. This study shows that the proposed approach has the potential to provide early warning about failure and provide information for monitoring coal mill operations. It can help the plant operators in preventing a derating

or trip unit

5 OPERATION PATTERN TO AVOID FAULTS IN COAL MILL

To avoid the failure of the coal mill, a change in the operating pattern is carried out from the recommended root causes and the steps follow the dynamic characteristics of the coal mill in chapter 2 which has been discussed [3]. The stage of the operational pattern based on root cause process is showed in Table 5.

TABLE 5
ROOT CAUSE FOR RECOMMENDATION OPERATION PATTERN COAL MILL

Rank	Root Cause (Based on FMEA Data PLTU Rembang)	Probability /Belief (%)
1	Improper Input	80
	1.1 Air Fuel Ratio Low	
	1.2 Coal Flow High	
	1.3 Inlet temperature Low	
2	Improper Sub equipment	20
	2.1 Grinder roll life time	
	2.2 Less spring grinding strength	
	2.3 Grinding roll does not rotate at start	
	2.4 The opening around the vane wheel is too wide	
2.5 Classifier is too close		

Based on the recommended operating pattern from the root cause and the characteristics of the dynamic model, to avoid excessive fault coal mill is shown in table 6 and Fig. 5 shown graphic after operation change.

Step 1, increase AFR (Air Fuel Ratio) with reduce coal flow, Step 2, increase primary air flow with decrease valve hot air dan increase valve cold air so the high amperage mill goes down and high temperature inlet to drop.

TABLE 6

ROOT CAUSE FOR RECOMMENDATION OPERATION PATTERN COAL MILL

VALUE	VARIABLE	NOTATION	ITEM	UNIT	EXISTING PARAMETER	DATA MANUVER OPERASI																	
						STEP 1				STEP 2				STEP 3									
						Wc				U _H				U _L									
INPUT VALUE	Coal Moisture	Mar	%	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	
	Coal Flow	Wc	kg/s	13,36	12,96	12,61	12,36	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1	12,1		
	Valve of Cold air	Wlmax	%	27,01	27,01	27,01	27,01	27,01	27,01	27,01	27,01	27,01	27,01	27,01	43,22	48,62	54,02	56,72					
	Valve of Hot air	Whmax	%	59,9	59,9	59,9	59,9	59,9	59,9	59,9	59,9	59,9	59,9	59,9	57	57	57	57	57	57	57	57	
	Primary Air Flow	Wair	kg/s	21,31	21,31	21,31	21,31	21,31	21,31	21,31	20,75	20,41	21,39	21,63	21,94	22,09							
OUTPUT VALUE	Inlet Air temperature	Tin	°C	318,6	318,6	318,6	318,6	318,6	318,4	317,9	317,5	305,1	301,2	297,4	295,6								
	Air Fuel Ratio	AFR		1,6	1,65	1,7	1,72	1,75	1,72	1,69	1,76	1,79	1,81	1,83									
	Raw coal content	Mc	kg	29,54	28,66	27,89	27,33	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	26,76	
	Coal Powder Content	Mpf	kg	21,8	21,15	20,58	20,34	19,91	20,27	21,01	21,73	20,35	19,91	19,49	19,29								
	Mill outlet temperature	Tout	°C	61,05	58,61	62,46	64,17	66,38	65,37	63,35	61,47	60,70	60,46	60,22	60,11								
	Amount Coal Powder	Wpf	kg/s	13,36	12,96	12,61	12,38	12,12	12,11	12,11	12,11	12,12	12,12	12,12	12,12	12,12	12,12	12,12	12,12	12,12	12,12	12,12	12,12
	Moisture Coal Powder	Mpc	kg	3,027	3,13	2,995	2,96	2,91	2,933	2,976	3,017	3,035	3,04	3,046	3,049								
	Current of Coal Mill	I	Ampere	43,02	42,15	41,39	40,88	40,32	40,38	40,51	40,64	40,39	40,32	40,24	40,2								

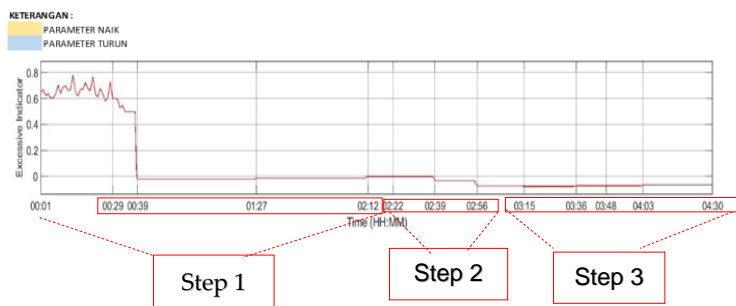


Fig. 5. Excessive Indicator monitor after operation change

6 CONCLUSION

Dynamic modeling simulations for changes in coal mill input parameters, namely U_L, U_H, W_c, M_{ar} can define the characteristics of changes in output parameters.

The failure simulation made by simulating the actual input parameter data for the Rembang PLTU defines the output of the type of excessive coal mill failure with a severe level after running for 4 hours 5 minutes.

Operational recommendations and maneuvers from modeling by increasing the AFR by reducing coal flow and increasing primary air flow (cold air openings) have succeeded in providing information on early detection of failures and can avoid excessive failures in the coal mill

ACKNOWLEDGMENTS

The authors would like to thank the Department of Mechanical Engineering, Diponegoro University, Semarang, for providing research facilities. The authors would also like to thank the management of the PLTU (coal-fired steam power plant) Rembang for the data sets used for research purposes.

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