Decision Support System for Coal Mill Fault Diagnosis in Coal-Fired Steam Power Plant

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Abstract

The coal pulverizer mill at PLTU (coal-fired steam power plant) Rembang is essential boiler equipment that processes coal raw materials into fine coal powder to perfect combustion in the furnace. In the operation of 4 coal mill units, delay and self-combustion often occurred due to using Low-Rank Call (LRC) coal with high moisture and volatile matter content. Several operation patterns are carried out to avoid delay and self-combustion, such as adjusting the primary air supply with a sufficiently high temperature and the suitable coal supply for the drying process in the coal pulverizer mill system. Unfortunately, the adjustment frequently causes the operating parameters to fall outside the standard limits. A dynamic simulation of the plant model that represents mass flow rate, heat transfer, and energy balance is performed to understand this problem. Simulation results can accurately reveal the actual coal mill operating conditions and monitor the effect of changes in operation patterns. For the failure diagnostic, the ANFIS method is utilized to describe three coal plant failures: excess coal, coal shortage, and coal explosion. Fuzzy logic is used to determine the type and magnitude of the error, while the Bayesian network is used to solve the root cause problem. The proposed technique is validated using historical data from the PLTU Rembang. It can be observed in the simulation results that the relative error of primary air flow, inlet temperature, mill motor current, and Air-Fuel Ratio are less than 4%.

Keywords: Dynamic model; Adaptive Neuro-Fuzzy Inference system (ANFIS); fault detection and diagnosis

Abstrak

Coal pulverizer mill di PLTU Rembang merupakan peralatan penting di dalam boiler yang berfungsi untuk menghancurkan bahan baku batubara menjadi serbuk batubara untuk mendapatkan pembakaran yang sempurna di dalam furnace. Dalam pengoperasian 4 unit coal mill, sering terjadi delay combustion dan self combustion karena penggunaan batubara Low-Rank Call (LRC) dengan kandungan moisture dan volatile matter yang tinggi. Beberapa pola operasi dilakukan untuk menghindari terjadinya delay combustion dan self combustion, seperti mengatur suplai udara primer dengan temperature yang cukup tinggi dan suplai batubara yang sesuai untuk proses pengeringan pada sistem coal pulverizer mill. Sayangnya, penyesuaian sering kali menyebabkan parameter operasi berada di luar batas standar. Simulasi dinamik dari model pembangkit yang mewakili laju aliran massa, perpindahan panas, dan keseimbanga nenergi dilakukan untuk mengatasi masalah ini.. Hasil simulasi dapat dengan baik mengungkapkan kondisi operasi coal mill yang sebenarnya dan memantau pengaruh perubahan pola operasi. Untuk diagnosis kegagalan, metode ANFIS digunakan untuk menggambarkan tiga kegagalan coal mill :kelebihan batubara, kekurangan batubara, dan ledakan. Logika fuzzy digunakan untuk menentukan jenis dan besarnya kesalahan, sedangkan jaringan Bayesian digunakan untuk menyelesaikan akar permasalahan. Teknik yang diusulkan divalidasi dengan menggunakan data historis dari PLTU Rembang. Dapat diamati pada hasil simulasi bahwa kesalahan relatif aliran udara primer, inlet temperature, arus motor coal mill, dan rasio udara-bahan bakar kurang dari 4%.

Kata kunci: Dynamic model; Adaptive Neuro-Fuzzy Inference System (ANFIS); fault detection and diagnosis

1. Introduction

The coal pulverizer mills were designed to operate using medium-calorie coal (MRC). However, with a limited supply of MRC, the coal pulverizer mill is forced to work using sub-bituminous low-calorie coal (LRC). The characteristics of this type of coal have high moisture and volatile matter content. The high moisture content causes delayed combustion in the furnace, and the high volatile matter easily causes this type of coal to undergo self-combustion. So in the pattern of operations carried out to avoid the occurrence of delayed 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.

In the existing mills, the primary air and coal flow rates are manually adjusted, causing variations in the operating conditions. These variations may lead to a mismatch between the primary air and coal flow rates as indicated by the values of AFR (Air Fuel Ratio) (normal range: 1.8 to 2.2) and Mill Outlet Temperature (MOT) (normal range: 58°C to 68°C) being lower than their allowable values. Consequently, the coal drying process in the mill is not optimum since the air velocity through the vane wheel is less than 7000 feet/min. Thus, more coal falls into the scrapper space than the coal that goes to the classifier, inlet pressure increases, and a plugging mill occurs.

Monitoring, optimization control, and diagnosis of coal mill faults can be mathematically modeled from mass flow analysis, heat exchange, and energy transfer balance. All entering or leaving heat in the coal mill is calculated quantitatively to reduce the number of unknown parameters [1]. 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. It showed that the model effectively reflects the dynamic characteristics of a pulverizing system [2]. A dynamic model of the coal mill system can be used for fault simulation to obtain massive fault sample data effectively based on the analysis of the primary air system, grinding mechanism, and energy conversion process [3].

A breakdown will occur in the coal mill's Distributed Control System (DCS) 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 mill operations. 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 [4].

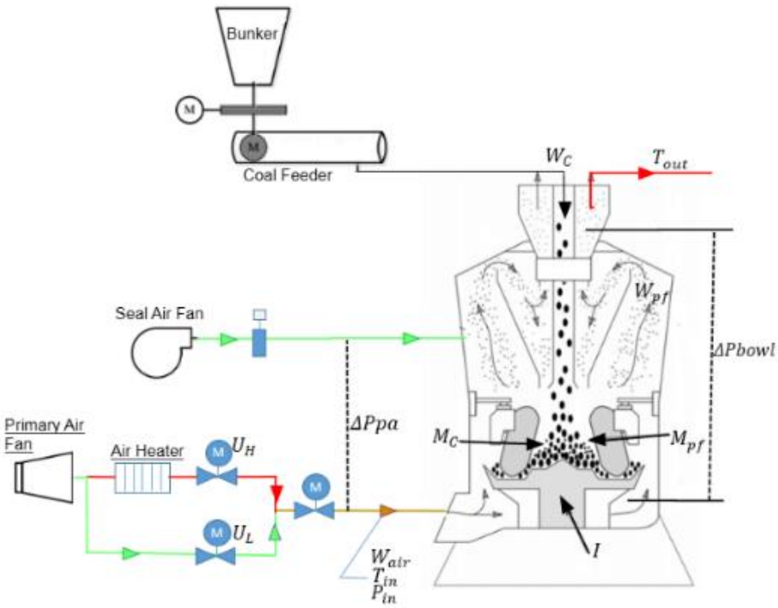


Figure 1. Schematic of coal pulverizer mill [1]

2. Materials and Methods

The method used in modeling the physical properties of the coal mill is dynamic modeling of the mass and energy balance system that can be applied authentically to the actual operating conditions of the coal mill as a step in monitoring changes in operating patterns. For the failure diagnosis, the ANFIS system and fuzzy logic are used to determine the type and magnitude of the error, while the Bayesian network is used to solve the root of the problem.
The proposed technique is validated by using historical data from PLTU Rembang.

2.1 Dynamic Model Coal 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. Coal mill modeling with nonlinear differential equations includes primary air flow W_{air},, coal quantity W_c, and outlet temperature θ_{out} [4].

2.2 Model Validation

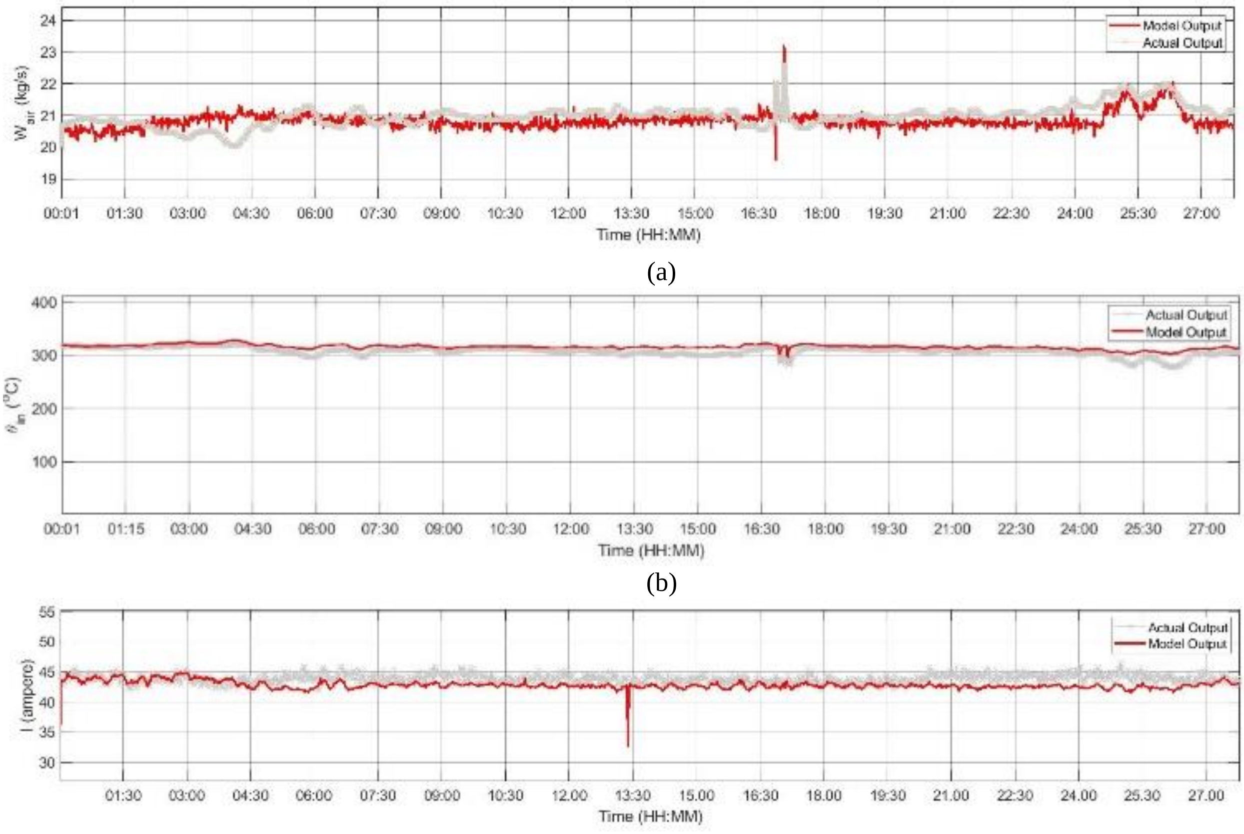
In this study, the lumped parameter modeling method is adopted with the following assumptions: 1) Low-Rank Call (LRC) coal modeling using coal moisture data parameters; 2) Weather changes are negligible, and the ambient temperature around the coal mill remains constant; 3) all coal passes the classifier; 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 are shown in Fig. 2. and Fig. 3, in which I and AFR are motor mill current and Air-Fuel Ratio, respectively. Based on a medium-speed coal mill model proposed by Y.Gao et al.[1].

Table 1. Specification of coal pulverizer mill

Item	Specification
Brand/manufacturer	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

Table 2. Identified model parameters

$W_L^{max} = 6$	$T_2 = 3.6765$	$K_1 = 0.1799$	$M_{metal} = 4131.7$
$W_H^{max} = 33$	$K_{conv} = 0.4522$	$K_2 = 0.8496$	$K_2 = 0.8496$
$T_1 = 10.3004$	$K_{pf} = 0.0795$	$K_3 = 14$	

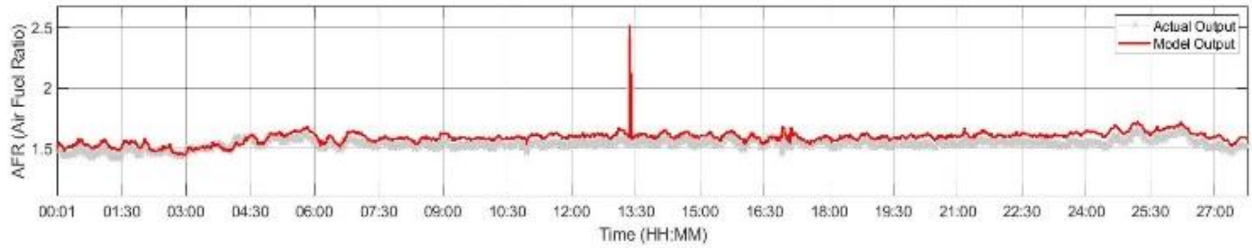


(a)

(b)

(c)

Figure 2. Comparison of actual and model outputs (W_{air}, θ_{in} and I)



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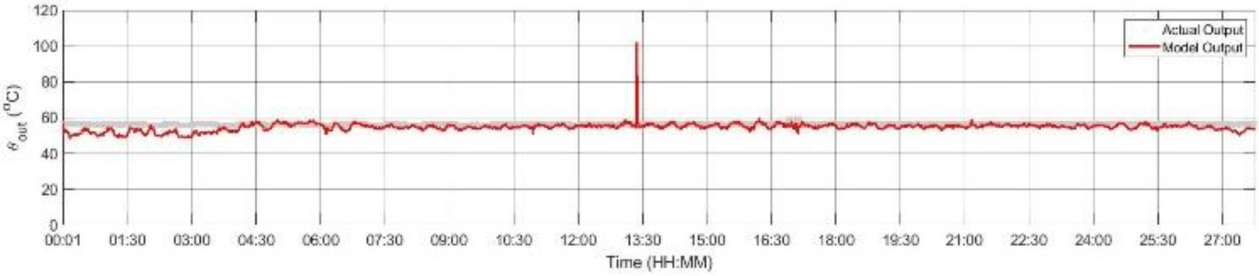

(b)

Figure 3. Comparison of actual and model outputs (AFR and θ_{out})

Table 3. The relative error between actual output and model output

Outputs of the object	W_{air}	θ_{in}	I	AFR	θ_{out}
Relative error (%)	1.18	0.58	0.2	3.91	7.28

The relative error between the model and the actual output is shown in Table 3. The relative error of W_{air}, θ_{in}, I, and AFR are less than 4% except for θ_{out}. This higher error in θ_{out} is because one crucial parameter in the model, coal moisture M_{ar} is assumed to have a constant value, while this parameter might vary in actual coal mill operations.

In the model, the effect of coal moisture on the energy balance of the coal mill is considered to increase the model's accuracy. All heat input into or output from the coal mill is calculated quantitatively to reduce the number of unknown parameters that need to be identified. After simulation and verification, this nonlinear dynamic model can be used for monitoring, optimizing control, and diagnosing coal mill faults because the model is proven effective in reflecting coal mill dynamics and has good precision. In the model, the effect of coal moisture on the energy balance of the coal mill is considered to increase the model's accuracy. All heat input into or output from the coal mill is calculated quantitatively to reduce the number of unknown parameters that need to be identified. After simulation and verification, this nonlinear dynamic model can be used for monitoring, optimizing control, and diagnosing coal mill faults because the model is proven effective in reflecting coal mill dynamics and has good precision.

2.3 Mill Faults

Various disturbances occurred in the coal mill system at the PLTU Rembang, such as excessive coal mills, shortages of coal mills, and fire coal mills. To avoid these disturbances, it is necessary to know the characteristics of the operating parameters that occur from each failure, which are as follows:

a. Excessive Coal Mill

Due to this fault, the pulverized coal-air flow to the burner reduces, and coal accumulation inside the mill increases [4]. If choking occurs, the burning coal-air mixture's flow rate will decrease, and the amount of accumulated coal inside the mill will keep increasing [5].

b. Shortage Coal Mill

This fault reduces the amount of coal in the mill [4]. When such a fault happens, the amount of coal inside the mill will decrease. The common reasons are blockage of the coal falling pipe, malfunctions of the coal feeder, etc. Such faults are the decrease of differential pressure between the inlet and the coal mill outlet, the reduction of the mill current, and the increased outlet temperature [5].

c. Fire Coal Mill

Mill fire or explosion is a fault that causes the possibility of combustion/ignition of coal inside the mill [4]. If this fault occurs, several signs can be observed: a sharp increase in the outlet temperature, a significant change in the wind pressure at the mill inlet, and even the combustion or ignition of coal inside the mill [5].

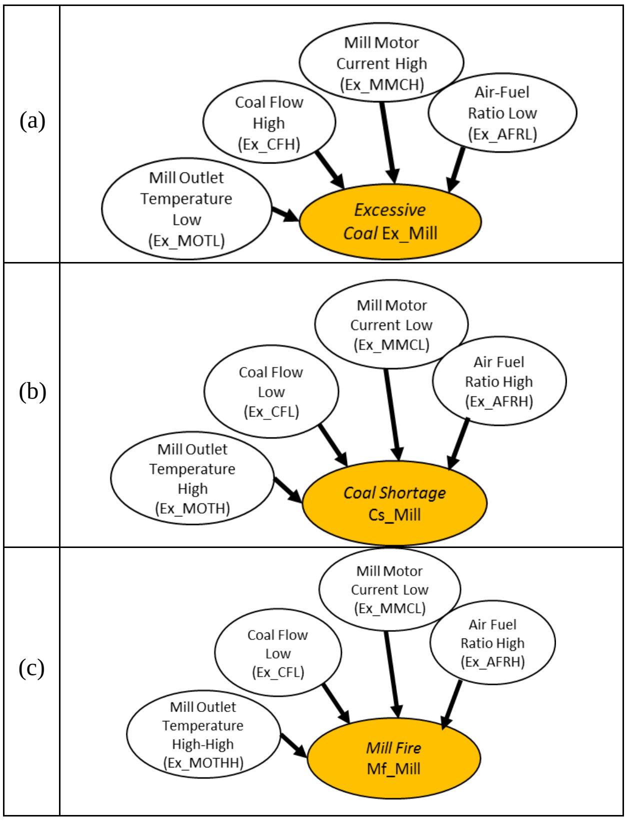

Figure 4. Bayesian network for the faults- (a) excessive in the mill, (b) shortage in the mill, (c) fire in the mill

Case Study – Excessive coal in the mill

The failure that occurred due to an excessive coal mill at PLTU (coal-fired steam power plant) Rembang had an impact on rejecting the pyrite mill that has coarse and fine coal materials. 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). Thus, the coal drying process in the mill was not maximized, resulting in high mill amperage due to more coal material falling in the scrapper chamber than out through the classifier as shown in Fig. 3. W. Fan et al. [5] discussed the general explanation of this condition. They suggested several possibilities, such as the high moisture content in the raw coal, improper adjustment of the air-to-coal ratio, low primary airflow rate, etc. Symptoms include increased bowl differential pressure (DP), current mill, and decreased outlet temperature [4]. There are many reasons for coal blockage, such as low primary airflow, excessive coal feed flow, low grinding capacity, and excessive coal moisture. However, any coal blockage will increase the amount of raw coal and coal powder stored in the mill [6].

Table 4. List of nodes for excessive fault

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

Mill problems due to all possible causes, such as improper air-coal input, changes in coal quality, incorrect settings, aging, problems in the reject system, and 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. The Bayesian network for excessive fault coal mill for root nodes is presented in Fig. 4.a.

2.4 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a simple data-learning technique that uses fuzzy logic to convert inputs of highly interconnected neural network processing elements and information connections into the desired output. Since ANFIS incorporates both the

ANN and the fuzzy inference method, it can manage nonlinear and complex problems within a unique structure. 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 of if-then [7]. ANFIS usually includes five layers: fuzzification, product, normalization, defuzzification, and summation. The ANFIS replaces the manual tuning of FIS for the prediction model [8]. The performance of the ANFIS can be improved by increasing the number of membership functions [9]. Table 5 is the rule base data training for excessive faults using the terminologies in Fig. 4(a). The ANFIS architecture consists of five layers as shown in Fig. 5.

Table 5. Rule base data training for excessive fault

Ex_CFH	Ex_AFRL	Ex_MMCH	Ex_MOTL	Ex_Mill
N	N	N	N	0
H	N	N	N	0.15
N	L	N	N	0.2
N	N	H	N	0.3
H	N	H	N	0.4
H	L	N	N	0.45
N	L	H	N	0.5
H	L	N	L	0.6
H	L	H	N	0.8
H	L	H	L	1.0
L	L	N	N	0
L	H	N	N	0
L	L	L	N	0
L	H	L	H	0

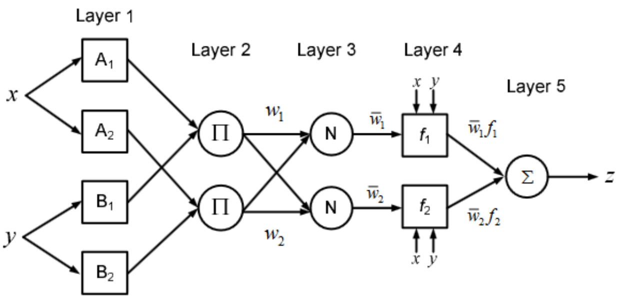

Figure 5. Two-input ANFIS architecture with first-order Sugeno fuzzy model and two rules [10]

Layer 1. Calculation of the degree of membership of the input values to the respective fuzzy sets (fuzzification).
Layer 2. Calculation of the activation levels for all rules. This layer calculates the firing strengths of each rule via multiplying the incoming signals and sends the product out [10].
Layer 3. Normalization of activation levels for all rules. Labeled N, indicating a normalization role [10].
Layer 4. Processing of normalized values and consequence parameter sets. Parameters in this layer will be referred to as consequent parameters [10].
Layer 5. The final result after sharpening is calculated (defuzzification). This node performs the summation of all incoming signals[10].

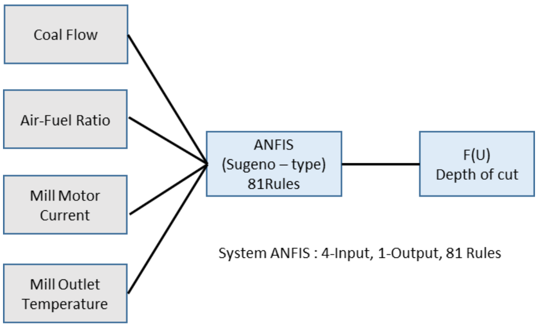

Figure 6. Adaptive Neuro-Fuzzy Inference System (ANFIS) model for coal mill showing input and output

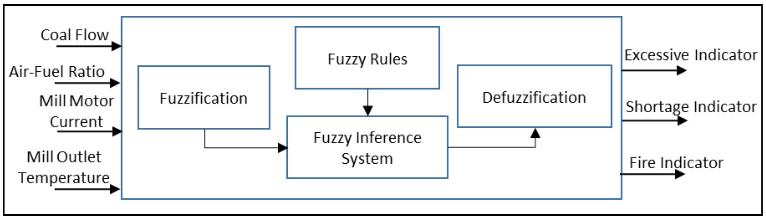

Figure 7. Fuzzy logic approach for mill fault

A fuzzy logic-based fault diagnosis scheme is used for detecting and identifying faults [11]. Fuzzy logic is based on linguistic variables that emulate human judgment and solve complex modeling problems subject to uncertainty or incomplete information. Fuzzy controllers can handle control problems when an accurate process model is unavailable, ill-defined, or subject to excessive parameter variation [12]. Three inputs were selected for the Fuzzy Inference System (FIS). The output of the FIS consists of an indicator condition for each error. The MATLAB fuzzy logic toolbox was used to implement the FIS system for coal mill FDD. The analysis structure using fuzzy logic is presented in Fig. 7. The output of the FIS consists of an indicator condition for each error.

3. Result and Discussion

The actual and reference value of the outlet temperature, air-fuel ratio, and fault indicators from 21-05-2021, 18:31 hrs to 23:02 hrs, are presented in Fig 8 and 9, respectively.

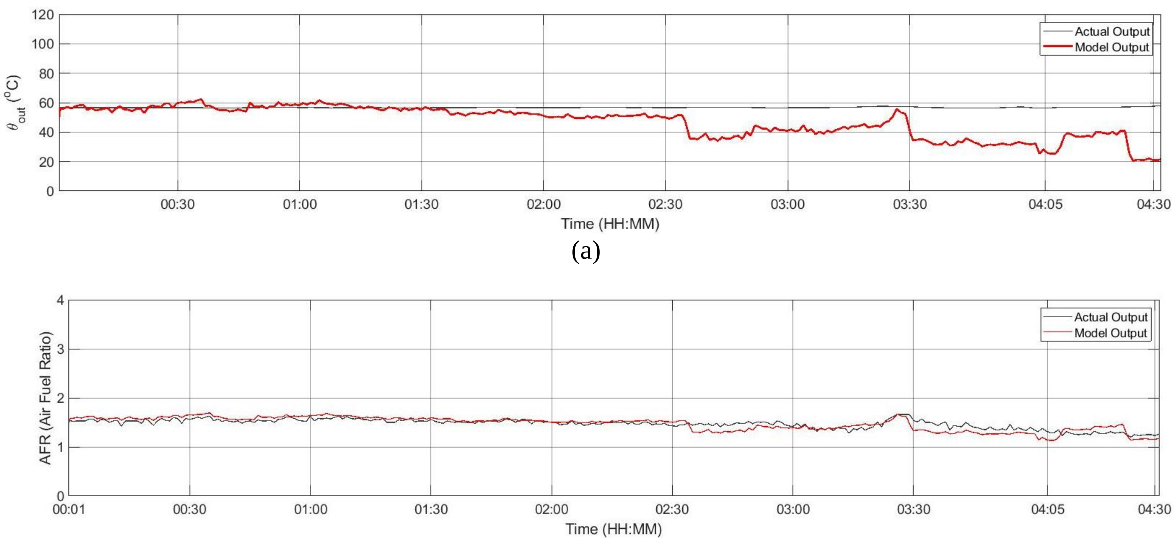

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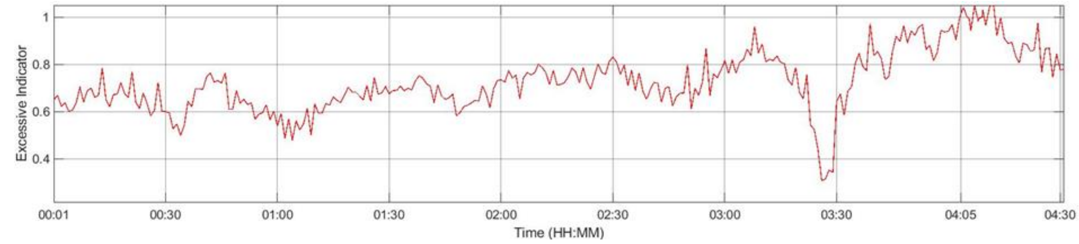
Figure 8. Actual and reference value for outlet temperature (ºC) and air-fuel ratio

On analyzing the results, it is seen that the plant was working normally, and the actual values were closely following the reference till 02:30 hrs. After that, the outlet temperature decreased, and the air-fuel ratio decreased. The actual outlet temperature and air-fuel ratio values were far from standard in this condition. The graphical analysis results in Fig. 9 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 can provide early warning about failure and information for monitoring coal mill operations. It can help the plant operators in preventing a derating or trip unit.

The plant history reported that a hammering operation was performed to remove the excessive amounts of the reject system of the mill at 02.30 hrs. The condition can be proven on the dynamic model graph for pulverized fuel mass presented in Fig.10 on rising at 02.30 hours, and actual evidence in the field is shown in Fig. 11.



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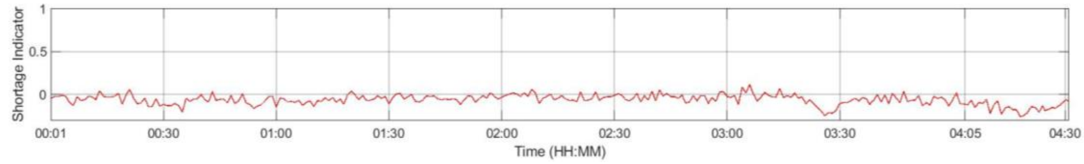

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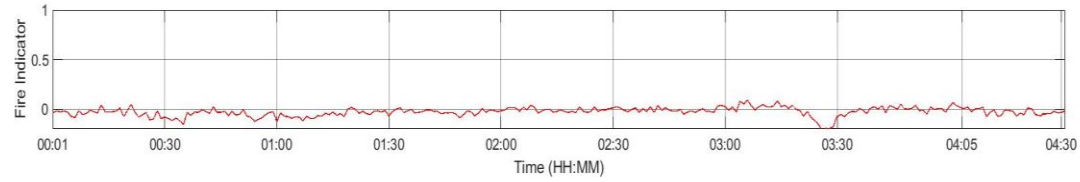

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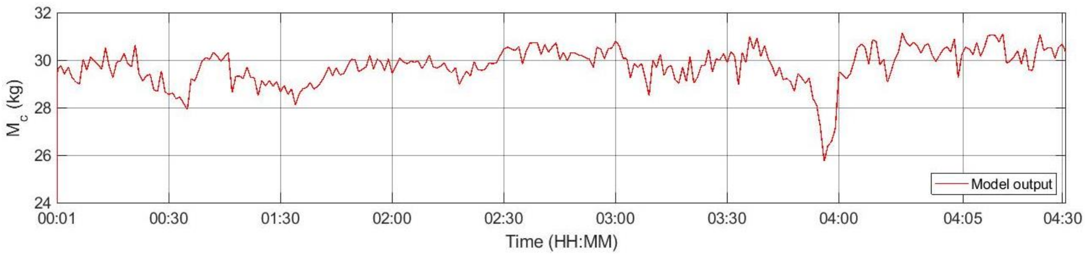
Figure 9. Various faults indicators-excessive, shortage, and fire indicators (0 to 1 scale)



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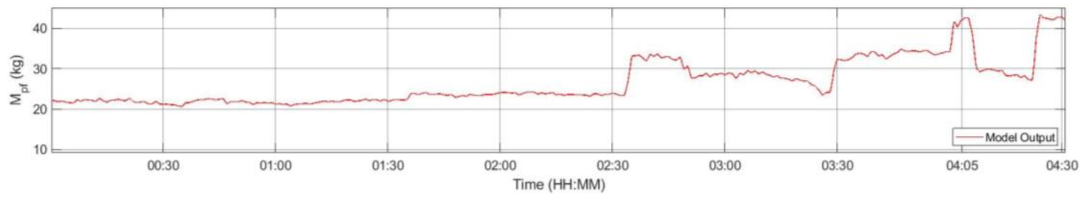

(b)

Figure 10. Estimation model result of raw coal content M_c (kg) and coal powder content M_{pf} (kg)

Figure 11. Actual pyrite reject

4. Conclusion

The results of the dynamic modeling validation of the actual data output of the Rembang PLTU with the model output have high accuracy: less than 4% error for W_{air}, θ_{in}, I, and AFR except for θ_{out} due the assumption of constant moisture while its actual value may vary with time. Simulation constructed using the input parameter data of the Rembang PLTU has successfully defined the output of excessive coal mill failure with a severe level after running for 4 hours and 5 minutes. It validated the simulation model results by increasing M_{pf}. This study considers the main errors that affect coal performance, such as excessive coal supply. Fuzzy logic inference systems have been applied to provide information about the magnitude of the error and an easy way to automate expert knowledge and account for modeling uncertainties. An operator can recognize early detection of disturbances/anomalies using inference systems. The inference systems can be helpful as a supervisory control in the operation of the coal pulverizer mill so that monitoring, optimization of control, and diagnosis of disturbances can be applied.

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References

[1] Y. Gao, D. Zeng, and J. Liu, "Modeling of a medium speed coal mill," *Powder Technol.*, vol. 318, pp. 214–223, 2017, doi: 10.1016/j.powtec.2017.05.015.

[2] Y. Gao, D. Zeng, J. Liu, and Y. Jian, "Optimization control of a pulverizing system on the basis of the estimation of the outlet coal powder flow of a coal mill," *Control Eng. Pract.*, vol. 63, no. March, pp. 69–80, 2017, doi: 10.1016/j.conengprac.2017.03.015.

[3] Y. Hu, B. Ping, D. Zeng, Y. Niu, and Y. Gao, "Modeling of coal mill system used for fault simulation," *Energies*, vol. 13, no. 7, 2020, doi: 10.3390/en13071784.

[4] V. Agrawal, B. K. Panigrahi, and P. M. V. Subbarao, "Intelligent Decision Support System for Detection and Root Cause Analysis of Faults in Coal Mills," *IEEE Trans. Fuzzy Syst.*, vol. 25, no. 4, pp. 934–944, 2017, doi: 10.1109/TFUZZ.2016.2587325.

[5] W. Fan, S. Ren, Q. Zhu, Z. Jia, D. Bai, and F. Si, "A Novel Multi-Mode Bayesian Method for the Process Monitoring and Fault Diagnosis of Coal Mills," *IEEE Access*, vol. 9, pp. 22914–22926, 2021, doi: 10.1109/ACCESS.2021.3055226.

[6] Y. Hu, B. Ping, D. Zeng, Y. Niu, Y. Gao, and D. Zhang, "Research on fault diagnosis of coal mill system based on the simulated typical fault samples," *Meas. J. Int. Meas. Confed.*, vol. 161, p. 107864, 2020, doi: 10.1016/j.measurement.2020.107864.

[7] I.M. El-Hasnony, S.I. Barakat, and R.R. Mostafa, "Optimized ANFIS Model Using Hybrid Metaheuristic Algorithms for Parkinson's Disease Prediction in IoT Environment," *IEEE Access*, vol. 8, no. September, pp. 119252–119270, 2020, doi: 10.1109/ACCESS.2020.3005614.

[8] W. Caesarendra, T. Wijaya, T. Tjahjowidodo, B. K. Pappachan, A. Wee, and M. I. Roslan, "Adaptive neuro-fuzzy inference system for deburring stage classification and prediction for indirect quality monitoring," *Appl. Soft Comput. J.*, vol. 72, pp. 565–578, 2018, doi: 10.1016/j.asoc.2018.01.008.

[9] H.A. Hendarto, Munadi, and J.D. Setiawan, "ANFIS application for calculating inverse kinematics of programmable universal machine for assembly (PUMA) robot," *2014 1st Int. Conf. Inf. Technol. Comput. Electr. Eng. Green Technol.ICITACEE 2014 - Proc.*, no. August 2015, pp. 35–40, 2015, doi: 10.1109/ICITACEE.2014.7065710.

[10] W. Caesarendra, T. Tjahjowidodo, and D. Pamungkas, "EMG based classification of hand gestures using PCA and ANFIS," *Proc. 2017 Int. Conf. Robot. Biomimetics, Intell. Comput. Syst. Robionetics 2017*, vol. 2017-Decem, pp. 18–23, 2017, doi: 10.1109/ROBIONETICS.2017.8203430.

[11] V. Kannan, M. Santhi, and D. Sureshkumar, "Multiple fault analysis using a fuzzy logic technique for an inverter control drive," *J. Mar. Sci. Technol.*, vol. 28, no. 1, pp. 51–57, 2020, doi: 10.6119/JMST.202002_28(1).0006.

[12] M.A. Sellitto, E. Balugani, R. Gamberini, and B. Rimini, "A Fuzzy Logic Control application to the Cement Industry," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1542–1547, 2018, doi: 10.1016/j.ifacol.2018.08.277.