

INTELLIGENT SOFT SENSING, DETECTION AND DIAGNOSIS OF FAULTS IN MEDIUM SPEED COAL MILLS

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INTELLIGENT SOFT SENSING, DETECTION AND DIAGNOSIS OF FAULTS IN MEDIUM SPEED COAL MILLS

by

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*Dedicated to my beloved parents,
Mrs. Tripta Agrawal and Mr. Sarvesh Agrawal
and
Almighty God*

CERTIFICATE

This is to certify that the thesis entitled “**INTELLIGENT SOFT SENSING, DETECTION AND DIAGNOSIS OF FAULTS IN MEDIUM SPEED COAL MILLS**” being submitted by **Ms. Vedika Agrawal** to the Indian Institute of Technology Delhi, for the award of **Doctor of Philosophy**, is a bonafide record of research work carried out by her under my supervision and guidance. The thesis, in my opinion, has reached the requisite standard fulfilling the requirements for the degree of Doctor of Philosophy. The results contained in this thesis have not been submitted elsewhere in part or full for the award of any degree or diploma.

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ABSTRACT

Coal mill is an essential component of coal fired power plant, which grinds the coal into fine powder and provides pulverized coal for efficient combustion. They can be a bottleneck in plant operation as the performance of the overall plant is greatly influenced by the mill downtime. Frequent changes in coal properties such as moisture, poor controls and several faults occurring in the mills are the major concerns affecting the efficiency of the milling system. It is required to closely monitor the operation of the milling system and isolate any abnormality in time. Currently, the operational issues in various equipments are identified by the judgement of experienced plant operators. As the information received at the control centre is huge, it is hard for the technical staff to analyze the data properly and take corrective measures in time to improve the availability and operation of the plant.

The main objective of the work is design and development of a novel method for intelligent decision support system for detection and diagnosis of common faults in the mills namely choking, coal shortage, and mill fire. Realizing the impact of high coal moisture on the combustion and availability of mills, a soft sensor for online estimation of moisture is also designed. It is realized that an automated early detection and diagnosis of mill faults can lead to significant savings due to reduction in maintenance costs and production losses. It ensures increased reliability and reduces the challenges involved in operation of the mills. A deeper review of the earlier works reveals that the works on fault detection and diagnosis (FDD) and soft sensing for mills are constrained by simplified models of coal mill employed for simulating the behaviour of mills under normal conditions. Further, the previous works focussed only on one fault and failed to provide any information regarding the severity and cause of the fault. It is also noticed that abundant literature is available in the area of FDD but their applicability and adaptation in the actual plants is limited.

In this work, firstly, an improved gray box dynamic model of coal milling system is derived to replicate the behaviour of coal mills under different operating conditions. The model is formulated using first principle conservation laws of mass and heat balance and plant data is utilized for estimating the unknown model parameters. The effectiveness of the model under start up, steady state, shutdown, and transient load change conditions is evaluated using data obtained from two actual power plants in India. The developed model is utilized for designing a cost effective soft sensor for online prediction of moisture content in coal, which is presently determined only once per day using time consuming laboratory tests. Extended Kalman filter (EKF) based state estimation is selected and

the results show that the online predictions by the soft sensor are in close agreement with the directional trend of per day moisture value.

A novel model based residual evaluation approach involving intelligent decision support system is considered for the purpose of early fault detection and diagnosis in mills. The work presents an intuitive application of fuzzy logic and probability theory where they are used in conjunction to solve the overall problem. The major symptoms, and causes for various faults in the mill are identified based on available literature and discussion with experienced plant operators. Knowledge base for these faults is built and fuzzy rule based system is designed for identifying the type, and severity of the faults. As the corrective action to be taken depends on the root cause of the problem, support for troubleshooting the root cause is also provided using Bayesian networks. Several steps are included to make the proposed mill FDD system fit for the real time plant deployment. The need of data preprocessing for improving data quality and adaptive learning of the model to evolve with slowly drifting measurements is discussed. Appropriate methods are chosen for these steps based on the nature of coal mill system. Simple methods are found to be suitable for missing values and obvious outlier treatment, while an elaborate method based on wavelet transform is selected for reducing the noise in the data. CUSUM based control charts are suggested for monitoring the slow evolving drift due to wear in the mill. Model parameters are retrained once change detection method issues an alert.

In order to develop a field worthy system that is relevant for real time applications, actual data from two different coal fired power plants in India is collected and used for validating the work. The performance of the proposed mill FDD system is computed using normal and faulty data obtained from mills of these plants. Total 47 fault cases and 150 randomly selected one day normal data are selected for quantifying the performance of the proposed algorithm. Ten case studies are detailed to demonstrate the capability of the proposed method. The validation results using actual plant data are found to be promising, which confirms that the proposed algorithm is effective for real time online FDD in power plant coal mills.

सार

कोयला पीसने की चक्की (मिल) कोयले से चलने वाले बिजली संयंत्र का एक अनिवार्य घटक है, जो कोयले को बेहतर पाउडर में पीसता है और कुशल दहन के लिए चूर्णित कोयला प्रदान करता है। मिल संयंत्र के संचालन में बाधा उत्पन्न कर सकते हैं क्योंकि समग्र संयंत्र का प्रदर्शन मिल से काफी प्रभावित होता है। मिलों में होने वाली अनेक तरह की त्रुटियाँ, खराब नियंत्रण और कोयले के गुणों में लगातार परिवर्तन जैसे कि नमी की मात्रा, मिलिंग सिस्टम की दक्षता को प्रभावित करने वाली प्रमुख चिंताएं हैं। मिलिंग सिस्टम के संचालन की बारीकी से निगरानी करना और समय पर किसी भी दोष का पता करना आवश्यक है। वर्तमान में, विभिन्न उपकरणों में परिचालन संबंधी मुद्दों की पहचान अनुभवी संयंत्र चालकों के फैसले द्वारा की जाती है। चूंकि नियंत्रण केंद्र में प्राप्त जानकारी बहुत बड़ी है, तकनीकी कर्मचारियों के लिए इतनी बड़ी जानकारी का ठीक से विश्लेषण करना और संयंत्र की सुचारू संचालन में सुधार के लिए समय पर सुधारात्मक उपाय लेना कठिन है।

इस काम का मुख्य उद्देश्य मिलों में सामान्य दोषों, जैसे संयंत्र में घुटन [चोर्किंग], कोयले की कमी और आग लगने का पता लगाने और निदान के लिए बुद्धिमान निर्णय समर्थन प्रणाली के लिए एक उन्नत पद्धति का विकास है। कोयले के दहन और मिलों की कार्य प्रणाली पर उच्च नमी के असर को पहचानते हुए, ऑनलाइन नमी की आंकलन लगाने का सेंसर भी बनाया गया है। यह महसूस किया गया है कि मिल दोषों का एक स्वचालित प्रारंभिक पहचान और निदान, रखरखाव लागत और उत्पादन हानियों में कमी के कारण महत्वपूर्ण बचत कर सकता है। यह ज्यादा विश्वसनीयता सुनिश्चित करता है और मिलों के संचालन में शामिल चुनौतियों को कम करता है। पिछली रचनाओं की गहन अध्ययन से पता चलता है कि मिलों के लिए गलती का पता लगाने, निदान (एफडीडी) और आंकलन मिलों के सामान्य व्यवहार का अनुकरण करने वाली कोयला मिल के सरलीकृत मॉडल की वजह से सीमित हैं। इसके अलावा, पिछली रचनाएं केवल एक गलती पर केंद्रित थीं और गलती की गंभीरता और कारण के बारे में कोई जानकारी प्रदान करने में विफल रही। यह भी पाया जाता है कि एफडीडी के क्षेत्र में प्रचुर मात्रा में साहित्य उपलब्ध है लेकिन वास्तविक संयंत्रों में उनके उपयोग और अनुसरण सीमित हैं।

इस काम में, सबसे पहले, कोल मिलिंग सिस्टम का एक बेहतर ग्रे बॉक्स डायनामिक मॉडल अलग-अलग ऑपरेटिंग परिस्थितियों में कोयला मिल के व्यवहार को दोहराने के लिए प्राप्त किया गया है। यह मॉडल द्रव्यमान और गर्मी संतुलन संरक्षण कानूनों के पहले सिद्धांत का उपयोग करके तैयार किया गया है और मिलों के डेटा का उपयोग अज्ञात मॉडल पैरामीटरों के आकलन के लिए किया गया है। शुरुआती, स्थिर स्थिति, शटडाउन, और क्षणिक लोड बदलाव की स्थिति के तहत मॉडल की प्रभावशीलता भारत में दो

वास्तविक विद्युत संयंत्रों से प्राप्त आंकड़ों पर परखी गयी है। विकसित मॉडल को कोयले में नमी की ऑनलाइन भविष्यवाणी के लिए एक लागत प्रभावी सेंसर डिजाइन करने में उपयोग किया गया है, जो कि अब तक काफी समय लगा कर, प्रयोगशाला परीक्षणों का उपयोग करके प्रति दिन केवल एक बार निर्धारित होता रहा है। एक्सटेंडेड काल्मन फिल्टर (ईकेएफ) आधारित स्टेट एस्टीमेट चुना गया है और परिणाम दिखाते हैं कि सेंसर द्वारा ऑनलाइन भविष्यवाणियां प्रति दिन नमी के मूल्य की दिशात्मक प्रवृत्ति के साथ निकट समझौते में हैं।

मिलों में शुरुआती दोष का पता लगाने और निदान के उद्देश्य के लिए बुद्धिमान निर्णय समर्थन प्रणाली से जुड़े एक अलग मॉडल आधारित मूल्यांकन को बनाया गया है। काम फजी लॉजिक और संभाव्यता सिद्धांत के एक सहज ज्ञान युक्त अनुप्रयोग का प्रतिनिधित्व करता है जहां उनका उपयोग त्रुटियों को हल करने में किया गया है। मिल में विभिन्न दोषों के लिए प्रमुख लक्षण और कारण उपलब्ध साहित्य के आधार पर और अनुभवी संयंत्र कर्मचारियों के साथ चर्चा करके पहचान की गई है। इन दोषों के आधार पर जानकारी बनायीं गयी है और फजी नियम आधारित प्रणाली को उपयोग करके दोषों के प्रकार और गंभीरता का पता लगाया गया है। जबकि सुधारात्मक कार्रवाई समस्या के मूल स्वरूप पर निर्भर करती है, समस्या के मूल कारणों की पहचान के लिए बायेसियन नेटवर्क का उपयोग भी किया गया है।

प्रस्तावित मिल एफडीडी प्रणाली को संयंत्र में उपयोग करने के लिए कई चरण बनाये गए हैं। गुणवत्ता में सुधार के लिए डेटा प्रीप्रोसेसिंग और मॉडल के अनुकूलन सीखने की आवश्यकता पर चर्चा की गई है। इन परियोजनाओं के लिए उपयुक्त तरीके कोयला मिलों के प्रकार पर निर्भर करता है। लापता मूल्यों और स्पष्ट बाह्य उपचार के लिए सरल तरीके चुने गए हैं, जबकि ववेलेट ट्रांसफॉर्म पर आधारित एक विस्तृत विधि को डेटा नॉइज़ को कम करने के लिए चुना गया है। मिल में उपयोग के साथ होने वाले परिवर्तन के कारण धीमी गति से ड्रिफ्ट को पकड़ने के लिए क्यूसम आधारित नियंत्रण चार्ट की सिफारिश की गयी है। परिवर्तन सूचना के आधार पर मॉडल पैरामीटर अपने आपको विकसित करता है।

वास्तविक समय के अनुप्रयोगों के लिए प्रासंगिक फ़ील्ड योग्य प्रणाली विकसित करने के लिए, भारत में दो अलग-अलग कोयले से चलने वाले ऊर्जा संयंत्रों का वास्तविक डेटा एकत्र किया गया है और कार्य को मान्य करने के लिए उपयोग किया गया है। प्रस्तावित मिल एफडीडी सिस्टम का प्रदर्शन इन संयंत्रों की मिलों से सामान्य और दोषपूर्ण डेटा का उपयोग करते हुए परखा गया है। कुल 47 दोष मामलों और 150 बेतरतीब ढंग से चुना हुआ एक दिन का डाटा चुना गया और उससे प्रस्तावित अल्गोरिथम की गुणवत्ता परखी गयी। दस मामले के विस्तृत अध्ययन से प्रस्तावित तरीके की परख की गयी है। वास्तविक संयंत्र डेटा का उपयोग करके किया गया सत्यापन परिणामों से मिलता है, जो यह पुष्टि करता है कि प्रस्तावित एल्गोरिथम विद्युत संयंत्र कोयला मिलों में वास्तविक समय के ऑनलाइन एफडीडी के लिए प्रभावी है।

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NOTATION AND ABBREVIATIONS

ANN	Artificial neural network
BN	Bayesian network
CAD	Cold air damper
CPT	Conditional probability table
CWT	Continuous wavelet transform
DAE	Differential algebraic equation
DCS	Distributed control system
DE	Differential evolution
DP	Differential pressure
DWT	Discrete wavelet transform
EKF	Extended Kalman Filter
FDD	Fault detection and diagnosis
FFT	Fast fourier transform
FIS	Fuzzy inference system
FL	Fuzzy logic
FMEA	Failure mode and effect analysis
FN	False Negative
FP	False Positive
FRBS	Fuzzy rule based system
GLR	Generalized likelihood rati
HAD	Hot air damper
HGI	Hardgrove grindability index
KF	Kalman filter
MF	Membership function
PCA	Principal component analysis
PF	Pulverized fuel
PID	Proportional integral derivative
RC	Residual current
RDP	Residual differential pressure
ROT	Residual outlet temperature
RCA	Root cause analysis
LFC	Load – following capability

MAD	Median of the absolute deviation of the median
MFT	Master fuel trip
MPC	Model predictive control
NRMSE	Normalized root mean square error
OT	Outlet temperature
SOM	Self-organizing map
SPC	Statistical process control
STFT	Short term fourier transform
SVM	State vector machine
TBT	Time before trip
TN	True Negative
TP	True Positive
TPH	Tonnes per hour
UKF	Unscented Kalman filter
WT	Wavelet transform

NOMENCLATURE

$\dot{m}_c^F$	Flow rate of coal from the feeder (kg/s)
	Flow rate of i^{th} size coal particles (kg/s) from:
	$XX = FB$: Feeder to the bowl zone
	$XX = BG$: Bowl to the grinding zone
	$XX = GS$: Grinding to the separator zone
$\dot{m}_{ic}^{XX}$	$XX = SC$: Separator to the classifier zone
	$XX = SB$: Separator to the bowl zone
	$XX = CFu$: Classifier to the furnace
	$XX = CB$: Classifier to the bowl zone
	Flow rate of mixed primary air (kg/s) to the:
$\dot{m}_{air}^X$	$X = S$: Separator zone
	$X = Fu$: Furnace
	Mass of i^{th} size coal particles accumulated (kg) in :
	$X = B$: Bowl zone
M_{ic}^X	$X = G$: Grinding zone
	$X = S$: Separator zone
	$X = C$: Classifier zone
$\dot{m}_{mois}$	Flow rate of moisture removed from the i^{th} size coal particles (kg/s)
$\dot{Q}_{in}$	Rate of heat flow entering the mill (kJ/s)
$\dot{Q}_{out}$	Rate of heat flow leaving the mill (kJ/s)
$\dot{Q}_{acc}$	Rate of heat accumulated (kJ/s)
H_g	Heat generated due to grinding (kJ/s)
M_m	Mass of the mill metal body (kg)
$\sigma_{FB}, \sigma_{FBE}$	Average moisture content in coal from the feeder to the bowl - grinding zone (fraction) , Online moisture estimate in coal from the feeder to the bowl-grinding zone (fraction)
σ_{out}	Average moisture content in the pulverized coal flowing to the furnace (fraction)
σ_{acc}	Average moisture content in the coal accumulated in the bowl - grinding zone (fraction)

T_{mair}	Temperature of mixed air flowing to the separator zone (deg C)
T_{out}	Temperature of coal-air mixture at the mill outlet (deg C)
T_a	Temperature of the ambient air (deg C)
ΔP_{mill}	Differential pressure across the mill (mbar)
cp_a, cp_c cp_w, cp_{met}	Specific heat of air, coal, water and metal respectively (kJ/kg-degC)
d_i	Average diameter of the i^{th} size group coal particles (mm)
d_{imax}	Maximum diameter of the i^{th} size group coal particles (mm)
d_{imin}	Minimum diameter of the i^{th} size group coal particles (mm)
I_{hg}	Hardgrove grindability index of the coal (deg H)
a_i	Distribution of i^{th} size particles in the raw coal (fraction)
B	Breakage matrix (fraction)
b_{ij}	Elements of matrix B , which represents the fraction of j^{th} size coal that is reduced to the i^{th} size group (fraction)
K_s	Comminution rate, which represents the fraction of coal in the i^{th} size group that is reduced in size as it passes under the rollers under the reference conditions (1/s)
γ_i	Comminution rate, which represents the actual fraction of coal in the i^{th} size group that is reduced in size as it passes under the rollers (1/s)
C_{1i}, C_{2i}	Classification functions for the i^{th} size group coal particles
P_{total} , I_{total}	Mill power consumption (kW) and motor current (A) respectively
M_v	Motor voltage (kV)
p_f	Power factor
M_{on}	Motor on/off signal (0/1)
ω	Angular velocity of the grinding table (rps)
N_{rol}	Number of rollers
τ_{bg}	Average residence time of coal in the bowl zone, moving towards the grinding zone (s)
τ_{gs}	Average residence time of coal in the grinding zone, moving towards the separator zone (s)

τ_{sc}	Average residence time of coal in the separator zone, moving towards the classifier zone (s)
τ_{sb}	Average residence time of coal in the separator zone, falling back to the bowl zone (s)
τ_{cfu}	Average residence time of coal in the classifier zone, moving towards the furnace (s)
τ_{cb}	Average residence time of coal in the classifier zone, falling back to the bowl zone (s)
k_{avf}	Pressure drop air flow parameter (mbar/(kg ² /s ²))
k_{CA}	Pressure drop coal accumulation parameter(mbar/(kg ³ /s ²))
k_{CE}	Pressure drop coal entrainment parameter (mbar/(kg ² /s))
k_{power}	Power consumption parameter (kJ/kg)
k_g	Heat due to grinding parameter