http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 13 (6): 1228-1233, 2014
ISSN 1812-5638 / DOI: 10.3923/itj.2014.1228.1233

Failure Warning Method of Pulverizing System Based on Multivariate State Estimation

Yongjie Zhai, Huiyuan Cui, Shilin Wang and Yan Li
Hebei Engineering Research Center of Simulation and Optimized Control for Power Generation,
North China Electric Power University, Baodingm, 071003, China

Abstract: Based on the multivariate state estimation, a new condition monitoring methods for the generator set is presented to reduce the maintenance costs of power generation equipment. A new and improved matrix in memory is given. It can achieve a good coverage of the normal operation status of the milling system. When there is a large difference between the estimated value and the actual measurement value, the existence of the fault is indicated. Sliding window residual statistical methods is used to analyze the residuals. When the residual trend is beyond the set threshold value, the system generates the warning. The real-time data of power plant is used to verify the method. The simulation results show that this method can achieve early failure warning effectively.

Key words: Multivariate state estimation, pulverizing system, sliding window, failure, warning

INTRODUCTION

Early-warning equipment in thermal power plants can timely find out the abnormal and hidden trouble of equipment operation. Repair before failure can significantly reduce the economic losses caused by the failure and has a strong engineering value.

In this study, the fault early warning method of milling system of thermal power plant has been researched, which is a modeling method based on Multivariate State Estimation Techniques (MSET) (Gross *et al*., 1997). MSET is a advanced pattern recognition technology by measuring the similarity between the signals in the normal operating range in order to complete the state estimate. According to the historical data, the normal operation state is used to establish the relationship between the various parameters in the definition of the system's normal state. The running state data of nonlinear milling system is indicated by the data of the sensor signal directly or indirectly. Despite the state vector is not necessarily linearly independent but it has a certain degree of correlation with the progress or occurrence of physical processes (Bockhorst *et al*., 1998). After the establishment of the model, for every new observations of the milling system, MSET estimates the true state of the system by learning state model. The estimated state is calculated by using a weighted combination between a learning state and weights state is determined by each learning mode overlap degree or similarity (Cheng and Pecht, 2007). By sliding window residuals statistical methods, the changes in the residual statistical characteristics is detected and analysed. Early-warning is taken, when the residual curve exceeds a threshold value set interval.

MILLING SYSTEM

The pulverizing system can be divided into two kinds of parts: pulverizing system and intermediate storage bunker system. The pulverizing amount of the pulverizing system at any time must be equal to the boiler fuel consumption, which is changed as the boiler load changes. Pulverizing system can be divided into positive pressure system and negative pressure system. Currently, the majority of domestic power plants using positive pressure pulverizing system and this paper studies this type of milling system.

In the positive pressure pulverizing system, primary air is divided into hot air and cold air, which are mixed for the proper temperature after each adjustment baffle into the coal mill (Hong-Yu *et al*., 2003). Raw coal from the coal feeder coal chute gose into the coal mill grinding bowls central parts to be crushed by the grinding roller. The crushed coal is dried and blown into separator by hot air (Ling-Tao *et al*., 2002). Qualified coal is fed directly into four corners of the burner through the four pulverized coal tube of the classifier exports; failed pulverized coal is returned to the grinding bowl to be crushed again. Four pulverized coal pipes are equipped with the outlet valve to prevent the furnace temperature flue gas from flowing backward into the coal mill by closing the valve. The milling system works is shown in Fig. 1. Since this milling

Corresponding Author: Yongjie Zhai, Hebei Engineering Research Center of Simulation and Optimized Control for Power Generation, North China Electric Power University, Baodingm, 071003, China

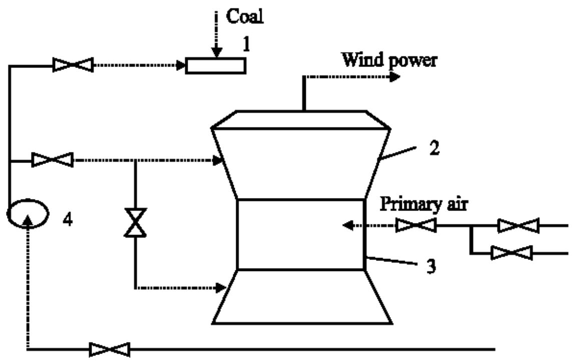

Fig. 1(a-d): Pulverizing system schematic, 1: Coal feeder, 2: Classifier, 3: Coal mill and 4: Sealed fan

system barotropic run, two high-pressure centrifugal seal fan is set up for sealing by above 9 kPa air, which is sent to the milling system equipment rotating parts (Quan-Gui *et al*., 2008).

Common faults in pulverizing system are that: coal mill full of coal, blocking coal, off the coal, spontaneous combustion in coal mills; the primary air duct blockage. In this paper, mill full coal is studied.

The reasons of coal pulverizer full coal are that: ill-monitoring of operating personnel, the large amount of given coal; the small amount of primary air; speed control devices malfunction, abnormal increase of coal feeder speed; too large coal gate open. Usually full coal fault can be judged from the following phenomenon: the full coal pulverizer current; the abnormal reduce of coal mill export wind temperature; the coal mill hot air baffle opening with a decrease in air volume; the amount of coal mill slag increasing with the almost all the coal powder in slag tank.

The condition of the milling system parameters is reflected: coal mill output, coal mill current, the amount of primary air, the temperature of the separator, coal mill hydraulic system variable residual loading; coal mill hydraulic system variable residual loading ascension, etc. These parameters can be used to model the pulverizing system to achieve the failure warning.

METHOD OF FAILURE WARNING BASED ON MSET

MSET-based early warning systems include two parts of the state estimation and fault detection.

State estimation: The state estimation is the normal operating state of the stored and current observation to compare and calculate an estimate of the current state of the system. The overall data within the operating range of a physical process can be expressed in matrix form, among them the columns of the matrix vector represents the measured results of a particular state. If overall data has m states and each state is represented by the monitoring process of the n variable data is measured of the variable i at the time point at. Storage matrix is defined by the sample data matrix:

$$D = \begin{bmatrix} d_{1,1} & \cdots & d_{1,m} \\ . & & . \\ . & & . \\ . & & . \\ d_{n,1} & \cdots & d_{n,m} \end{bmatrix} = \begin{bmatrix} x_1(t_1) & \cdots & x_1(t_m) \\ . & & . \\ . & & . \\ . & & . \\ x_n(t_1) & \cdots & x_n(t_m) \end{bmatrix} \quad (1)$$

The training process of MSET comprises to collect enough historical operational observation data system under normal operating conditions, so that the process storage matrix may cover the full dynamic range of normal operation of system (Cassidy *et al*., 2002). Once the process memory matrix is created, MSET can be used for the dynamic behavior of the system estimates. X_{obs} represents the observation vector that was observed of the system at each time point. Comparing the operating state of the current observation and storage, MSET calculate the state estimation X_{obs} (Singer *et al*., 1997):

$$X_{est} = D.(D^T \otimes D)^{-1}.(D^T \otimes X_{obs}) \quad (2)$$

When the process is normal, the new MSET input observation vector is located in process memory matrix represents the normal work of the space inside and is close to D matrix of some historical observation vector, so that the estimate of the corresponding MSET has a high precision (Hines and Usynin, 2005). When hidden faults appear, due to dynamic characteristics change, input observation vector will deviate from normal working space. From D matrix historical observation vector combination cannot construct the corresponding accurate estimate. It makes the estimation precision drop and the residual between observation and estimate increase (Black *et al*., 1998).

There are two key areas in the state estimation: the generation of the collected historical observation vector K and the construction of process memory matrix D. Historical data should meet the following requirements, which is used to generate a collection of historical observation vector K: covering a long enough period of running time; each data expressing a normal state of the device object; while it meets each variable in each group sampled value, the sampled value must be in the same moment. Process memory matrix is constructed, MSET should select some special status point from historical observation vector collection. These must include the maximum and minimum values of each of the variables in the system firstly, because these values are a manifestation of a special state of the system and then use the same pitch selected other data.

Failure detection: Sliding window residual statistical method is used in fault detection. In many statistical test methods, sliding window residual statistics can continuously reflect the change of residual distribution characteristics and the fastest makes system variable be normal or not decision.

When the system is working properly, MSET estimation accuracy is very high. The mean of the estimated residuals is close to zero and standard deviation is smaller. When the system occurs to failure hidden danger, the work characteristics change.

The observation vector set is taken as the MSET model's input, the estimated output of observation vector collection and the residual series are calculated. Using a sliding window statistical method, the residual continuous real-time mean is calculated from the residual sequence. If residual mean absolute value maximum of identification sequences is noted as E_v, threshold standard of equipment fault symptoms diagnosis is:

$$E_v = \pm k_1 E_v \tag{3}$$

$$S_v = \pm k_1 S_v \tag{4}$$

In the equation, according to the identified operation experience and can be made by the field operator. When using the non-parametric model to estimate the input, there is a certain uncertainty. For simplicity, it is supposed that residual obeys the mean and variance of unknown normal distribution. In the calculation of the sliding window residual series in which the mean and standard deviation, which need to give confidence for the mean and standard deviation of the confidence interval. Residual series for the unknown population mean and variance of the normal distribution, the confidence interval of the mean and standard deviation confidence are that:

$$\left[\bar{X}_s - \frac{S_s}{\sqrt{N}} t_{\alpha/2}(N-1), \bar{X}_s + \frac{S_s}{\sqrt{N}} t_{\alpha/2}(N-1)\right] \tag{5}$$

$$\left[\frac{\sqrt{N-1}S_s}{\sqrt{\chi^2_{\alpha/2}(N-1)}}, \frac{\sqrt{N-1}S_s}{\sqrt{\chi^2_{1-\alpha/2}(N-1)}}\right] \tag{6}$$

where, N, $\bar{X}_s$ and S_s are the width of the sliding window, the mean and standard deviation; andare t-distribution and χ^2 the distribution of $\alpha/2$ sub-sites.

MILLING SYSTEM MODELING

According to the real time data structure process storage matrix: In this study, the studies data was from a domestic power plant, using direct blowing pulverizing system. The observed vector includes that:

- No. 1 coal mill output (T/H)
- No. 1 coal mill current (A)
- No. 1 coal mill the amount of primary air ($\times 10^4$Nm^3/4)
- No. 1 coal mill the temperature of the end of the separator (°C)
- No. 1 coal mill hydraulic system variable residual loading (MPa)
- No. 1 coal mill hydraulic system variable residual loading ascension (MPa)

These observation vectors are used to model. The operation data of the unit from 2011/06/29 to 2011/07/08 is selected and the data (a total of 120 sets of data) from 00:00 to 22:00 h is sampled in every two hours. This period is normal operation state. The real-time data is shown in Fig. 2.

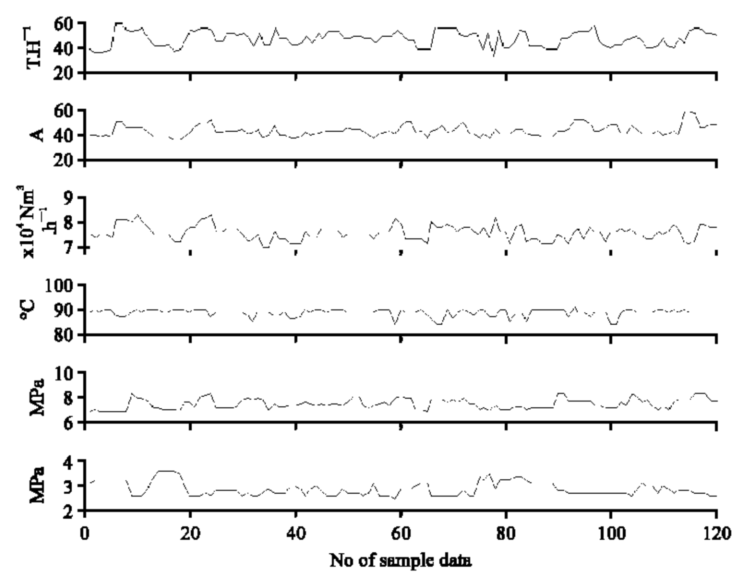

Fig. 2: Real-time data map

According to the real time data, state estimation is taken to get process storage matrix D. Each column of the process of the memory matrix is the operational representative state of the system. Process memory matrix is constructed, MSET should select some special status point from historical observation vector collection. These must include the maximum and minimum values of each of the variables in the system first. Because these values are a manifestation of a special state of the system. A detailed description is as follows. For a system or a process, every relevant variables between (0, 1) is divided into h parts. In 1/h step, several observation vectors are searched out to join matrix D from the set of K. The method of adding the observation vector in the process matrix D is shown in Fig. 3. After constructing the process memory matrix, the state estimation is conducted.

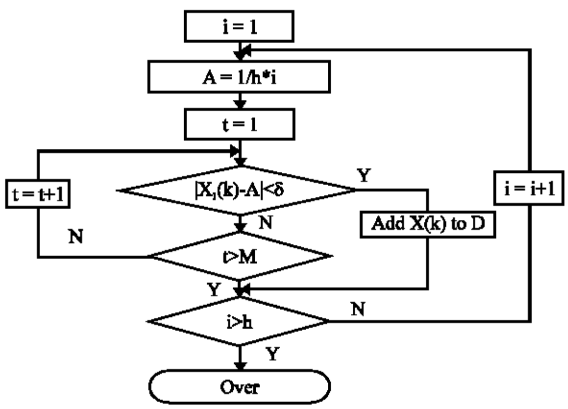

Fig. 3: Construction process memory matrix D

State estimation: The running state of the current observation X_{obs} and storage is compared to calculate an estimate of the current state of the system X_{est}. The parameters are shown in Fig. 4, which is taken from the normalized residuals of the statistical properties of the sliding window. Here sliding window width is set to n = 6.

The residual maximums of parameters are calculated: coal mill output $E_v = 0.078$, coal mill current $E_v = 0.068$, primary air flow $E_v = 0.1$, the temperature of the end of the separator $E_v = 0.029$, coal mill hydraulic system variable residual loading $E_v = 0.033$, coal mill hydraulic system variable residual loading ascension $E_v = 0.08$.

The residual of pulverizer's current before normalized is counted by using sliding window. The width of the sliding window is set as n = 6. The result is shown in Fig. 5.

After running, the maximum absolute value of the coal pulverizer current residuals mean is 3.1A. Equipment failure signs diagnostic threshold standard as. Based on the operating experience of our definition of article is 2, so the coal mill current threshold is 6.2A.

Predictive failure: As a result of the full coal failure, the current of the coal mill has an upward trend, so it is necessary to observe and estimate the current. Figure 6 is fault current of estimate and observation value contrast diagram.

Using the sliding window residuals statistical to process and simulate these failure residuals and the width of the sliding window is set to N = 6.The statistical characteristics of their corresponding residual sliding window is shown in Fig. 7.

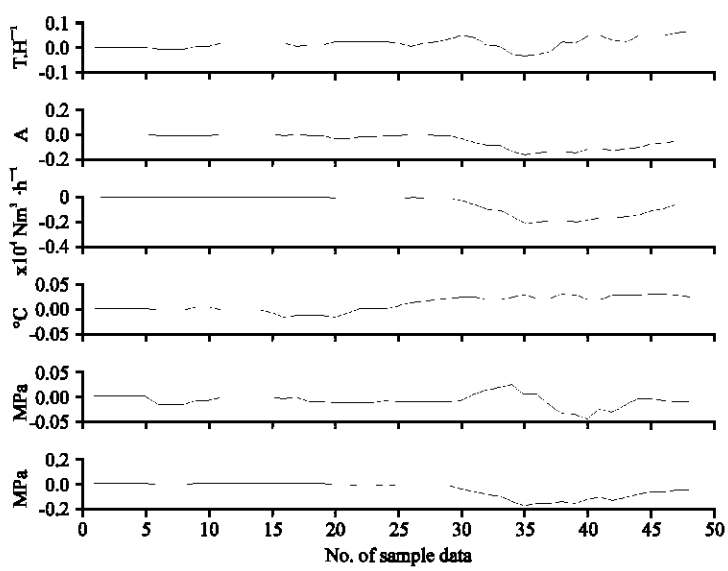

Fig. 4: Residual sliding window statistical properties

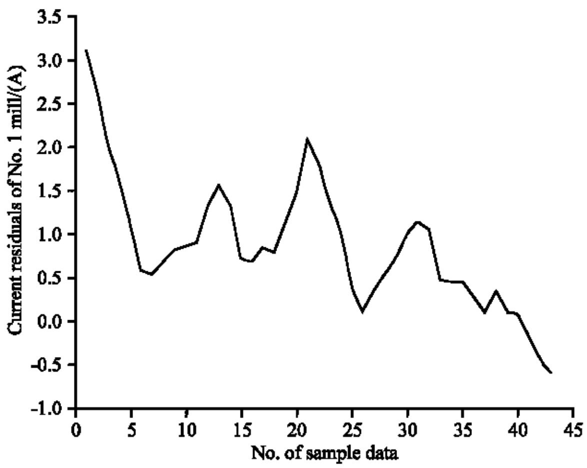

Fig. 5: Residual of mill current sliding window statistical properties

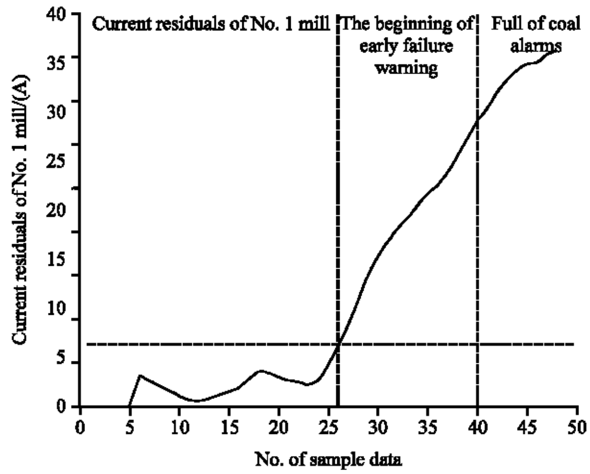

Fig. 7: Residual of mill current sliding window statistical properties

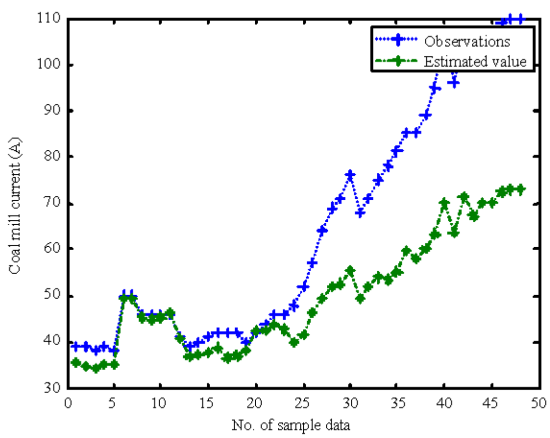

Fig. 6: Estimated and observed values of mill's current

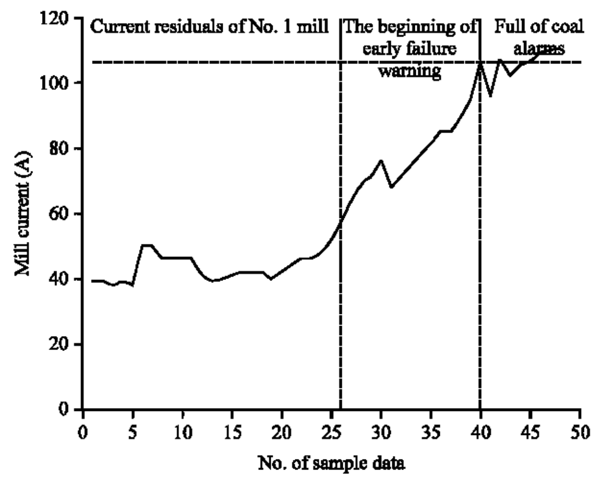

Fig. 8: System warning map

From Fig. 7, the residual of mill current sliding window statistical properties has an upward trend .At the 26 of data points, the current exceeds the mean threshold value 6.2A, starting the early fault warning at the moment. When there is a failure, the coal mill current curve is shown in Fig. 8. In Fig. 8, the whole period of the current data is divided into normal operation state, early warning status and alarm state. When the coal mill is in normal operation and current residual is not more than average threshold value, it is the normal operation state. When current residual is more than average threshold, they enter the early warning condition. When the current continue to rise significantly, in data point 40 place and current is more than coal mill alarm value 106 A, make a full coal alarm signal.

As it can be seen, the warning moment is earlier than the alarm time in the system, so that it achieves the purpose of early warning.

CONCLUSION

For generating set real-time data to carry on the analysis research, under the premise of without any increase in hardware cost monitoring unit important parts working condition, timely find hidden trouble of equipment failure. There is great practical value for the power plant.

In this study, it uses the multivariate state estimation method. Based on the real-time field data, tectonic processes memory matrix and state estimation model. When there is equipment failure risk, the residual distribution characteristics of the MSET model estimates change. According to the residuals trend, with the set threshold compared to achieve the early failure warning. Full of coal failure analysis, the method is able to detect abnormal changes in the working condition of the milling system, to verify the effectiveness of the method.

REFERENCES

Black, C.L., R.E. Uhrig and J.W. Hines, 1998. System modeling and instrument calibration verification with a nonlinear state estimate technique. Proceedings of Maintenance and Reliable Conference, May 12-14, 1998, Knoxville, TN., pp: 12-14.

Bockhorst, F.K., K.C. Gross, J.P. Herzog and S.W. Wegerich, 1998. MSET modeling of crystal river-3 venturi flow meters. Proceedings of International Conference on Nuclear Engineering, January 5, 1998, San Diego, CA.

Cassidy, K.J., K.C. Gross and A. Malekpour, 2002. Advanced pattern recognition for detection of complex software aging phenomena in online transaction processing servers. Proceedings of Dependable Systems and Networks, June 23-26, 2002, Washington, DC., USA., pp: 478-482.

Cheng, S.F. and M.G. Pecht, 2007. Multivariate state estimation technique for remaining useful life prediction of electronic products. Proceedings of AAAI Fall Symposium Artificial Intelligence for Prognostics, November 2007, Arlington, VA., pp: 26-32.

Gross, K.C., R.M. Singer, S.W. Wegerich, J.P. Herzog and R. Van Alstine, 1997. Application of a model-based fault detection system to nuclear plant signals. Proceedings of 9th International Conference on Intelligent Systems Application to Power System, July 6-10, 1997, Seoul, Korea.

Hines, J.W. and A. Usynin, 2005. MEST performance optimization through regularization. Nucl. Eng. Technol., 37: 177-184.

Hong-Yu, W., Liu-Chao and Z. Zhi-Tao, 2003. Ball coal storage pulverizing system test and its saving energy and reducing consumption. Thermal Power Generat., 8: 32-34.

Ling-Tao, X., Li-Jun and Z. Xue-Zhong, 2002. Medium-speed coal mill inlet a volume measurement error processing. Thermal Power Generat., 4: 17-18.

Quan-Gui, F., Y. Wei-Ping and Y. Shun-lin, 2008. Principles of Boiler. China Electric Power Press, Beijing, China.

Singer, S., K. Gross, J. Herzog, S. Wegerich and W. King, 1997. Model-based nuclear: Power plant monitoring and fault detectiontheoretical foundation. Proceedings of 9th International Conference on Intelligent Systems Application to Power System, April, 1997, Seoul, Korea.