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Performance Assessment of a Class of Industrial Fans With Substantial Process Variability for On-Condition Monitoring and Contol System Design

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Abstract

This paper presents a statistical quality control study for on-condition monitoring of draught fans in a steelmaking process. The study proposes a procedure for obtaining consistent estimates of peak vibration levels for performance assessment the machines based on independent measurements of the variable assuming the time between successive occurrences of the peak vibration were distributed with a probability density function.

Keywords: statistical quality control, probability density function, experimental design and modelling, vibration monitoring, on-condition performance assessment.

1. Introduction:

The development of experimental design and modeling of deterministic systems with substantial process variability [1, 2] have grossly enhanced the success of statistics for application to on-condition monitoring of rotating machines. The factors which aid selection of a particular machine for vibration monitoring under statistical quality control scheme [3, 4] are mainly its criticality to production and safety as well as manpower requirement for data acquisition [5, 6]. The statistical quality control of the machinery via vibration measurements due essentially to chance and assignable causes [7] in the measured data are caused by in-built defects and age of the machine. Also human errors, wrong spares and lubricants as well as wear and tear may cause deterioration in the current state of the rotating parts of the machine [8, 9]. The vibrations arising from such deterioration are attributed to assignable causes [4, 7]. Because chance causes are inherent in the machine, there is hardly anything to do about the related variability, and so it must be taken into account when establishing the base line vibration level for the machine. In this respect when a machine is operated within the control limits it is considered to be subject to chance causes only and when it drifts, it is attributed to assignable causes. Thus in the assessment of the machine, it is the assignable causes that are the greater worry to the quality controller, since they contribute to the out-of-control state of the machine during operation.

The statistical quality control concept [4] has been employed for quantitative analysis of large volumes of data acquired for on-condition monitoring of time-varying and discrete-time systems. The generic nature of the concept [10 – 12] enables it to be adopted globally to manage the problems of large variations of a process parameter from the desirable levels. The application of the concept to the various processes in a steel industry [13] has acknowledged the success of the technique in the resolution of a wide range of problems in other areas. The application of statistical quality control approach to constant monitoring of the state of the plant machinery has led to improved performance in quality assurance and process control.

The purpose of this study was to develop a statistical quality control scheme for on-condition monitoring and performance assessment of industrial fans in a steelmaking process using vibration measurements obtained on the machines, and to propose a procedure for obtaining consistent estimates of peak vibration levels in the operation of the machines.

Method And Materials

The draught fans considered in this study were assumed to be completely controllable and observable. Their dynamics were represented generally by a linear discrete-time process using the difference equation

$$x(k+1) = A(k)x(k) + B(k)u(k), \quad x(0) = x_0 \tag{1}$$

where $u(k)$ is an *r*-dimensional random vector process with the following statistical properties

$$E[u(k)] = m(k) \tag{2}$$

$$E[u(k_1) - m(k_1)][u(k_2) - m(k_2)]^T = K(k_2, k_1) \tag{3}$$

$$E[x(k)] = \phi(k, 0)x_0 + \sum_{i=0}^{k-1} \phi(k, i+1)B(i)E[u(i)] \tag{4}$$

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The analytical approach which often has some computational advantages is to derive a deterministic equation whose solutions are the desired mean and covariance matrix of $x(k)$. Taking the expectation of both sides of (1) yields

$$E[x(k+1)] = A(k)E[x(k)] + B(k)E[u(k)], \qquad E[x(0)] = x_0 \tag{5}$$

This is a deterministic linear difference equation which yields as its solution the expected value of $x(k)$. To derive the covariance of $x(k)$, we subtract (5) from (1) to obtain $x(k+1) - E[x(k+1)]$ and then post-multiply both sides of the resulting equation by $[x(x+1) - E[x(k+1)]]^T$ and then take the expectations of both sides.

Maximum Likelihood Estimate

If there exists an unknown parameter β defined in the function of the known form $(P(X, \beta))$ and X takes the specific values z, Cramer-Rao bound gives the smallest possible variance with which an estimate of β can be determined. Now, let $\hat{g}(z)$ be an unbiased estimate of the given function $g(\beta)$. Since it is unbiased, we write

$$E[\hat{g}(z)] = g(\beta) \tag{6}$$

i.e.,

$$\int_{-\infty}^{+\infty} \hat{g}(z)P(z)dx = g(\beta) \tag{7}$$

since z was drawn from the process which generated X, it has the same probability density function

$$p(z) = P(X, \beta)|_{x=z} = L(z, \beta) \tag{8}$$

Re-writing (7)

$$\int_{-\infty}^{+\infty} \hat{g}(z)L(z, \beta)dz = g(\beta) \tag{9}$$

Differentiating with respect to β gives

$$\int_{-\infty}^{+\infty} \left(\hat{g}(z)\frac{\partial L}{\partial \beta} dz \right) = g'(\beta) = \frac{dg}{d\beta} \tag{10}$$

Since $L(z, \beta)$ is a probability function

$$\int_{-\infty}^{+\infty} L(z, \beta)dz = 1 \tag{11}$$

and its differential with respect to β is zero, that is,

$$\int_{-\infty}^{+\infty} \frac{\partial L}{\partial \beta} dz = 0 \tag{12}$$

then

$$\int_{-\infty}^{+\infty} g(\beta)\frac{\partial L}{\partial \beta} dz = 0 \tag{13}$$

Substituting (13) from (10) gives

$$\int_{-\infty}^{+\infty} [\hat{g}(z) - g(\beta)]\frac{\partial L}{\partial \beta} dz = g'(\beta) \tag{14}$$

We now consider the log-likelihood function as follows:

$$L(z, \beta) = \log_e L(z, \beta) \tag{15}$$

$$\frac{\partial L}{\partial \beta} = \frac{1}{L}\frac{\partial L}{\partial \beta} \tag{16}$$

Substituting in (14) gives

$$\int_{-\infty}^{+\infty} [\hat{g}(z) - g(\beta)]L\frac{\partial L}{\partial \beta} dz = g'(\beta) \tag{17}$$

Now from the Schwartz inequality

$$\left\{ \int_{-\infty}^{+\infty} [\hat{g}(z) - g(\beta)]^2 Ldz \right\}\left\{ \int_{-\infty}^{+\infty} \left(\frac{\partial L}{\partial \beta} \right)^2 Ldz \right\} \geq (g'(\beta))^2 \tag{18}$$

where $$\left\{ \int_{-\infty}^{+\infty} [\hat{g}(z) - g(\beta)]^2 \, L dz \right\} = Var \;\; \hat{g}(z) \tag{19}$$

and $$\left\{ \int_{-\infty}^{+\infty} \left(\frac{\partial L}{\partial \beta} \right)^2 L dz \right\} = E\left[\left(\frac{\partial L}{\partial \beta} \right)^2 \right] \tag{20}$$

Thus for any unbiased estimate the lower bound on the variance of the estimate is given by Cramer-Rao bound as follows:

$$Var \;\; \hat{g}(z) \geq \frac{[g'(\beta)]^2}{E\left[\left(\frac{\partial L}{\partial \beta} \right)^2 \right]} \tag{21}$$

If $\hat{g}(z)$ is an unbiased estimate of β, i.e., $g(\beta) = \beta$

Therefore

$$g'(\beta) = \frac{dg}{d\beta} = 1 \tag{22}$$

$$Var \;\; [\hat{\beta}] \geq \frac{1}{E\left[\left(\frac{\partial L}{\partial \beta} \right)^2 \right]} \tag{23}$$

Example

In this example, we obtained an estimate of the mean vibration level based on independent measurements of the variable $X(x_1, x_2, ..., x_N)$ for the plant machinery with the time between successive data acquisition to be distributed with a probability function of the form

$$P(X; Q_1, Q_2) = \frac{1}{Q_1 \sqrt{2\pi}} \exp \left[\frac{1}{2} \left(\frac{x - Q_1}{Q_2} \right)^2 \right] \tag{24}$$

which describes the probability that the parameters Q_1 and Q_2 caused the measurements $X(x_1, x_2, ..., x_N)$ to occur. We express this function as a product of the individual functions

$$L(Q_1, Q_2, ... / x_1, x_2, ..., x_N) = \prod_{i=1}^{N} L(Q_1, Q_2, ... / x_i)$$

$$= \left\{ \frac{1}{Q_2 \sqrt{2\pi}} \exp \left[\frac{1}{2} \left(\frac{x_1 - Q_1}{Q_2} \right)^2 \right] \right\} \left\{ \frac{1}{Q_2 \sqrt{2\pi}} \exp \left[\frac{1}{2} \left(\frac{x_2 - Q_1}{Q_2} \right)^2 \right] \right\} ...$$

$$= \frac{1}{\left(Q_2 \sqrt{2\pi} \right)^N} \exp \left[\frac{1}{2} \sum_{i=1}^{N} \left(\frac{x_i - Q_1}{Q_2} \right)^2 \right] \tag{25}$$

For covariance, we define the log-likelihood function

$$L(Q_1, Q_2, ... / x_1, x_2, ..., x_N) = \log_e (Q_1, Q_2, ..., / x_1, x_2, ..., x_N)$$

$$= \log_e L = -N \log_e \left(Q_2 \sqrt{2\pi} \right) - \frac{1}{2} \sum_{i=1}^{N} \left(\frac{x_i - Q_1}{Q_2} \right)^2 \tag{26}$$

which we maximized with respect to Q_1, Q_2 by equating to zero the partial derivatives of L as follows:

$$\frac{\partial L}{\partial Q_1} = \frac{\partial \sum_{i=1}^{N} \log_e P(x_{i;} \; Q_1, Q_2, ...)}{\partial Q_1} = 0 \tag{27}$$

and $$\frac{\partial L}{\partial Q_2} = \frac{\partial \sum_{i=1}^{N} \log_e P(x_{i;} \; Q_1, Q_2, ...)}{\partial Q_2} = 0 \tag{28}$$

Maximizing with respect to Q_1 and Q_2 gives

$$\frac{\partial L}{\partial Q_1} = \frac{1}{Q_2^2}\sum_{i=1}^{N}\left(x_i - Q_1\right) \quad (29)$$

$$\frac{\partial L}{\partial Q_2} = \frac{N}{Q_2} + \frac{1}{Q_2^2}\sum_{i=1}^{N}\left(x_i - Q_1\right)^2 \quad (30)$$

Letting $\frac{\partial L}{\partial Q_1} = \frac{\partial L}{\partial Q_2} = 0$ gives the maximum likelihood of the estimates as follows

$$\hat{Q}_1 = \frac{1}{N}\sum_{i=1}^{N} x_i = \bar{x} \quad (31)$$

$$\hat{Q}_2 = \left(\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2\right)^{\frac{1}{2}} \quad (32)$$

From the Cramer-Rao bound

$$Var\left(\hat{\beta}\right) = -\frac{1}{E\left(\frac{\partial^2 L}{\partial \beta^2}\right)} \quad (33)$$

we obtain, for Q_1,

$$\frac{\partial^2 L}{\partial Q_1^2} = -\frac{N}{Q_2^2} \quad (34)$$

$$Var\left[\hat{Q}_1\right] \geq -\frac{1}{\left(-\frac{N}{Q_2^2}\right)} = \frac{Q_2^2}{N}$$

so that (35)

showing that the estimate is consistent with $N \to \infty$ as $Var\left[\hat{Q}_1\right] \to 0$.

Measuring Instruments

The main instruments employed in this study for on-condition performance assessment were B&K vibration meter, model 2511 equipped with a tunable band pass filter model 1621 and a recorder, model 2306, and a B&K impulse precision sound level meter, 2209 adapted for vibration measurement via a B&K integrator, type ZR 0020. These instruments were portable and were operated with a detachable magnetic pick-up accelerometer, type 4370.

Procedure

Prior to measurements, sensing points were mapped out on the machines taking into consideration the areas on the machine frame which absorb forces from the rotating parts. The magnetic pick-up accelerometer was then placed on these points one after the other, and by sweeping the vibration signals across a frequency range $0.2\ to\ 20\,Hz$ the reference spectral responses for the machines were obtained. These helped to establish the frequencies at which the several plant defects studied in this investigation were manifest. The machines considered in this study are shown in table 1.

Table 1Machines Covered In The Statistical Quality Control Concept

Machine	Speed (rpm)	Power Rating (KW)
Wet Scrubber Fan	1486	450
Shaft Furnace Deduster	14861	132
Reformer Flue Gas Fan	984	560
Combustion Air Blower	1480	160

Wet Scrubber Fan

This was employed for waste gas dedusting in the plant. Its performance was routinely monitored to avoid sudden breakdown. Dust particles were discharged from the fan in slurrified form. This plant was interlocked with gas supply to the iron ore dryer such that when the operation of the fan was interrupted that of the ore dryer was equally stopped. Any malfunctioning will result in atmospheric pollution. The economic implication of this is that the iron ore dust which otherwise would have been recycled within the process was now lost to the atmosphere. This therefore underlines the important nature of this plant to the entire steelmaking process. The main feature of the scrubber is that the impeller and the blades were rubberized to protect them from direct attack by the highly abrasive slurrified iron ore dust. With age, this coating became badly worn-out thereby exposing the blades to wear and corrosion. Also, the abraded patches on the impeller blades due to age were not evenly distributed. The combined effect of these resulted in dynamic imbalance and high vibration levels. The unpredicted nature of this problem, often led to unplanned stoppages in production. Through on-condition vibration monitoring, a baseline warning and action limits of $9.0\ mm/\sec.$ and $11.0\ mm/\sec.$ respectively were established.

Shaft Furnace Deduster

This is a suction fan for unconsumed gases in the shaft furnace operation to prevent them from accumulating and discharging to the atmosphere. The high vibration level recorded for this machine was due to uneven distribution of caked slurrified iron ore deposits on the impeller blades. These were subsequently scrubbed off and the entire impeller hosing cleaned. This was followed by double-plane dynamic in-situ balancing to bring down the vibration level. Our on-condition monitoring and control was able to establish a satisfactory vibration level of $12.5\ mm/\sec.$ for this plant. The upper warning and action limits were established as $24.0\ mm/\sec.$ and $35.0\ mm/\sec.$ respectively.

Flue Gas Fan

This was connected to the exhaust of flue gases from the steam reformer which supplied reformer gases to the shaft furnace. On-condition monitoring revealed high vibration level of this unit at the rotating frequency of the machine. It was desirable to establish a mean vibration level for this machine on which to base the set point. From the data acquired over several weeks of monitoring, a safe mean vibration of $2.5\ mm/\sec.$ and an upper warning and control limits of $3.9\ mm/\sec.$ and $4.8\ mm/\sec.$ respectively.

Combustion Air Blower

This machine supplied the air required for combustion of natural gas in the steel reheating furnace in the rolling mill. The application of statistical quality control to study this blower began in earnest following a breakdown of the plant that was traced to misalignment of the impeller shaft. The repairs involved principally in-house fabrication of the impeller shaft and the coupling. Vibration monitoring was subsequently carried out from which the mean vibration was computed as $16\ mm/\sec..$ Although this value was higher than that obtained before the breakdown, the operation of the machine was adjudged stable.

DISCUSSION AND CONCLUSIONS

This paper has chosen a number of plant machinery with substantial process variability to demonstrate the wide use of on-condition monitoring technique, particularly of an investigative nature, for qualitative assessment of the machine performance based on independent vibration measurements, assuming the time between successive occurrences of the peak vibration were distributed with a probability density function. To this end, a vector linear differential equation of the form (36) was formulated using the principle reported in [10, 11]. The approach was based on independent measurements of the process variables for estimating the mean value of peak vibration levels in the operation of the machines.

Since the only random term on the *RHS* of (39) is the process $u(\tau)$, then by taking the expected value of both sides and interchanging the order of integration with respect to τ and the operation of expectation, it follows that

$$\frac{dx(t)}{dt} = A(t)x(t) + B(t)u(t), \quad x(0) = x_o \tag{36}$$

The function $x(t)$ is an n-vector. Now, by letting $u(t)$ be an r-dimensional vector random process with the following statistical properties:

$$E[u(t)] = m(t) \tag{37}$$

$$E[u(t_1) - m(t_1)][u(t_2) - m(t_2)]^T = K(t_2, t_1) \tag{38}$$

where $K(t_2, t_1)$ is an $(r \times r)$ matrix which is the covariance matrix of $u(t)$, the solution is obtained in terms of a convolution integral and expressed as:

$$x(t) = \phi(t, t_o)x_o + \int_{t_o}^{t} \phi(t,\tau)B(\tau)u(\tau)d\tau \tag{39}$$

where $\phi(t, t_o)$ is the state transition matrix defined as:

$$\phi(t,\tau) = \exp\{A(t-\tau)\} \tag{40}$$

$$E[x(t)] = \phi(t, t_o)x_o + \int_{0}^{t} \phi(t,\tau)B(\tau)E[u(t)]d\tau \tag{41}$$

Thus in order to obtain the mean of the random process $x(t)$, we derived the differential equation by the mean of the input process $u(\tau)$ $[E[u(\tau)] = m(\tau)]$, using the covariance of $x(t)$ given by [10, 11]:

$$Cov[x(t_1), x(t_2)] = E[x(t_1) - E[x(t_1)]][x(t_2) - E[x(t_2)]]^T \tag{42}$$

From (39) and (41) we have

$$x(t) - E[x(t)] = \int_{t_o}^{t} \phi(t,\tau)B(\tau)[u(\tau) - E[u(\tau)]]d\tau \tag{43}$$

Substituting (43) into (42) and interchanging the integration and expectation operations yield:

$$Cov[x(t_1), x(t_2)] = \int_{t_o}^{t_1}\int_{t_o}^{t_2} \phi(t_1,\tau)B(\tau)E(\ [u(\tau) - E[u(\tau)]]$$
$$[u(\sigma) - E[u(\sigma)]]^T\ )\ B^T(\sigma)\phi(\sigma, t_2)d\sigma d\tau \qquad (44)$$

which simplifies to

$$Cov[x(t_1), x(t_2)] = \int_{t_o}^{t_1}\int_{t_o}^{t_2} \phi(t_1,\tau)B(\tau)K(\sigma,\tau)B^T(\sigma)\phi^T(t_2 - \sigma)d\sigma d\tau \qquad (45)$$

If the input is a zero mean white process with covariance matrix

$$K(\tau,\sigma) = Q(\tau,\sigma)\delta(\sigma - \tau) \qquad (46)$$

then (45) was simplified considerably as follows:

$$Cov[x(t_1), x(t_2)] = \int_{t_o}^{t_1} \phi(t_1,\tau)B(\tau)QB^T(\tau)\phi^T(t_2,\tau)d\tau \qquad (47)$$

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