# Developing an on-Line Machine-Status Monitoring System using Vibrations Analysis

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**Abstract:** ***A machine complex monitoring system model was designed and analyzed deliberating on the human involvement in the machine operations. In this paper a deliberation is done to the performance of both Offline and Real-time condition monitoring systems and their divergence from the online monitoring system. The non-defected monitored machine complex (MC)'s safety, machine component malfunction and the rate of its deterioration up to its enduring time are quantified by vibro-parameters or diagnostic signals that can highlight them within set acceptable deviations. The model illustrated the (component) unit's state and the whole machine complex's observability and controllability. The mathematical model developed in this paper assures that the procedure of dynamic diagnostics and forecasting of potentially hazardous dilapidation of component/units' state in machine complex basing on phase trajectory of life cycle which permits full use of equipment resource in keeping its safety and maintainability is efficient and effective in all construction heavy vehicles.***

**Keywords:** Monitoring system, Observation equipment, Machine component (unit), Machine complex (MC)

## 1. Introduction

This project tested the hypothesis that construction vehicles downtime due to mechanical failures can be reduced to closely non occurrence by using formulated methods of automatic condition monitoring system. It targets the most frequent challenges on machine complex for the future operational sustainability solutions. The subsequent failure of a machine complex results in breakdown and prolonged downtime, which negates the production rate. Once rotating machinery defects, it definitely produces complex fluctuations due to moving and nonlinear properties of dynamical systems [1, 2]. The subsequent result is dynamical structures of vibration data from rotating machinery are difficult to reveal. The unit state variables for this model include the distinct fractional worn out functions and their rates of wear. In this model observations assist to transmit malfunction of a unit component of the machine complex from an abrupt failure to a slow and steady inefficiency.

A dynamical system generally produces complex fluctuations, which relate to underlying dynamics of the studied system[3]. These fluctuations are the variables that are to be monitored and constraint this research paper. Monitoring system can be best expressed as an integration of observatory equipment that can either be controlled or cannot be controlled by human, in supervising the state or functionality of the machine complex[4].

Signals such as vibration, current, temperature, image, etc., are observed in state monitoring of machines complexes. The vibration signal process is one of the most general methods in the fault detection and condition monitoring of rotating machinery [5]. Previous researchers and writers have carried out the evaluations of the disoriented patterns that appear in most mechanical systems. In large rotating machine complexes this disoriented performance is as a result of the interactions in the rotor/bearing/stator system [5-7]. Thus the need to carry out monitoring which can best be done fractionally, that is checking on a specific unit technical state. A unit component's technical state is supervised by observing its functional change and alerts on any deviation from the set limits. This deviation is known as the system nonlinearity and can occur in the discontinuous stiffness, damping, surface friction and impact. Nowadays most nonlinear features, including approximate entropy and sample entropy, are of great use in monitoring dynamical behavior of complex systems[8].

In this research paper monitoring therefore enhances a malleable transition of failure from abrupt to gradual and giving warning to maintenance personnel to carry a preventive maintenance (PM) which thus eliminates machine downtime. The diagnostic and monitoring system operates within some specific speeds which are given in this model in order to approximate enduring operational failures according to observability criterion. Monitoring accuracy upheld close to non error margin enhances breakdown reduction and subsequently increases the machine running time[9].

Online monitoring is made feasible by automatic systems with operations which do not rely on the machine construction phenomenon. The machine complex is composed of hydraulic systems which encompass cylinders, seals, pistons, the fluid; and bearings including other rotating and fixed parts[10]. These numerous parts have specific technical dimensions they should meet to ensure total functionality and efficiency of the machine. They are the components that are diagnosed and monitored prior to their failure as well as minimizing dynamic or static errors.

The principle of information completeness (π-principle) during the choice of state diagnostic features in conditions of prior uncertainty is formulated[11]. According to this principle features should arrange a complete group in statistical sense including both all known and supplemented features in the selected base of signals. This allows significant decrease in probability of defects passing, diagnostic features of which in this base are unknown. The most common and broadband signal base is vibration that's why obtained conclusions will be correct for other signal bases (current, temperature, etc.)[12, 13].

## 2. Methods

### 2.1 Online monitoring data acquisition and processing

Diagnostic signals (vibroparameters) is the data obtained from sensors attached to different locations of the machine complex. This data is preprocessed to clean and convert it into a form which enables extraction of condition indicators. The vibroparameters (data) preprocesing involves the transformation between time and frequency domain; noise reduction (through filtering/smoothing); detrending, offset removal and missing-value removal.

The figure below illustrates the preprocessing work flow of data mined from the machine being monitored.

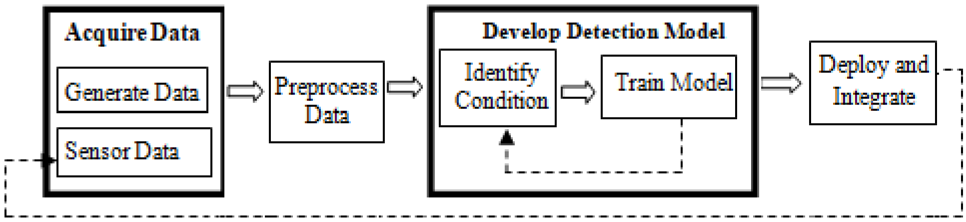


**Figure 1:** Sensor data (vibro-parameter) from machine complex on which algorithm is deployed

Basically, this data is preprocessed before analysis in order to identify potential condition indicators and a measure that predictably changes when the system performance weakens. The transformed signal (preprocessed) is further analyzed to give a condition indicator signal.

### 2.2 On-line machine condition monitoring using condition indicator (vibration) signals

The data acquisition apparatus in this paper are sensors mounted on roller ball bearings of the machine complex to monitor any changes in vibrations and then perform prognostics with the signals obtained.

A mathematical model designed herein this states that the static state approximations only define the static system variables exclusive of the dynamic system states so to use it in control techniques won't be adequate. Taking in the Aleksei M Bruevich's work which states that:

$$S_1 = S_0 + S(t) = S\left(n_{0,}p_{0,}\right) + \sum_{j=1}^{m} \frac{\partial S}{\partial q_j} \Delta q_j \ (t) \quad (1)$$

The technical state of the machine complex's unit $S_1$ depends on its operation mode $S_0$ and level of obtained errors.

here $S_0 = S\left(n_{0,}p_{0,}\right)$ is a unit component which describes mechanisms with minimum, close to none technological and operational errors, and functions in the range of nominal speed ($n_0$) and loading ($p_0$) modes whilst $\Delta q_j = X_j$ where j- is the default mechanism inaccuracy (t = 0), which serve as the datum of wear process, or generalized as the level of mechanism degradation and level of its ageing; $\frac{\partial S}{\partial q_j}$ is sensitivity of generalized error S to j-error of the mechanism according to corresponding generalized coordinate $q_j$. Here and after, to simplify the writing of this argument (t) is given for denoting, significantly in this case, dependence of parameter against time on the reviewed interval.

The monitoring system here is mathematically modeled basing on the equation of state variables as follows:

$$\{(\dot{S}(t)\} = [A]\{S(t)\} + [B]$$
$$\{Y(t)\} = [C]\{S(t)\} + [D]\{U\} \qquad \ldots\ldots\ldots\ldots (2)$$

where {S(t)} is a vector of unit wearing functions of m dimensionality, in which every component describes its technical structural parameter which is a subject to estimation and describing enduring partial resource of unit according to this generalized parameter, has in time multimodal character by virtue of partial errors summing equation 1; whilst $\{\dot{S}$ (t) } is a vector of wearing speed (wear, reduction of fluent operation, safety, residual resource) also having multimodal character; and {U} is a vector of dimensionality control variables (p+k) including varying tasks of unit's operation mode $\{U_p(t)\}$ and factors of human influence during the control and maintenance of object $\{U_k(t)\}$.

{Y(t)} is a vector of dimensionality diagnostics signals $n \geq m$ measured by monitoring system. The Matrice [A], [B], [C], [D] represent correspondently square matrix of the system; $[A] = [a_{ij}]$ a rectangular matrix of control, then $[B] = [b_{ij}]$ determines the influence of human actions to the unit state; (matrix of output) $[C] = [c_{ij}]$ the observation matrix, determines observability of internal state; then $[D] = [d_{ij}]$ the transfer matrix, determines the influence of operating and maintenance personnel to the unit's vibration parameters.

Elements of matrix [A] are random processes of which values are found according to the mathematical expression at a given time. Elements of matrix [B], [C], [D] are coefficients of corresponding regression equations. Monitoring system is quite manageable as the machine complex is observable on conditions that matrix ranks [A] and [C] have concurred, and there is no zero columns in the last one.

The dimensionality of vector {S(t)} in matrix [A], the matrix that determines a level of real observability of the unit state, can be used depending on statistics of each component/units failures. A rule applies that components {S(t) are inaccessible for direct observation and are estimated according to indirect measurements. {U} is a management vector which changes at irregular intervals during the start-stop and maintenance of the system. Between these moments {U} = const. (constant). The increase of diagnostic signals (vibroparameters) is directly proportional



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to the increase of wear, loss of safety and decrease of the remaining useful life of the machine complex in whole:

$$\{\Delta Y\} = [C]\{\Delta S\}, \quad \{\dot{Y}(t)\} = [C]\{\dot{S}(t)\}$$
$$\{Y_{NDP}\} = [C]\{S\}, \quad \{\dot{Y}_{NDP}\} = [C]\{\dot{S}_{NDP}\} \quad \text{………….. (3)}$$

Each i-generalized error expresses partial function of unit wear. The changes of (i) in time (trend) highlights the total trends including structural parameters $X_j(t)$, and, in common has multimodal character. The rate of changes in diagnostic features, i.e vibroparameters, is unambiguously obtained by weighted sum of correspondent unit error change rates. The increase of vibroparameters vector $\{\Delta Y_n\}$ is directly proportional to the increase of component's wearing vector (generalized errors – structural parameters) $\{\Delta S_m\}$, and the increase of initial diagnosed errors of the unit's mechanisms $\{\Delta X_k\}$.

Creating an orthogonal diagnostic feature $\{Y_i\}$ is the preliminary objective of diagnostic and monitoring systems, correspondingly representing formulated orthogonal classes of failures $\{S_i\}$. This definately corresponds to the reduction of observation matrix $[C]$ to a diagonal square matrix defining one-one (regressive) relation between diagnostic feature and corresponding generalized error. Now, the challenge of condition monitoring is to correctly interprete the formation of this generalized error considering the rate of failures classes' appearance.

During that time it is discovered that about 90% are misalignment cases, whereas 7% imbalances are observed. Then the remaining percentage is for vibrovelocity growth and other factors. Therefore such intepretation of reasons to consequences, reasons being errors which results in vibrations (consenquences), is likened to reducing observation matrix to diagonal square form which corresponds to condition monitoring. If there is no such interpretation it leads to parameter monitoring (vibration, temperature, etc.). Mostly failures of units such as destruction of friction surface and weakening of fastening are immeasurable strong scales (ratios of intervals). Given these cases values of measured diagnostic features i.e vibroparameters are used to measure such failures according to equation (3). It is coherent to obtain technical state of unit basing on partial component of its vector of state $\{S(t)\}$ which has the maximum value $S_{max}(t)$ amongst the other diagnosed parameters of this unit.

The hazards on a unit technical state are a result of partial component $S_{max}(t)$, of which is the maximal one among all wear rates of diagnosed unit. Technical state of units set in the machine complex corresponds to partial component of its vector of a state which has the maximum value among all diagnosed parameters of all units in the machine complex. Now, the hazard of the machine complex state is also a result of the partial component $S_{max}(t)$ which is the maximal one among all wear rates of all units in machine complex.

These formulations are also correct for the space of diagnostic features in accordance with generalized mathematical model given on equations (2) and (3). The technical state of component/unit and the machine complex in whole is obtained by partial component of diagnostic features vector $Y_{max}(t)$ which is observed by the diagnostic and monitoring system among unit components and whole machine complex. The hazard of a unit component and that of the whole machine complex state is defined by maximal partial component of vibroparameters trend growth rate $\dot{Y}_{max}(t)$ which is observed by the diagnostic and monitoring system among all rates of unit components and the whole machine complex following suit. The required operating speed of the diagnostic and monitoring system is obtained by the highest speed of functionality loss and the least reserve of established component/unit limiting state:

$$F = \frac{1}{T} = Max\left(B\frac{\dot{S}_{NDP}}{S_{NDP}}\right) = Max\left(B\frac{\dot{Y}_{NDP}}{Y_{NDP}}\right) \quad \text{……. (4)}$$

Equation (4) bring about B which describes the standard of approximation algorithm of the measured diagnostic features growth rate. Given models and their description are the main factors of investigative methods and the diagnostic and monitoring system with functionally undefined structure. The component/unit state and the vibration on the life interval has a dynamic model that is developed considering human involvement which establishes the exponential form of the relationship between analytical features, structural constraints and the enduring life. Equation (5) illustrates the established dynamic model:

$$\{\dot{Y}\} = [a]e^{[a]T}\{Y_0\}$$
$$\{\dot{S}\} = [C]^{-1}[a]e^{[a]T}\{Y_0\} \quad \text{……… (5)}$$

This model entirely presents the machine complex units' state dynamics using the the dynamics of analytical features of power, changes in temperatures, vibrations and also the rate of their changes. These factors manipulates the individual unit component's operability and its enduring life span. The functional irregularities of a unit component such as warping and breaking are a manifestation of human involvement in the functionality of the machine complex due to some inconsistences in meeting operational demads such as cooling water, correct oil type and adherence to component's life span. These human errors leads to accute increases in temperature, vibrations or total cease of the machine complex. The technical state dynamic model of a square matrix of diagonal error transformation is obtained by;

$$\Delta S_i = \frac{\partial S_i}{\partial q_i} . \Delta X_i(t);$$
$$\dot{S}_i = \frac{\partial S_i}{\partial q_i} . \ \dot{X}_i(t) \quad \text{…………………. (6)}$$

The vibro-signal in a dynamic model for an orthogonal feature is shown as:

$$\Delta Y_i = C_{ii} . \Delta S_i(t);$$
$$\dot{Y}_i = C_{ii} . \dot{S}_i(t) \quad \text{………………….. (7)}$$

For the square diagonal matrix cases, the errors transformations are as follows;

$$\Delta Y_i = C_{ii} . \frac{\partial S_i}{\partial q_i} . \Delta X_i;$$
$$\dot{Y}_i = C_{ii} . \frac{\partial S_i}{\partial q_i} . \dot{X}_i \quad \text{………………….. (8)}$$

The mathematical model established in this paper assures that the procedure of dynamic diagnostics and forecasting of potentially hazardous dilapidation of component/units' state in machine complex basing on phase trajectory of life cycle



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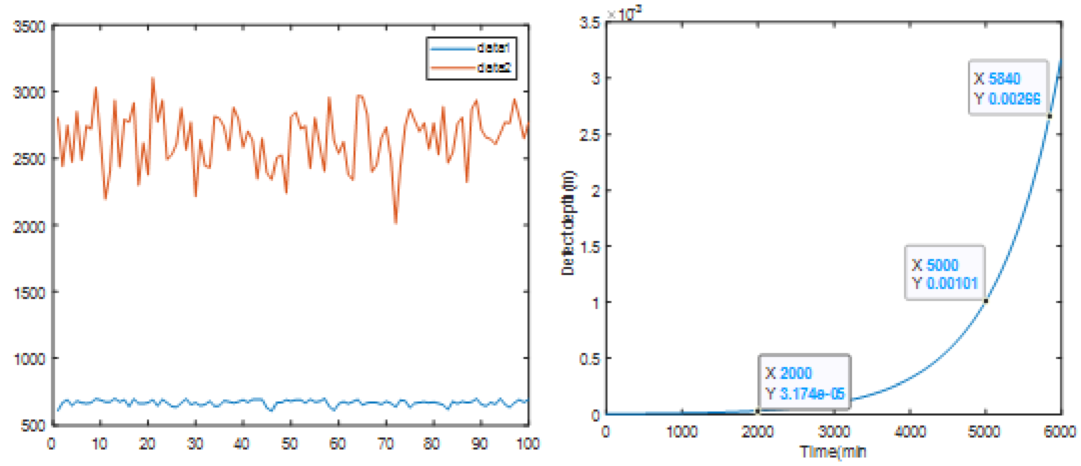
which permits full use of equipment resource in keeping its safety and maintainability is efficient and effective in all construction heavy vehicles.

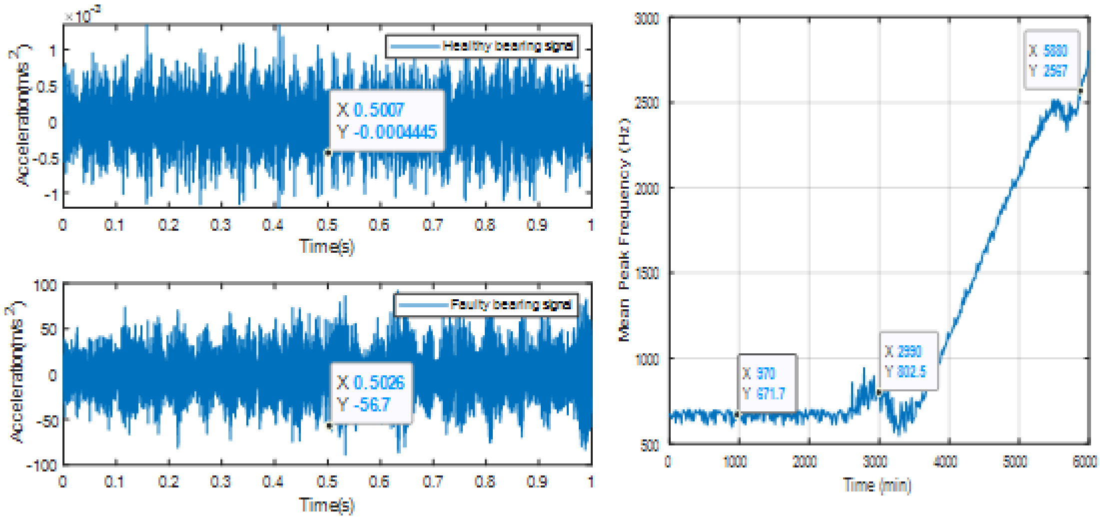
## 3. Results and Discussion




(a)

(b)

(a) Sensor signal from a healthy bearing (blue) and a faulty bearing (red); (b) Change of defect depth in different segment of data;

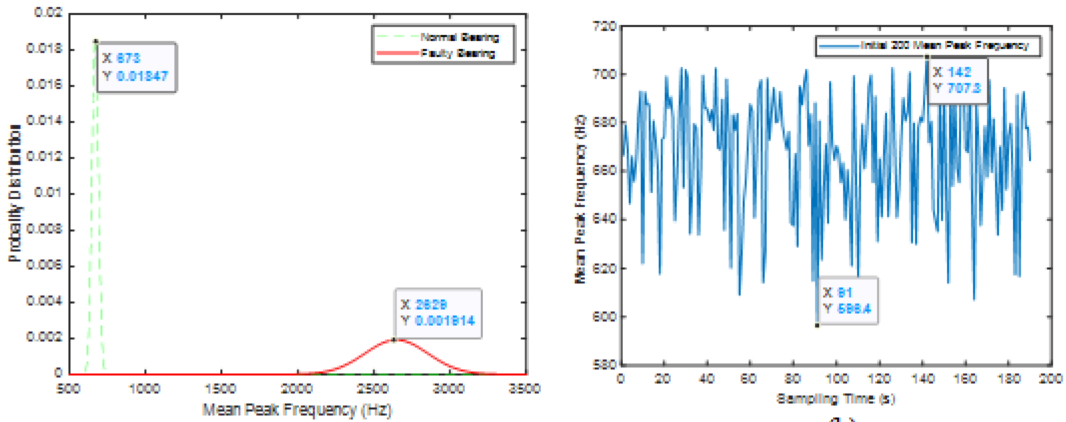



(c)

(d)

**Figure 2:** Bearing condition monitoring trends, (c) Vibro-displacement signal of a healthy and faulty bearing; (d) The extracted Mean Frequency against the increase in time

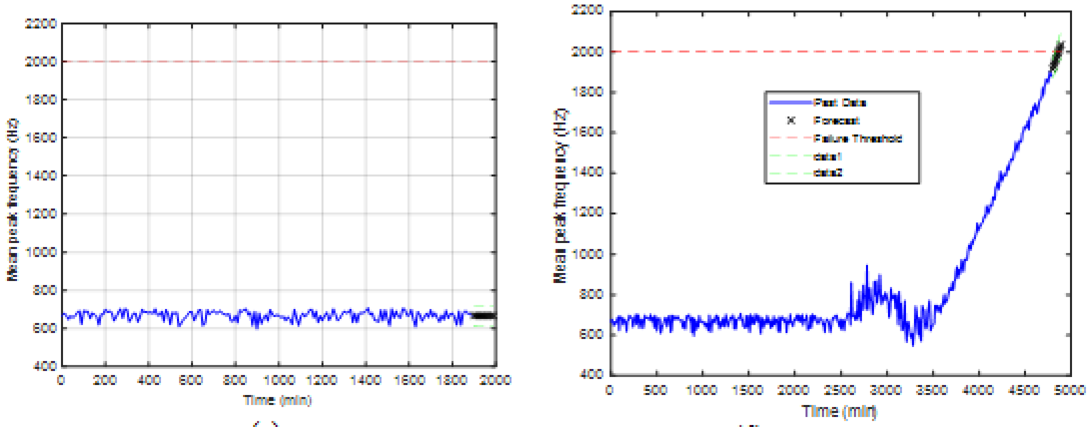
**The Mean Peak Frequencies of the two bearings:**




(a)

(b)

**Figure 3:** (a) The graph depicts the probability distributions of the Mean Peak Frequencies for the two bearings. (b) The signal in the first 200 seconds is a mixture of noise and consistence in frequency level, this initial dynamic model has an acceptable fit.




(c) (d)

**Figure 4:** (c) The graph depicts a normal running of the bearings since the signal is far below the set threshold. (d) The vibration frequency reached the threshold value thus giving alarm of malfunction.

In this paper the practical realization of the designed mathematical model in monitoring systems is achieved by the use of Matlab software application. The extend of prediction accuracy ranges up to 15 times the period of observation with flaws of far less than 5%. This is quite an endorsement to the designed monitoring model. Bearings are the key rotating components on construction vehicles and are prone to failure such that their health status determines the operational availability of the machine complex.

In the analysis it is realized that the mean peak frequencies obtained accurately depicts the differences healthy bearing from the faulty one.

The machine performance can be efficiently monitored through the set thresholds in vibration signals and noises produced. Machine health forecasting is made possible and accurate predictions were witnessed which help to prepare for a potential malfunction. The batch mode of updating the time series done in this model captures instantaneous trends. This updated time series with the graphs shown in figure 2 is used to compute a ten step ahead forecasting.

## 4. Conclusion

The frequency trends depicted by this mathematical modeling confirm that online health monitoring is effective and efficient to achieve smooth running of machine vehicles. The calculated specific function of a component's wear and its rate is defined by generalized errors, structural parameters and the rate of its growth, and is offered for use as variables of the component's condition.

The technical condition of the machine system and its corresponding risk of its operability loss are given to be evaluated according to the minimum residual operability and maximum rate of its functionality loss, which is observed by diagnostic and monitoring systems. Online monitoring allows the failures transition of a component from a sudden failure to gradual or repair before failure.

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