Model-Based Prognostics Under Non-stationary Operating Conditions

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ABSTRACT

The paper presents a novel approach for prognostics of faults in mechanical drives under non-stationary operating conditions. The feature time series is modeled as an output of a dynamical state-space model, where operating conditions are treated as known model inputs. An algorithm for on-line model estimation is adopted to find the optimal model at the current state of failure. This model is then used to determine the presence of the fault and predict the future behavior and remaining useful life of the system. The approach is validated using the experimental data on a single stage gearbox.

1. INTRODUCTION

An important emerging feature of new generation of condition monitoring systems enables prediction of future evolution of the fault and thus enables the plant personnel to accommodate maintenance actions well in advance. Even more, it can predict the remaining useful life of the component under changing operating condition, thus providing information to operators on how the different operating regimes will lengthen or shorten the components useful life. This is a relatively new research area and has yet to receive its prominence compared to other condition monitoring problems (Heng, Zhang, Tan, & Mathew, 2009).

The focus in this paper will be on mechanical drives. They are the most ubiquitous item of equipment in manufacturing and process industries as well as transportation. During the operational life-cycle, these items are subjected to wear, fatigue, cracks and other destructive processes. These processes can not be directly observed or measured without interrupting the operation of the machine. The extent of the damage has to be inferred from the available signals, which are usually vibrations, acoustic emissions, oil contaminants, etc.

In this work, we follow an established approach for model-based prognostics, which is to model the fault progression using a dynamical model. This approach has been applied to specific cases where the exact model of the fault was derived. The model, combined with an appropriate state estimation algorithm (e.g. Particle Filter) can be used to estimate the current state and predict its future evolution (M. Orchard, Kacprzynski, Goebel, Saha, & Vachtsevanos, 2008; M. E. Orchard & Vachtsevanos, 2009; Zhang et al., 2009; DeCastro, Liang, Kenneth, Goebel, & Vachtsevanos, 2009). However, most of the authors assume constant operating conditions of the machine. Recently, (Edwards, Orchard, Tiang, Goebel, & Vachtsevanos, 2010) analyzed the impact of variable operating conditions on the remaining useful life in terms of uncertainty.

The aim of this work is to propose a new approach toward model-based prognostics in which the operating conditions are considered as a measured input into the model. Because the exact relations between the model inputs, fault dimension and measured signals are hard to derive, we propose an algorithm for on-line estimation of these relations. The model obtained in this manner can therefore be used to determine the current state and trend of the fault, predict its future evolution in different operating regimes and estimate its remaining useful life (RUL).

The paper is organized as follows. Section 2 presents the conceptual idea behind the proposed approach for a general setup. Section 3 introduces the algorithm for model estimation that can be used to apply the proposed approach. Section 4 presents the experimental setup that was used to collect the data for algorithm validation. Section 5 shows the results in terms of estimating the current state and trend of the fault and predict its future evolution. Finally, Section 6 summarizes the most important results and outlines the directions for further research.

2. THE IDEA OF THE PROPOSED APPROACH

Let us assume that there exists at least one feature that provides the information about the current extent of the fault in a mechanical system and its value is available trough noisy measurements. Furthermore, different operating conditions affect the extent and the rate of change of the underlying fault as well as the current feature value. Finally, when the fault occurs, its progression can be described by a stochastic dynamical process (Gašperin, Juričić, Boškoski, & Vižintin, 2011).

Following the above assumptions, the evolution of fault dimension in time can be described by the following model (M. E. Orchard & Vachtsevanos, 2009):

$$\mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\theta}) + \mathbf{w}_t \tag{1a}$$

$$\mathbf{y}_t = \mathbf{g}(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\theta}) + \mathbf{v}_t \tag{1b}$$

where $\mathbf{x}_t$ is the system state, $\mathbf{y}_t$ is the observed feature value, $\mathbf{u}_t$ is the vector of model inputs, $\boldsymbol{\theta}$ is the vector of model parameters, finally $\mathbf{w}_t$ and $\mathbf{v}_t$ are random variables describing system and measurement noise, respectively. The first equation in the model represents the fault evolution dynamics and the second one describes the feature extraction. Assuming that the values of the model parameters $\boldsymbol{\theta}$ are known, this model can be used to predict the future evolution of the fault for any given sequence of the operating conditions (fixed or variable) $\mathbf{u}_t$.

Nonlinear models (1) are a very powerful description of the process dynamics and can describe a broad range of dynamic behavior. Usually the estimation methods include only a specific family of models, e.g. as shown by (DeCastro et al., 2009) or rely on approximation methods (M. Orchard et al., 2008). If linearized, the expression (1) takes the form (Gašperin et al., 2011)

$$\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{B}\mathbf{u}_t + \mathbf{w}_t \tag{2a}$$

$$\mathbf{y}_t = \mathbf{C}\mathbf{x}_t + \mathbf{D}\mathbf{u}_t + \mathbf{v}_t \tag{2b}$$

In the model (2), $\mathbf{w}_t$ and $\mathbf{v}_t$ are random variables that follow a normal distribution:

$$\begin{bmatrix}\mathbf{w}_t \\ \mathbf{v}_t\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}0 \\ 0\end{bmatrix}, \begin{bmatrix}\mathbf{Q} & \mathbf{S} \\ \mathbf{S}^T & \mathbf{R}\end{bmatrix}\right) \tag{3}$$

If the functions governing the dynamical behavior of the fault in (1) are known, the linear approximation can be computed analytically. However, this has only been done for a limited number of special cases and for a general setup, the model parameters have to be assumed unknown. To alleviate this problem we propose a data-driven approach for modeling and prognostics, where the parameter of the linear model (2) are estimated on-line based on the past data of the feature value.

The benefit of using a linear model is that the parameter estimation algorithm can be implemented with minimal computational load and the analysis of the model (in terms of stability) is less demanding than in the nonlinear case. The downside is that linear model can only adequately describe the system in a limited subspace of fault dimension and operating conditions. However, this is partially alleviated by on-line parameter estimation that provides an updated model as soon as the conditions change.

2.1 Prognostics under variable operating conditions

It is well known (Heng et al., 2009) that the changes in operating conditions (e.g., load, temperature) can greatly affect the fault in mechanical systems. A schematic representation of different scenarios is given in Figure 1, where it can be seen that under more favorable load, the life of the machine can be significantly extended.

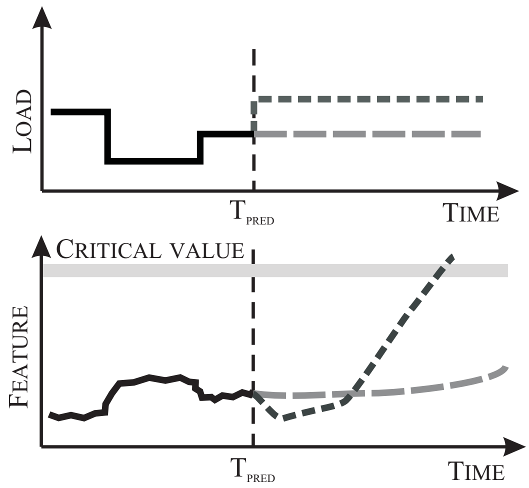

Figure 1. Fault progression under different load scenarios

The exact relations between them and the fault dimension can be obtained by advanced and complex modeling approaches, which are usually not applicable to real-world condition monitoring problems. The main advantage of implementing the approach presented here is that it offers a systematic solution to finding the relation between the machine operating conditions, feature value and fault dimension. The added functionality of our solution can be summarized as follows:

- **Detection of fault progression**: The approach can separate the fault evolution dynamics from the dynamics enforced by the variable operating conditions. This means that we can detect the rate at which the fault is progressing.

- **Estimation of the remaining useful life**: If the future load profile of the machine is known, it can be used as an input to the model and predict the future evolution of the fault.

3. MODEL ESTIMATION

In this chapter we will address the problem of estimating unknown model parameters of the linear state-space models (2). Estimating the state-space models is challenging because the internal system states are not directly observed and therefore all the information about them has to be inferred form the measured data. The state sequence can be estimated from the data, but the procedure requires the knowledge of the model parameters. As this is usually not the case, an approach that allows both the estimation of system states and unknown model parameters is required.

3.1 Maximum likelihood estimator

Suppose $\mathbf{x}$ is a random variable with probability density function $p(\mathbf{x}|\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of unknown parameters. Let $\mathbf{X}_T = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T\}$ be the set of observed values. The probability density function of $\mathbf{X}_T$ is

$$p(\mathbf{X}_T|\boldsymbol{\theta}) = p(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T|\boldsymbol{\theta}) \tag{4}$$

The pdf $p(\mathbf{X}_T|\boldsymbol{\theta})$ is deterministic function of $\boldsymbol{\theta}$ and is referred to as the *likelihood function*. A reasonable estimator for $\boldsymbol{\theta}$ could then be to select the values in such a way that the observed realization $\mathbf{X}_T$ becomes as likely as possible. Maximum Likelihood (ML) estimator for unknown parameters is defined by

$$\hat{\boldsymbol{\theta}}_{ML}(\mathbf{X}_T) = \arg\max_{\boldsymbol{\theta}} p(\mathbf{X}_T|\boldsymbol{\theta}) \tag{5}$$

where the maximization is performed with respect to $\boldsymbol{\theta}$ and for a fixed $\mathbf{X}_T$.

Rather than (5) it is often convenient to operate with the log-likelihood function.

$$L(\boldsymbol{\theta}) = \log p(\mathbf{X}_T|\boldsymbol{\theta}) \tag{6}$$

Since logarithmic function is monotonically increasing, maximizing the likelihood function is the same as maximizing its logarithm,

$$\hat{\boldsymbol{\theta}}_{ML}(\mathbf{X}_T) = \arg\max_{\boldsymbol{\theta}} L(\boldsymbol{\theta}) \tag{7}$$

3.2 Likelihood function for dynamical models

Consider a dynamic state-space model, where $\mathbf{Y}_T = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T\}$ are the measured system outputs, $\mathbf{X}_T = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T\}$ is the unobserved sequence of system states and $\boldsymbol{\theta}$ is vector of model parameters. A straightforward way to define the maximum likelihood parameter estimator for this case is

$$\hat{\boldsymbol{\theta}}_{ML}(\mathbf{Y}_T) = \arg\max_{\boldsymbol{\theta}} p(\mathbf{Y}_T|\boldsymbol{\theta}) \tag{8}$$

where the data likelihood function can be expressed using chain rule

$$p(\mathbf{Y}_T|\boldsymbol{\theta}) = p\left(\mathbf{y}_1|\boldsymbol{\theta}\right) \prod_{t=2}^{T} p\left(\mathbf{y}_t|\mathbf{Y}_{t-1}, \boldsymbol{\theta}\right) \tag{9}$$

However, it is convenient to consider the log-likelihood function

$$L(\boldsymbol{\theta}) = \log p(\mathbf{Y}_T|\boldsymbol{\theta}) = \sum_{t=2}^{T} \log p\left(\mathbf{y}_t|\mathbf{Y}_{t-1}, \boldsymbol{\theta}\right) + \log p\left(\mathbf{y}_1|\boldsymbol{\theta}\right) \tag{10}$$

And the maximum likelihood estimator is thus

$$\hat{\boldsymbol{\theta}}_{ML}(\mathbf{Y}_T) = \arg\max_{\boldsymbol{\theta}} p(\mathbf{Y}_T|\boldsymbol{\theta}) = \arg\max_{\boldsymbol{\theta}} L(\boldsymbol{\theta}) \tag{11}$$

A closer look at the expression $p(\mathbf{y}_t|\mathbf{Y}_{t-1}, \boldsymbol{\theta})$ in (10) reveals that it depends on system states. Indeed

$$p(\mathbf{y}_t|\mathbf{Y}_{t-1}, \boldsymbol{\theta}) = \int p(\mathbf{y}_t|\mathbf{x}_t, \boldsymbol{\theta}) p(\mathbf{x}_t|\mathbf{Y}_{t-1}, \boldsymbol{\theta}) d\mathbf{x}_t \tag{12}$$

The formulation of the above integral is problematic and in general case no closed form solutions exist.

3.3 The Expectation-Maximization algorithm

The expectation-maximization algorithm can solve the ML estimation problem in the case of incomplete or missing data. Therefore, if the states $\mathbf{X}_T$ are considered as missing data, this algorithm can be successfully deployed to solve the system identification problem. Consider an extension to (8).

$$\hat{\boldsymbol{\theta}}_{ML}(\mathbf{X}_T, \mathbf{Y}_T) = \arg\max_{\boldsymbol{\theta}} \log p(\mathbf{X}_T, \mathbf{Y}_T|\boldsymbol{\theta}) \tag{13}$$

The EM algorithm then solves the problem of simultaneously estimating system states and model parameters by alternating between two steps. First, it approximates the likelihood function with its expected value over the missing data (E-step), and secondly maximizes the likelihood function w.r.t. $\boldsymbol{\theta}$ (M-step). A short overview of the algorithm will be presented, while a more detailed explanation can be found in (Haykin, 2001; Gibson & Ninness, 2005).

1. Start with initial parameter estimate $\boldsymbol{\theta}_0$.
2. **Expectation (E) step**:
   Compute the expected value of the complete data log-likelihood function.
   $$Q(\boldsymbol{\theta}, \boldsymbol{\theta}_k) = E_{p(\mathbf{X}_T|\mathbf{Y}_T, \boldsymbol{\theta}_k)}\{\log p(\mathbf{X}_T, \mathbf{Y}_T|\boldsymbol{\theta})\} \tag{14}$$
3. **Maximization (M) step**:
   Compute the optimal parameter vector value by maximizing the function $Q(\boldsymbol{\theta}, \boldsymbol{\theta}_k)$.
   $$\boldsymbol{\theta}_{k+1} = \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \boldsymbol{\theta}_k) \tag{15}$$
4. If convergence criteria are not satisfied, set $k = k + 1$ and return to step 2.

According to the EM algorithm, the first task is to compute the expected value of the complete data log-likelihood function

$$Q(\boldsymbol{\theta}, \boldsymbol{\theta}_k) = E_{p(\mathbf{X}_T|\mathbf{Y}_T, \boldsymbol{\theta}_k)}\{\log p(\mathbf{X}_T, \mathbf{Y}_T|\boldsymbol{\theta})\} \tag{16}$$

where the joint likelihood of the measured output and system states can be written as

$$p(\mathbf{Y}_T, \mathbf{X}_T|\boldsymbol{\theta}) = p(\mathbf{y}_1, \ldots, \mathbf{y}_T|\mathbf{x}_1, \ldots, \mathbf{x}_T, \boldsymbol{\theta})p(\mathbf{x}_1, \ldots, \mathbf{x}_T|\boldsymbol{\theta})$$
$$= p(\mathbf{x}_1|\boldsymbol{\theta}) \prod_{t=1}^{T-1} p(\mathbf{x}_{t+1}|\mathbf{x}_t, \boldsymbol{\theta}) \prod_{t=1}^{T} p(\mathbf{y}_t|\mathbf{x}_t, \boldsymbol{\theta}) \tag{17}$$

Taking into account Gaussian distributions and ignoring the constants, the complete data likelihood function can be written as

$$-2\log p(\mathbf{X}_T, \mathbf{Y}_T|\boldsymbol{\theta}) = \log|\mathbf{P}_1| + (\mathbf{x}_1 - \boldsymbol{\mu}_1)^T\mathbf{P}_1^{-1}(\mathbf{x}_1 - \boldsymbol{\mu}_1)$$
$$+ \sum_{t=1}^{T}(\mathbf{x}_{t+1} - \mathbf{A}\mathbf{x}_t - \mathbf{B}\mathbf{u}_t)^T\mathbf{Q}^{-1}(\mathbf{x}_{t+1} - \mathbf{A}\mathbf{x}_t - \mathbf{B}\mathbf{u}_t)$$
$$+ \sum_{t=1}^{T}(\mathbf{y}_t - \mathbf{C}\mathbf{x}_t - \mathbf{D}\mathbf{u}_t)^T\mathbf{R}^{-1}(\mathbf{y}_t - \mathbf{C}\mathbf{x}_t - \mathbf{D}\mathbf{u}_t)$$
$$+ T\log|\mathbf{Q}| + T\log|\mathbf{R}| \tag{18}$$

The expected value of the above expression can be maximized by the following choices (Gibson & Ninness, 2005):

$$\begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix} = \boldsymbol{\Psi}\boldsymbol{\Sigma}^{-1} \tag{19}$$

$$\begin{bmatrix} \mathbf{Q} & \mathbf{S} \\ \mathbf{S}^T & \mathbf{R} \end{bmatrix} = \boldsymbol{\Phi} - \boldsymbol{\Psi}\boldsymbol{\Sigma}^{-1}\boldsymbol{\Psi}^T \tag{20}$$

where

$$\boldsymbol{\Phi} = \frac{1}{T}\sum_{t=1}^{N} E_{p(\mathbf{X}_T|\mathbf{Y}_T,\boldsymbol{\theta}_k)}\left\{\begin{bmatrix}\mathbf{x}_{t+1} \\ \mathbf{y}_t\end{bmatrix}\begin{bmatrix}\mathbf{x}_{t+1}^T, \mathbf{y}_t^T\end{bmatrix}\right\} \tag{21}$$

$$\boldsymbol{\Psi} = \frac{1}{T}\sum_{t=1}^{N} E_{p(\mathbf{X}_T|\mathbf{Y}_T,\boldsymbol{\theta}_k)}\left\{\begin{bmatrix}\mathbf{x}_{t+1} \\ \mathbf{y}_t\end{bmatrix}\begin{bmatrix}\mathbf{x}_t^T, \mathbf{u}_t^T\end{bmatrix}\right\} \tag{22}$$

$$\boldsymbol{\Sigma} = \frac{1}{T}\sum_{t=1}^{N} E_{p(\mathbf{X}_T|\mathbf{Y}_T,\boldsymbol{\theta}_k)}\left\{\begin{bmatrix}\mathbf{x}_t \\ \mathbf{u}_t\end{bmatrix}\begin{bmatrix}\mathbf{x}_t^T, \mathbf{u}_t^T\end{bmatrix}\right\} \tag{23}$$

and the required expected values of the system states can be computed using a standard Kalman smoother (Haykin, 2001).

The estimated values of model parameters at a time instance T, along with the estimated state sequence and the model structure defined by (2) constitute the model of the fault dynamics at this particular time instance and is labeled $\mathcal{M}_T$.

3.4 Algorithm Summary

The presented algorithm, adopted for machine health estimation and prognostics can be summarized as follows:

1. Select time window N and set $T = N + 1$.
2. Run the EM algorithm for model estimation using past data $y_{T-N}, y_{T-N-1}, \ldots, y_T$ and $u_{T-N}, u_{T-N-1}, \ldots, u_T$.
3. Use the estimated model $\mathcal{M}_T$ and state $\mathbf{x}_T$ to analyze the fault and predict future behavior of the system.
4. When the new feature value is collected, set $T = T + 1$ and return to step 2.

4. Case Study

For the purpose of the development and verification of the model-based prognostics tools, the experimental test bed has been used (Figure 2). It consists of a motor-generator pair with a single stage gearbox. The motor is a standard DC motor powered through DC drive. A generator is being used as a break and the generated power is being fed back in the system, thus achieving the breaking force.

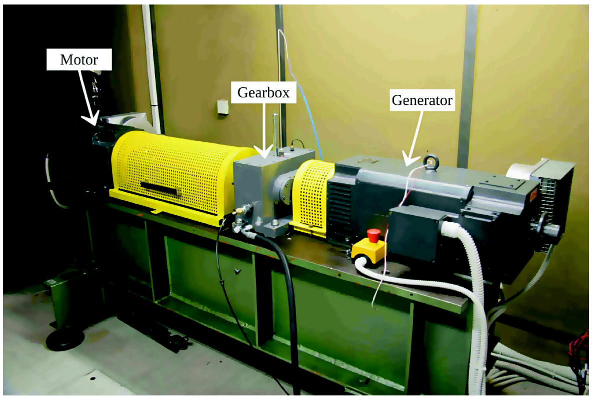

Figure 2. The test bed

The most informative and easily accessible signals that offer information on gear health are vibration signals (Combet & Gelman, 2009). In our setup, the vibration signals are acquired from a sensor placed on the output shaft bearing.

4.1 Experimental run

The set of gears was subjected to a time-varying load profile. The speed was kept constant throughout the experiment. Vibration signals were acquired every 5 minutes and each acquisition took 5 seconds.

The complete experiment lasted approximately 180 hours. At the end extensive pitting damage was clearly visible on both gear and pinion, as shown in Figure 3.

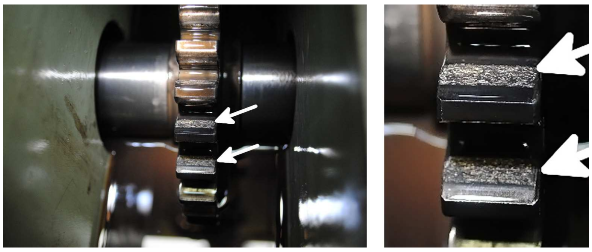

Figure 3. Gear condition after 180 hours of operation

4.2 Gear fault dynamics

The main source of vibrations in meshing gears originates from the changes in the bending stiffness of the gear teeth as well as variations in the torsional stiffness of the shafts and supporting bearings (Howard, Jia, & Wang, 2001). As gear teeth rotate through the meshing cycle the overall bending stiffness changes according to the number of teeth present in the meshing contact. Under constant operating conditions, these variations are expressed as a spectral component positioned at the gear mesh frequency.

A localized fault alters the original tooth stiffness profile. This alteration occurs every time the damaged tooth enters a meshing contact. This localized fault affects the produced vibrations by the appearance of an additional modulation component around the original gear mesh frequency (Randall, 1982). As the fault progresses and spreads on all teeth the changes in the gear mesh frequency component become more apparent.

As our goal is to perform the earliest possible estimation of the remaining useful life of the observed gears, we have based our algorithm on the information contained in the signal's energy portion extracted from the sidebands around the principle gear mesh component. This value was computed for each vibration acquisition session and the corresponding time series represents the feature values.

In terms of modeling the gear fault dynamics the feature value is the model output while the known inputs into the model are torque and temperature. The model inputs and outputs are shown in Figure 4.

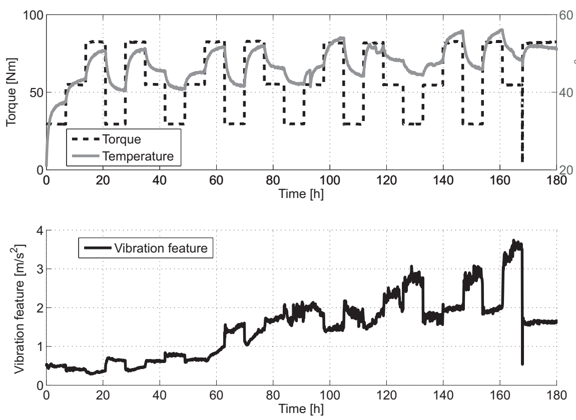

Figure 4. Top: torque and temperature (inputs), Bottom: vibration feature (output)

5. RESULTS

The developed algorithm for model estimation was implemented with the sample size of $N = 200$, which corresponds to approximately 16 hours. The unknown model parameters are:

$$\boldsymbol{\theta} = [\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}, \mathbf{Q}, \mathbf{R}] \tag{24}$$

where $\mathbf{Q}$ and $\mathbf{R}$ are covariance matrices of Gaussian random variables $\mathbf{w}_t$ and $\mathbf{v}_t$, respectively. The model structure is defined by selecting the number of hidden states, measured inputs and outputs. In our case, the state dimension is $m = 2$, the number of inputs is $n = 2$ (torque and temperature) and the model has $d = 1$ measured output (vibration feature). The unknown model parameters are thus matrices with the following dimensions:

$$\mathbf{A} \in \mathbb{R}^{m \times m}, \mathbf{B} \in \mathbb{R}^{m \times n}, \mathbf{C} \in \mathbb{R}^{d \times m},$$
$$\mathbf{D} \in \mathbb{R}^{d \times n}, \mathbf{Q} \in \mathbb{R}^{m \times m}, \mathbf{R} \in \mathbb{R}^{d \times d} \tag{25}$$

Prior to running the algorithm, these parameters have to be initialized to some values. In this problem formulation, the selection of the initial values is not crucial as the likelihood function for linear system is unimodal and there is no threat of divergence. The values of all the matrix entries were thus set to a neutral value of 0.1.

5.1 Detecting the trend of the fault

After a model $\mathcal{M}_T$ is obtained at a certain time point T, it can be analyzed to determine the current trend of the fault, even under variable operating conditions in the period of data acquisition. This is made possible because the state-space model can distinguish between the feature dynamics that is due to the variable operating conditions (model input matrix $\mathbf{B}$) and the dynamics due to the fault progression (system state matrix $\mathbf{A}$). Therefore, by analyzing the eigenvalues of the system matrix $\mathbf{A}$, one can determine weather the fault progression has a stable dynamics (i.e. it will remain of a constant size) or unstable dynamics (i.e. the fault dimension will increase in time).

A more illustrative way to present this is by visualizing the future evolution of the feature value at constant operating conditions. In Figure 5, this is done for two different times T_{pred}, one with stable and one with unstable dynamics.

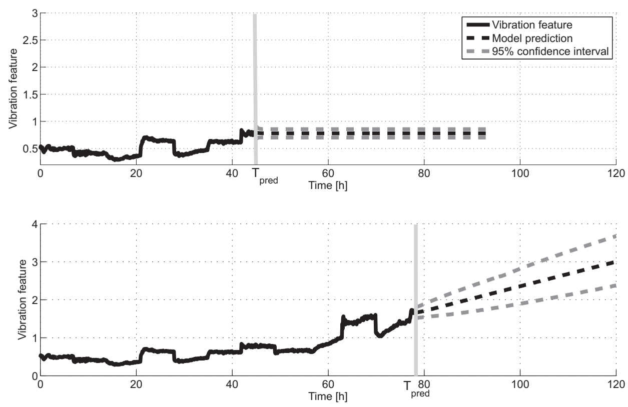

Figure 5. Detection of the fault progression at non-stationary operating conditions

It can be seen that in the first case (Figure 5 (top)), the predicted feature value is constant, which means that the fault will not progress. The T_{pred} here was $44h$ and no fault was indeed present at that time. In the second case (Figure 5 (bottom)), the model was estimated at $T_{pred} = 78h$, where the fault started to increase and the model thus predicted the gradual increase of the feature value even at a constant load.

5.2 Model-based prognostics under non-stationary conditions

The model $\mathcal{M}_T$ includes all the information about the current fault state as well as the relation between the operating conditions and the fault. Therefore it can be used to predict the evolution of the fault under variable operating conditions. For example, if the future time profile of the load is known, the model can predict the feature time series for that specific load profile. The example of such a prediction is shown in Figure 6

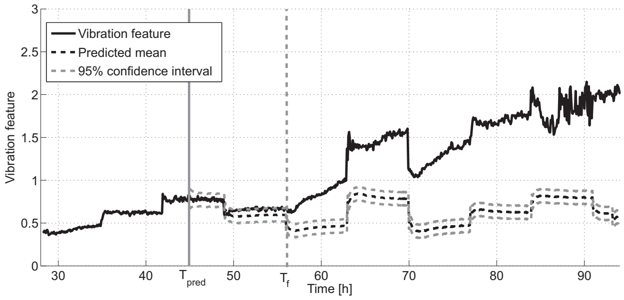

Figure 6. Long term prediction under variable load at $T_{pred} = 44h$

It can be seen that the model predicted a stable fault dynamics and the changes in the feature value only occur due to changes in the load. In the actual experiment, the initial fault occurred around the time $T_f = 55h$, which is impossible to predict with the model that is based only on the data up to time $T_{pred} < T_f$.

Effect like this may occur because the underlying model is linear and serves only as a local approximation. However, it is crucial to note that if such a fault occurs, it is reflected in the feature values data and the algorithm will quickly incorporate the new data into the model and produce the updated parameter values.

After the model is adapted to the new data, the prediction is updated and a result of a later prediction is shown in Figure 7. It can be seen, that the actual feature value almost always lies within the 95% confidence interval of the prediction.

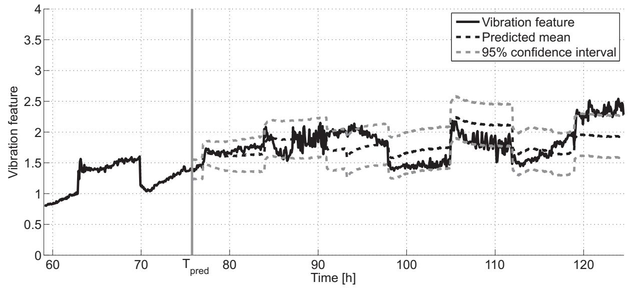

Figure 7. Long term prediction under variable load at $T_{pred} = 75h$

6. Conclusions

The paper presents a new approach for model-based prognostics of mechanical drives under non-stationary operating conditions. The novelty of the proposed algorithm lies in the use of dynamical model to describe the relations between operating conditions, fault dimension and vibration feature value. The model assumes linear relations between these quantities which can be interpreted as a local approximation of the otherwise complex nonlinear relations. The benefit of this approximation is that the model parameters can easily be estimated on-line. This means that the model is constantly updated as new data arrive.

The approach was validated on a laboratory test bed using a single-stage gearbox and vibration sensors. The problem was to detect and predict the faults in gear and the model analysis and prognostics on the experimental data validated our hypotheses.

Future work will include validation of the approach for estimation of the remaining useful life of the gear and examine how the RUL depends on the load profile. However, to properly conduct this study, further experiments are required.

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