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PROGNOSIS OF WEAR PROGRESS BASED ON REGRESSION ANALYSIS OF CONDITION MONITORING PARAMETERS

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ABSTRACT

For the maintenance personnel the key questions in every day life are: Is everything working properly and if not should we do something? It is especially important to know when some action should be taken i.e. will the machine in question hold until the next scheduled maintenance or does it not? Considering this from the condition monitoring point of view it is important to get a reliable indication of an upcoming failure so early that the necessary maintenance tasks can be planned well in advance and really perform them when the production machinery is stopped for scheduled maintenance. It is not an easy task to predict from measured parameters how quickly the fault will progress. The paper discusses some possible models for the progress of condition monitoring parameters i.e. how the condition monitoring parameters indicate the development of wear as a function of time. The prediction of the development/increase of these parameters is based on regression analysis techniques. The choice of these models is discussed keeping in mind that for practical purposes they should be simple and fast to use. The models are tested with some very common components which suffer from a type of wear which tends to progress with increasing speed towards the end of the life of the component. The first example is from tool wear monitoring where the life of the tool is very short and the measured values usually follow a certain trend and the second example is from a bearing test where the trend of the measured parameter is not that obvious. In both cases the suggested regression analysis technique works very well and can give prognosis of the further development of the monitored parameter.

KEYWORDS

Rotating machinery, wear progress, bearing fault, tool wear, condition monitoring, monitoring parameters, regression analysis, diagnosis, prognosis

INTRODUCTION

In the industry the maintenance personnel need to know when to take action i.e. when it is necessary to carry out maintenance.

Usually, due to economical reasons, the maintenance actions should be performed during a specific period of time when normal production is not disrupted i.e. they should be postponed until the next scheduled maintenance. The big question in this planning of maintenance is: How do the maintenance personnel know how long the machinery keep on running if an indication of some developing fault has been seen e.g. in the condition monitoring signals? Normally the decision whether or not to stop the machinery immediately or whether production may continue is based on the experience of the maintenance personnel. Skilled personnel who have many years of experience might have seen a similar case and can therefore say with some kind of reasonable probability whether the component will hold or not. Unfortunately this kind of diagnosis is not always correct i.e. every now and then the diagnosis is wrong and the production equipment has to be stopped which in turn causes unscheduled maintenance action with very high costs. The problem could be avoided if good methods of prognosis existed, that could well in advance predict how the fault will develop based on condition monitoring data. Unfortunately this is not the case, this kind of models are available but only for a rather limited number of cases. Especially, this kind of wear models are not available for rotating machinery. The wear progress models are not well known and also it is not known how the monitored parameters indicate the wear rate. Another factor that makes the situation even more challenging is the fact that often the start of the wear progress is some odd situation which has possibly only lasted for a very limited amount of time, e.g. the loads have for some time increased to such a high level that wear has started or something has momentarily gone wrong with lubrication so that tribological surfaces have suffered.

Vibration monitoring

The judgement of condition monitoring parameters is typically based on amplitude levels, i.e. if the amplitude of a certain parameter e.g. root mean square (rms) value of vibration velocity in a specified frequency range exceeds a predefined value a fault condition is diagnosed. The diagnosis can be based on broadband analysis i.e. the signal is not filtered [1]. Normally an unfiltered broadband or overall measurement that provides the total vibration energy between 10 and 10000 Hz is used for this type of analysis. The overall analysis does not provide any innovation pertaining to the actual machine problem or failure mode. Changes in both the speed and load of machinery will have a direct effect on the overall vibration levels of the machine, which makes it very problematic in practise to diagnose whether a fault is developing. Narrowband trending, like broadband, monitors the total energy for a specific bandwidth of vibration frequencies [1]. The technique uses vibration frequencies representing specific machine components or failure modes. This method provides the means to quickly monitor the mechanical condition of critical machine components, not just the overall machine condition. The technique provides the ability to monitor the condition of gear sets, bearing and other machine components without manual analysis of vibration signatures. As in the case of broadband trending, changes in speed, load and other process parameters will have a direct, often dramatic, impact on the vibration energy produced by each machine component or narrowband. To be meaningful, narrowband values must be adjusted to the actual production parameters. Unlike the two trending techniques above, signature analysis (frequency analysis) provides a representation of each frequency component generated by a machine [1]. Vibration signatures can be used to determine the specific maintenance required by plant machinery. Most vibration-based condition monitoring programmes use some form of signature analysis in their programme. In this kind of monitoring some kind of warning limits are used. There can actually be a number of limits so that, if the amplitude of vibration at some frequency is below a certain limit, the situation is considered good, and if it then gets higher, it is considered as a warning. The latter case could result in that the interval between measurements is decreased and then if the amplitude exceeds a certain value, it is considered that a fault is present which should be taken care of very quickly. Even more limits could be used, i.e. if the amplitude gets higher than the previous limit, the machine has to be stopped immediately. The vibration standards also recognise some kind of prognosis [2] i.e. if the trend (linear regression) drawn from three last measurements indicate that an alarm limit would be reached before the next scheduled measurement, the situation is considered as a warning. The term alarming rate of change has been used to describe this kind of situation. Naturally, the maintenance personnel are expected to take measures in this kind of situation, e.g. at least additional measurements should be made prior to the next scheduled measurement.

Wear models

Wear of rotating machinery is a very complicated phenomenon since normally there are two surfaces in interaction though they are separated with a lubrication fluid. Basically two types of wear progression can be distinguished i.e. progressive and cumulative [3]. An example of the progressive type of wear process is the wear volume of a plain journal bearing, operating with some metal-to-metal contact. After running-in, there might be a stable period with a constant wear rate, until the bearing clearance is high enough to change the dynamic behaviour of the shaft, causing an accelerating wear process. A ball bearing gives an example of the cumulative type of wear process. After some minor running-in wear, the wear rate is almost zero for a long period of time. During this period, surface fatigue damage accumulates. Fatigue cracks are initiated, and after some time the first metal flakes start to loosen from the surface of a bearing race. In addition to the above, quite often the development of a fault starts when something abnormal takes place either in relation to lubrication or load. When an initial fault has occurred wear usually progresses with an increasing if not exponentially increasing rate. Based on a number of studies, Onsoyen [3] has summarized a simple model for the wear depth shown in Eqn. 1.

$$h(t) = h_o + h't \quad (1)$$

where h(t) is the wear depth, t is the time, h_o is the contribution from running-in and h' is the wear rate (the increase in wear depth per unit of time). The time to failure is the time t_c until h(t) reaches a critical wear depth h_c. In [4] it was assumed that the wear progression during the tests had been of a progressive type [3] so that the wear behaviour at the beginning was described as mild wear and at the end as severe wear [5]. To fulfil this assumption, a simplified numerical expression for the wear rate was chosen see Eqn 2 [4].

$$h'(t) = A^* t_c/(t_c - t) \quad (2)$$

where A is a coefficient which does not vary as a function of time t. For simplicity, running-in wear is not accounted for in the above expression. By integrating the above formula, a numerical expression for the wear depth has been developed as shown in Eqn. 3 [4].

$$h(t) = - A^* t_c^* \ln(1 - t/t_c) \quad (3)$$

Assuming that vibration at some frequency is a function of the physical irregularity of the contact surface, i.e. the fault and initial vibration which is caused by unbalance, loads in the motor etc., vibration follows the format of wear depth shown in Eqn. 3. This kind of development of vibration level is schematically shown in Figure 1.

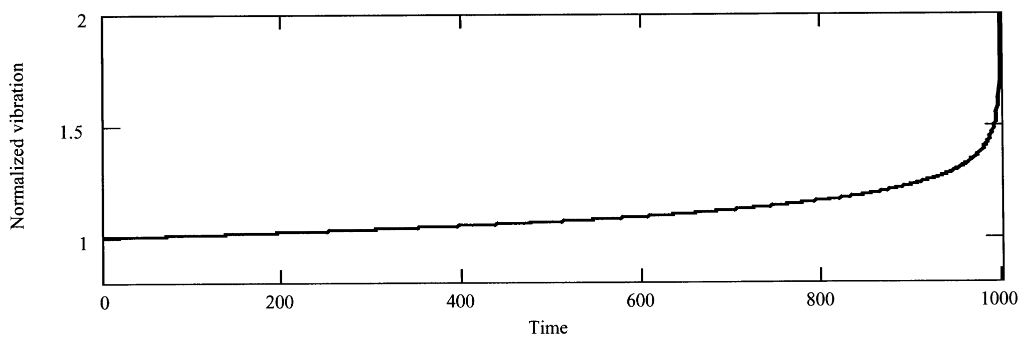

Figure 1. Normalized vibration showing schematically the influence of progressive wear.

It should be noted that, even though the formula in Eqn. 2 chosen for wear rate development is very simple, the curve shown in Figure 1 very well follows the type of wear development curves shown in literature. It also fits well with recorded vibration data, i.e. very often vibration in rotating machinery starts to increase exponentially when a failure has occurred and is developing in size. In wear prognosis the purpose is to be able to diagnose the current state of wear and to predict the development of wear based on possible wear models. Naturally it would be even more tempting to try to develop a method that could be used for many types of components suffering from different types of wear.

POSSIBLE FUNCTIONS FOR WEAR MONITORING AND PROGNOSIS

Most of the diagnosis tools that are used today are based on their capability to recognise or classify the changes in the parameters that they follow. For example autoregressive models can well be used to recognise the change in measured parameters especially if the process is stable, i.e. when the models have been defined based on recorded data they can distinguish when a change has taken place. Assuming that it would also be possible to model the behaviour of condition monitoring parameters in faulty situations as a function of the fault, it would be possible to predict with these models how much time there is left until complete failure of the machinery. Unfortunately this type of approach is not practical because of the amount of modelling involved. It can be claimed that another very popular approach today i.e. Artificial Neural Networks (ANNs) suffer from similar kind of restriction. ANNs are typically good in classification tasks i.e. for diagnosis of changes in the situation. For example if a net has been trained with measured parameters in a good condition of a machine they are capable of recognising a change in the parameters and thus diagnose a possibly faulty situation. In [6] Nandi gives a good comparison of the classification success rate of various ANNs and also Support Vector Machines (SVMs) approaches together with simple thresholding, and methods like Principal

Components Analysis (PCA). It is very interesting to note the trend that if the diagnosis method is very simple but relies on more sophisticated features (bispectrum) the results are rather good, and if the diagnosis method is more sophisticated, more reliable classification results can be reached with more basic features (statistical and spectrum). But then again the opposite seems also to be true, i.e. with sophisticated approaches based on sophisticated features the results are not as good and similarly using simplistic approaches with simple features does not give that reliable results. However, it is very time consuming to try to teach ANNsto recognise different phases of fault development. It is by no means an impossible task but for the method it possibly is not the best way of using them. Neural nets have been successfully used for prediction or prognosis when the approach is based on a number of input parameters and the development of only one or very few output parameters is predicted. It can be claimed that in condition monitoring the goal is quite different. In condition monitoring the purpose is to be able to do prognosis of the development of the health of the machinery in question based on a minimum number of inputs. When building diagnostic systems rule based approaches offer the possibility of effectively programming the rules of thumb used in condition monitoring standards, e.g. if the measured vibration parameter has become twice that it originally was in the beginning of the trending, then a fault is developing and the machine will probably only last one month etc. Now if it were possible to model the wear development as shown in the previous chapter of this paper it would be easier to predict the development of the condition of the machinery. Unfortunately, in the case of rotating machinery it is very seldom the case that the exact wear development of the machinery could be modelled. However, the idea with the use of regression analysis is to be able to adopt the previous development of the monitored parameter and then based on this and the knowledge of typical development of similar cases to be able to predict the future i.e. do prognosis of the future development of the condition monitoring parameter in question and in this manner do prognosis of the development of wear and predict when the machine part will collapse so that the machine will not be able to work properly. In practice condition monitoring should be easy to perform and the number of transducers that are needed should be very limited. Also because of economical reasons the human involvement should be minimal and even the computers used for recording and diagnosing the data should be as cheap as possible so that the monitoring system could in practise be widely used. Based on the above, regression analysis techniques offer a number of advantages that are listed below:

- Smoothens the variation of the data between individual measurements.
- Makes it possible to remember the history of the measured parameter with a limited number of terms stored in a database or a file i.e. it is sufficient to store only the summary terms.
- Makes it easier to notice trends in the data.
- Makes it possible to predict the future, i.e. how much time there is before the component will be totally destroyed.
- Enables percentage prognosis, e.g. it is possible to predict 3 percent in the future in stead of using an arbitrary value like one day that would be the case if the prognosis would be based on prognosis of some amplitude values measured earlier (which would have been measured at constant intervals).

- Makes it possible for the prognosis to be based on the trend of the parameter in question i.e. the prognosis can be based on how the parameter is developing as a function of time, in stead of a single amplitude value which can vary a lot from case to case due to varying loading conditions, structural differences etc.
- The results of the regression analysis can be used as input to different kind of models e.g. ANN and SVM and if the regression models are used for the prognosis i.e. the values of the parameters are predicted then the diagnostic models can be used for prognosis.

Ln Function

The logarithmic wear curve and consequently vibration parameter model would at first sight look rather a promising basis for regression analysis and has actually been tested in [7] but as a function it is very problematic in the sense that parameter t_c has to be known in beforehand or otherwise the mathematics become very laborious and the actual solution of the regression curve would be based on iteration resulting in that the whole idea of using a simple approach with a very limited number of summary terms would be ruined.

3rd Order Polynomial

In [7] the third order polynomial of the type shown in Eqn. 4 proved to be very promising for tool wear monitoring.

$$y(t) = at^3 + bt^2 + ct + d \qquad (4)$$

Where y(t) is the monitored parameter as a function of time, a, b, c and d are regression coefficients and t is time. Similarly, good results with the third order function are reported in [8] for monitoring the development of a bearing fault. However, the third order polynomial regression curve does seem to have some drawbacks. If it is tested against the type of vibration parameter curve shown in Figure 1 it would not be flexible enough to adopt the exponential shape in the end of the life of the component. Another very important factor is that if the regression function has been used for a long time it tends to get very stable, i.e. if in practise, it would have been used for five years for monitoring a bearing in the industry it would take very long time for high parameter values to change the indication of the regression curve. Due to the drawbacks of the 3rd order polynomial another basically as simple regression function has been developed i.e. higher order polynomial that emphasizes current data with a limited number of terms.

Polynomial Model of Higher Degree with Limited Number Of Terms

The idea with higher order polynomial regression function which has a limited number of terms and emphasizes current data, is really to be able to adopt the trend that can be seen in many of the condition monitoring parameters, i.e. exponential growth of the parameter towards the end of the life of the component when wear is taking place with increasing speed, see Figure 1. Higher order polynomial can mimic the ln-function to a certain extent. Figure 2 shows the end of the life-part of the same simulated ln-function as in Figure 1. In Figure 2 the regression analysis is based on data that is supposed to be available when only about three percent of the lifetime remains. Together with the ln-function is shown the prediction made with a higher degree polynomial, the third degree polynomial regression function, and also the first order regression as suggested by the standard [2]. The prognosis made with the higher degree function (e=9, f=6, g=3, constant=1, k=0.95, see Eqn. 5) gives the best estimate what is going to happen even though it does not give a clear view how rapidly the monitored parameter is changing if wear would be taking place as fast as indicated in Figure 1. The reason for third degree polynomial for not to work at all is simply the fact that in this function all the data is equally weighted, i.e. current data is not emphasized and consequently the function reacts very slowly to the change. Based on the above it is suggested that the benefits of polynomial model of higher degree regression analysis that emphasizes current data, are:

- Higher order function reacts sufficiently quickly to the changes for the maintenance personnel to react, even if the fault in the end of the life of the component is increasing in size and severity very rapidly.
- Emphasizing current data is another means to make the analysis quick enough to adapt the current changes. (In fact in the approach given in [2] emphasis is given to only the three last measurements which actually tends to make the method in some cases rather too sensitive, even to the extent that it might be difficult to say how reliable the prognosis is when at one time it shows descending trend and then after the next measurement the situation seems to be critical.)
- Higher order function is especially suitable for rotating machines where the fault, when initiated, often develops with an exponentially increasing rate caused by the fact that when the fault gets bigger the loads get bigger which in turn increases the rate of wear etc.
- Emphasizing current data makes it possible to use the approach also in case of varying loading conditions assuming that the consequences in the amplitudes of the parameters that are used in the analysis are limited, or information of the change of loading condition can somehow be passed to the diagnosis model/system.

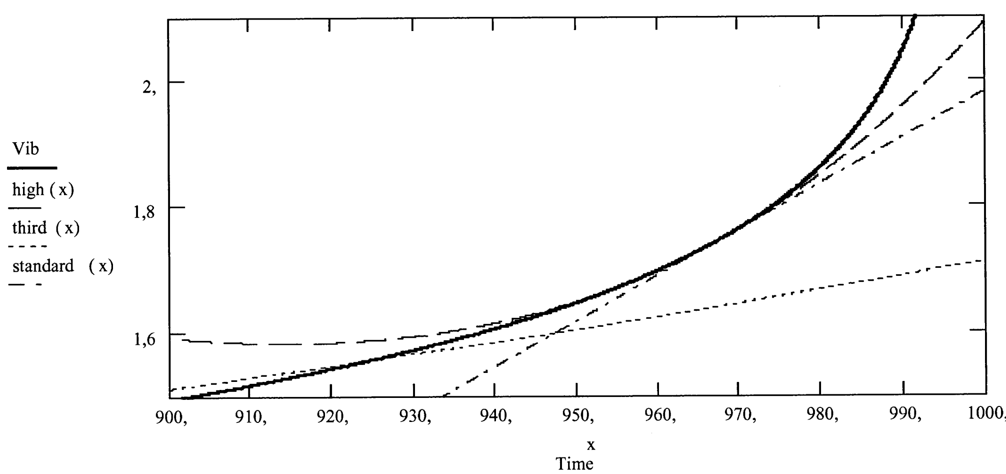

Figure 2. Prognosis of the development of a monitoring parameter based on regression analysis, Vib=data also shown in figure 1, high(x)=higher degree polynomial current data emphasised, third(x) = 3rd degree polynomial, standard(x)=regression as suggested in standard.

It is possible in practise to fine-tune the way the regression analysis emphasises past and current data. If the load varies (indication as a parameter or as a change of relation parameters of which one is more sensitive to the load than the other) it is possible to make the analysis more sensitive to current data so that the functions adapt to the current status more quickly, and then let the emphasizing move to the direction of putting more weight to the history, and consequently make the regression curve more stable. The development of the function given in Eqn. 5 follows the principles given for example in [9].

$$y(t) = at^{e} + bt^{f} + ct^{g} + \text{constant} \qquad (5)$$

Where y(t) is the monitored parameter as a function of time, a, b and c are regression coefficients and t is time. Parameters e, f and g define the degree of the function and there is also a constant in the function. The solution given in [9] is based on the idea of minimizing the sum of the squares of residuals where the residual means the difference between the observed and the estimated response. The minimization of the sum of the squares of residuals is done by finding the partial derivatives for a, b and c. These derivatives are then set equal to 0 to form a system of normal equations. In case of Eqn. 5 there are three unknown terms i.e. a, b and c and three equations. In this solution, in the end there are nine summary terms that need to be calculated and saved for the definition of the regression function. It is often good practice to normalize the parameters that are fed to the regression curve and, as a consequence of that, it is practical to use a constant in the equation that has a value of one/unity. Equation 5 actually becomes a second order polynomial regression function if e is set to 2, f to 1 and g and the constant are set to 0. Similarly the function corresponds to third order polynomial regression function if e is set to 3, f to 2 and g to 1 and the constant is set to 1. However this kind of function is not really the complete third degree polynomial since the constant is given and not calculated which of course could be done if the number of unknowns in the linear set of equation would be increased to four. In order to make regression function more sensitive or aggressive the degree of terms can be increased e.g. e can be set to 9, f to 6 and g to 3. Naturally this kind of function does not have all the features of a complete higher degree function but it is as easy to calculate as the second degree function and still behaves especially towards the end of life of a component very sensitively assuming that the later measurements are emphasised at the cost of the values in the beginning. Introducing a term shown in Eqn. 6 does this.

$$p = k^{(n-i)} \qquad (6)$$

Where n is the current total number of samples, i the index in the calculation summary terms and k is the constant that defines how much weight the early terms get when all the terms in the calculation of summary terms are multiplied with p. Typically k can have a value such as 0.99 if the process is stable with frequent measurements where as a value such as 0.6 would mean that the last measurements are very much emphasised just like the case is with the standard [2]. Actually the method given in the standard [2] corresponds to the use of the first derivative of the regression curve as a means to predict the future assuming that regression curve is behaving in a similar manner as the final three data points suggest. It is suggested that it is practical to use a general form higher order regression polynomial with a constant term of one/unity when the process is stable and the analysis is based on a normalised parameter, i.e. it starts from one, and this way it is possible to monitor the development. However, if the process varies, e.g. because of varying load conditions, it is not practical to use the coefficient in the prognosis because, it in a way stabilises the starting point which is not true. Instead the power of the third term could be zero which in practise means that actually the value of the constant/coefficient, when calculated in this way can have different values as the loading condition varies (which also means that the regression function actually has to be made rather easily adaptive to the current state, i.e. it should not stick to the old value very strongly, i.e. k has a low value.)

TESTS

Two examples of the use of the proposed approach are given. The first example deals with tool wear monitoring which is a very similar problem as that of condition monitoring of rotating machinery. The big difference actually is that tool wear takes place in a very short time scale compared to the wear of machine components. However, the signals being monitored and their behaviour are very similar, and therefore tool wear monitoring is very suitable for testing purposes. In fact, because of the short timescale, monitoring is of even greater importance in the case of tool wear than with condition monitoring of components of rotating machinery. The other example deals with bearing failure, which is one of the most, if not the most common part of rotating machinery that is monitored. The chosen example is somewhat more complicated than an ordinary case even though it is from laboratory tests with constant loading, but it is really showing the potential of the chosen approach to deal with more complicated shapes of signal history.

Tests with drills

Figure 3 shows the results of tests with twist drills (diameter10.2 mm, cutting speed 22 m/min, feed 140 mm/min). The measured parameter is standard deviation of vibration velocity. Figure 3 shows the situation when the twist drill is still in quite good condition and it can still be used. The regression curves of a higher degree polynomial ($e = 9$, $f = 4$, $g = 0$, constant = 0 and $k = 0.99$) and the third degree polynomial predict that the level of the signal will stay more or less at the same level as has been recorded earlier. Since standard deviation is a very sensitive condition monitoring parameter and varies quite a lot, in this kind of a test the use of linear prognosis based on three last measurements, as suggested in [2], is not practical. The data shown in Figure 4 is from the same test as in Figure 3, only from a later stage of the life of the tool in question. From Figure 4 it is possible to see that both the higher degree polynomial and the linear approach according to reference [2] indicate the end of the life of the tool very well but the third order function seems to react a bit too slow. The main difference between the higher order and third order function is the fact that in the higher order regression function current data is emphasised compared to the preceding data ($k=0.99$, see Egn. 6). From this example of tool wear monitoring it can be concluded that higher order regression function that emphasises current data with a limited number of terms seems to work very well with this data.

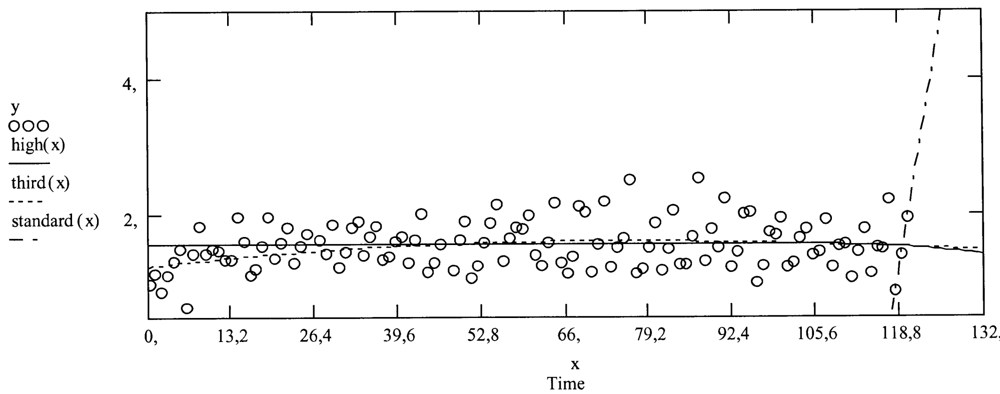

Figure 3. Standard deviation of horizontal vibration velocity of a twist drill, about 1/3 of life time remaining, y=normalised measured values, high(x)=higher degree regression function, third(x)=third order regression function, standard(x)=three point regression according to standard.

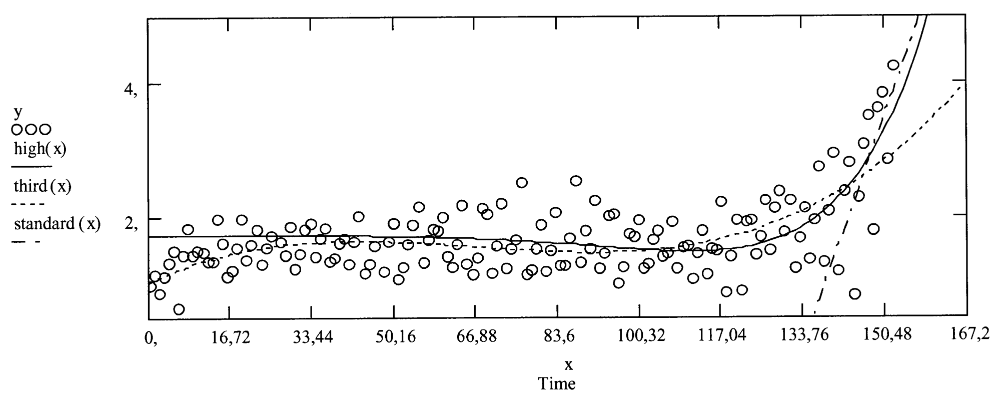

Figure 4. Standard deviation of horizontal vibration velocity of a twist drill, almost complete life time shown, y=normalised measured values, high(x)=higher degree regression function, third(x)=third order regression function, standard(x)=three point regression according to standard.

Tests with bearing data

Figure 5 shows the results of a bearing test in laboratory with a small bearing. The measured parameter is the normalised rms-value of vibration velocity. Together with the measured parameter also the higher degree polynomial regression function (e=9, f=4, s=0, constant=0, k=0.99) and the third degree polynomial regression function as well as linear regression as suggested in [2] are shown. All of the three regression techniques seem to indicate that an immediate increase of the measured parameter could be expected, i.e. the prognosis is that the bearing will suffer from a failure within near future. However, it should be noted that the rate of the increase of the measured parameter at this moment is possibly not that strong that it would mean that the component should not be used anymore.

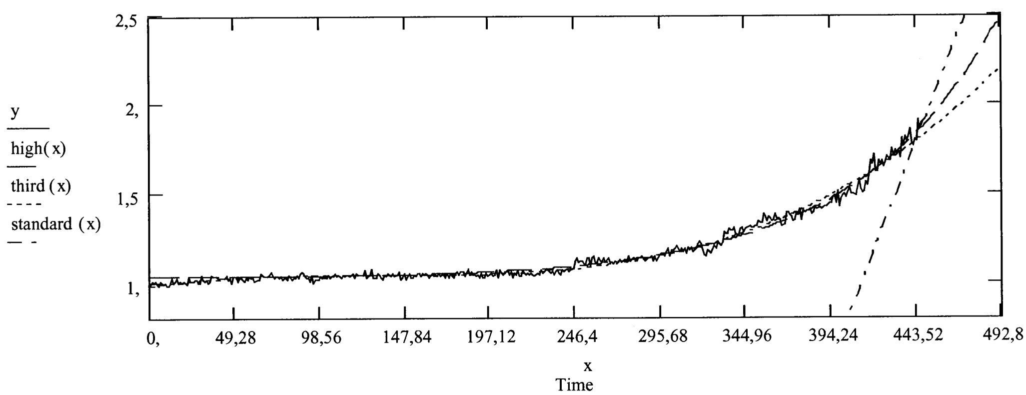

Figure 5. Averaged vibration velocity rms-value from a bearing test, about half the life time of the bearing, y=rms value, high(x)=higher degree polynomial regression function, third(x)=third degree polynomial regression, standard(x)=linear regression based on the last three measured values.

At the specific moment which is studied in Figure 5, linear regression based on the last three measured values gives the highest estimate, higher degree polynomial gives the next highest and third degree polynomial gives the lowest estimate for the following measurement values. This result is very natural since the third degree function gives more emphasis to the past history than higher degree polynomial function and the linear estimation is really based on only the latest data.

Figure 6 shows the results from the same bearing test in laboratory as shown in Figure 5, but now from a much later stage of the test. Together with the vibration velocity rms-value the same regression functions are as shown in Figure 5 are also shown in Figure 6. At this moment in time of the test, linear regression based on the last three measured values gives an indication of rapidly decreasing trend but it should be noted that this type of regression varies a lot if the signal has not been averaged so that the data points represent a long period of time.

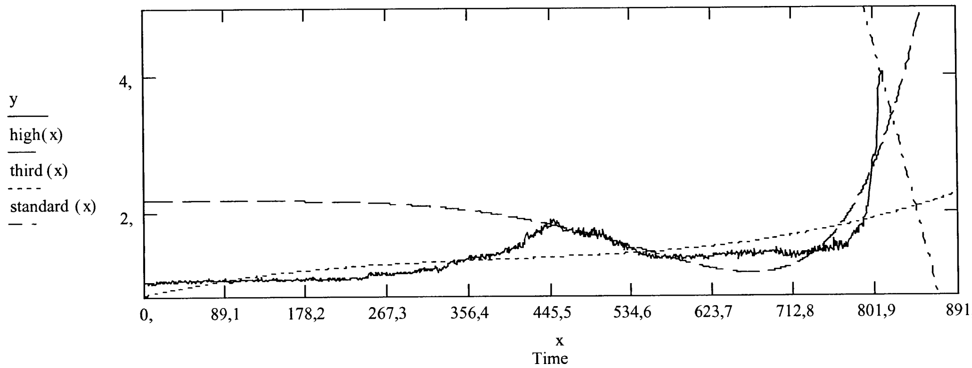

Figure 6. Averaged vibration velocity rms-value from a bearing test, total life time of the bearing, y=rms value, high(x)=higher degree polynomial regression function, third(x)=third degree polynomial regression, standard(x)=linear regression based on the last three measured values.

The third degree polynomial does not really follow the measured values because it gives so much weight to the earlier part of the measured rms-value. The higher degree polynomial, which emphasises the current data more than the data from the beginning of the test, gives a relatively close estimate of the measured signal. In this test the bearing actually suffered from a complete failure at the moment shown in Figure 6. Based on the tested data it could be suggested that the higher order polynomial regression function which emphasises current data and which is calculated with limited number of terms seems to follow the condition monitoring parameters even in a rather complex case so that it can give reasonable estimates of the very near future, i.e. predict the trend of the measured parameter or, in other words, it can be used for the prognosis of the development of condition monitoring signals. It should be noted that when a function is used for the prognosis of the development of a monitoring signal it is not of great importance how closely that signal actually shows what has happened in the past. Another finding is that if a method that is extremely sensitive to current data is used it is important to use averaged data so as to get rid of the extreme variation of the regression function. However there is a problem related to this, i.e. how to define how many points are used in the averaging process so that the function is not made too slow-moving to react to the changes of the measured signal.

CONCLUSION

For the maintenance personnel relying on condition based maintenance it is of great importance to know when they should perform the maintenance actions. Is it possible to carry on with production until the next scheduled maintenance or should the production be stopped immediately? A similar problem exists with machine tools and especially with the cutting tools that are used and changed very frequently. The question is when should the tool be changed, since a worn tool can cause a lot of damage but also the changing of tools too frequently causes excessive downtime and higher tool costs. Due to the complicated nature of wear it is not easy to predict the future, especially since in rotating machinery wear tends to progress exponentially towards the end of the life of the component in question. In this paper some possible models for the development of condition monitoring parameters are given i.e. how the condition monitoring parameters may indicate the development of wear as a function of time. The prediction of the progressive change of these parameters is based on regression analysis techniques. The models have been developed keeping in mind that, for practical purposes, they need to be simple and fast to use. In practise, a high degree polynomial regression function that has a limited number of terms and that emphasises current data seems to work very well with a simulated exponentially developing wear. The developed function also works well in the case of monitoring drill wear and bearing failure. The real benefit of a regression function is that it can into some extent predict the future i.e. give a prognosis of wear development based on condition monitoring parameters.

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