Detecting misalignment of a claw clutch using vibration measurements

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Abstract

Coupling misalignment is a fairly common fault in rotating machines and causes excessive loads to bearings and other machine components. In general, misalignment and its severity can be detected reliably using vibration measurements. Misalignment is typically detected on the basis of the velocity spectrum. An increase in amplitude at rotational frequency and its harmonics are an indication of misalignment or a bent shaft. However, the behaviour of a claw clutch (jaw coupling) is very different as compared with a conventional elastic coupling. This paper presents the results of research where the detection of claw clutch misalignment is investigated based on acceleration signals. Real order derivatives and $l_p$ norms are calculated from the signals. In a test rig, which is used in this study, different degrees of misalignment are generated by moving a motor in the horizontal direction with steps of 0.1 mm. The tests were carried out at five rotational frequencies. Studies show that after a certain level of misalignment, the claw clutch gives rise to impacts that induce high frequency vibrations.

Keywords: Condition monitoring, diagnostics, misalignment, claw clutch, jaw coupling, real order derivatives, fractional derivatives, $l_p$ norms

1. Introduction

Various types of misalignment between two rotating shafts are a fairly common fault type in machinery. There can be axial, offset (parallel) and angular misalignment or combinations of them. Misalignment can be caused by the incorrect mounting of machines. It may also arise from differences between the tolerances of the jointed parts, inaccuracy during manufacturing, and the heating or wearing of parts. Coupling misalignment between two rotating shafts causes excessive loads to other components of the machine and especially to bearings\(^{1,2}\). Offset misalignment induces the highest loads.

Different types of couplings have significant differences in the allowed misalignment. A flexible coupling is a fairly common coupling type and allows for some axial,
radial and angular displacement between shafts. The need for this is evident when the 
mounting of shafts cannot be implemented with a sufficiently high tolerance or 
there is relative displacement between shafts during rotation. The manufacturer 
provides recommendation for specific allowable displacements, depending e.g. on 
coupling size and the hardness of the elastic elements of the coupling. In practice, 
it is not always possible to follow these guidelines.

In general, it is fairly simple to detect coupling misalignment based on vibration 
measurements. In conventional cases displacement and velocity measurements are 
good ways of detecting misalignment and evaluating its severity\(^{(3,4)}\). However, it 
depends essentially on the construction of the coupling how vibration measurements 
should be used in order to detect misalignment. The behaviour of a claw clutch (jaw-
type coupling), which is studied in this paper, is clearly different under misalignment 
as compared with a conventional elastic coupling. Excessive misalignment of a claw 
clutch does not cause any major increase in low-frequency vibrations, which can 
be detected reliably using displacement and velocity measurements. In this case it 
is better to use signals and features, which are sensitive to impact-like faults and 
high frequency vibrations\(^{(5)}\). Therefore, the acceleration signal and higher order 
derivatives were utilised in this study. With the help of advanced signal processing 
methods, it is possible to find a very sensitive indicator for detecting misalignment 
of claw clutch.

This paper discusses offset misalignment of claw clutch, which can cause very high 
loads in other parts of the machine. Offset was generated in the test rig by moving 
the motor in the horizontal direction in relation to the driven shaft. The feature 
extraction for the measured acceleration signals was performed using real order 
derivatives and \(l_p\) norms.

2. Test rig

A test rig (Figure 1), which consists of an electric motor and a belt transmission 
between two shafts, has been used here to obtain information on the behaviour of 
the claw clutch under various degrees of misalignment. The test rig was originally 
built by PIM Bt. and was later modified in Mechatronics and Machine Diagnostics 
Laboratory in Oulu. It is a convertible small device with 0.18 kW AC motor. The 
motor and the driven shaft are coupled by means of a claw clutch with a four-tooth 
elastic element (spider). The type of the coupling is ROTEX GS 14, manufactured 
by KTR. More information about the test rig can be found in\(^{(5)}\), where the same 
test rig has been used.

Measurements were carried out using eight accelerometers, a tachometer and a sound 
level meter simultaneously. The accelerometer types are Wilcoxon Research 726 and 
IMI 621B51. The first of them has a frequency range (±3 dB) up to 15 kHz and 
the second one up to 20 kHz. Measurements were performed in the LabVIEW 
environment by means of three analog input modules (NI 9233) and a four-slot
USB chassis (NI cDAQ-9174), which confirm simultaneous measurements from all the channels. Each combination of a sensor, cable and measurement channel was calibrated using a vibration calibrator (B&K 4294). The sample rate was 50 kHz and the time period for continuous data collection was about 80 seconds in each case. The tests were carried out with 5 different rotational frequencies between 8 – 23.5 Hz. In this paper, only the signals from one horizontal accelerometer of the bearing 1 (Figure 1) were investigated. All changes in alignment during testing took place in the horizontal plane, and both vertical and angular alignment was kept constant. Changes in alignment were generated by moving the motor with steps of 0.1 mm to both sides of optimum alignment, and measurements were made in 17 different positions. Horizontal displacement was performed by means of two dial gauges. More information about the testing arrangement can be found in earlier studies by Lahdelma et al. (5).

![Test rig](image)

**Figure 1. Test rig**

### 3. Signal processing methods

Machine diagnostics based on vibration measurements often only utilises few well-known features, which are effective in some common situations. Advanced signal processing offers many possibilities for more reliable, early fault detection. This paper utilises the derivation of acceleration signals and weighted $l_p$ norms, for the purposes of improving sensitivity, so that the order of derivative and order of norm can be a real number instead of an integer. In addition, dimensionless vibration indices are calculated for combining two different features into a single more powerful feature.
3.1 Order of derivation

Fault detection depends essentially on the order of derivative. Faults that mainly induce low frequency vibrations, such as unbalance or a bent shaft, can be detected successfully using signals whose order of derivative is low. Displacement or velocity signals were usually used in these cases. Acceleration measurements are needed for the early detection of faults, such as bearing faults, which induce vibration in the high frequency band. Sensitivity can often be improved considerably by means of higher order derivatives, especially in fault cases where impacts or friction occurs. For all fault types it is probable that the best sensitivity cannot be reached only with a signal whose order of derivative is an integer. The use of real order derivatives enables more sensitive indicators to be found for different cases of fault detection \(^{(6,7)}\).

The most efficient way of derivating signal \(x(t)\) is a procedure where three main steps are performed in the frequency domain. At first a fast Fourier transform (FFT) is used for the signal \(x(t)\) in order to obtain the complex components \(\{X_k\}\), \(k = 0, 1, 2, ..., (N-1)\). The corresponding components of the derivative \(x^{(\alpha)}(t)\) are calculated with the formula

\[
X_{\alpha k} = (i\omega_k)^\alpha X_k. \quad (1)
\]

The signal \(x^{(\alpha)}(t)\), where the order of derivation is \(\alpha \in \mathbb{R}\), can be produced using the inverse Fourier transform \(\text{FFT}^{-1}\) for sequence \(\{X_{\alpha k}\}\), \(k = 0, 1, 2, ..., (N-1)\).

For sinusoidal signal \(x = X \sin \omega t\) the real order derivative is

\[
\frac{d^\alpha x}{dt^\alpha} = \omega^\alpha X \sin(\omega t + \alpha \frac{\pi}{2}) = X_\alpha \sin(\omega t + \varphi_\alpha), \quad (2)
\]

where \(\alpha \in \mathbb{R}\) is the order of derivation, the amplitude \(X_\alpha = \omega^\alpha X\) and the change of the phase angle \(\varphi_\alpha = \alpha \frac{\pi}{2}\). \(^{(6,7)}\)

3.2 Weighted \(l_p\) norms

Let \(X\) be a vector space and \(a \in \mathbb{R}\). The norm satisfies the following axioms\(^{(8)}\):

(N1) \(|\langle x, y \rangle| \geq 0 \forall x, y \in X, |\langle x, y \rangle| = 0\) if and only if \(x = \theta\),
(N2) \(|\langle x + y, z \rangle| \leq |\langle x, z \rangle| + |\langle y, z \rangle| \forall x, y, z \in X\) (triangle inequality),
(N3) \(|\langle ax, y \rangle| = |a| |\langle x, y \rangle| \forall a \in \mathbb{R} \text{ and } \forall x, y \in X\).
The norm is clearly an abstraction of our usual concept of length. Let \( p \in R \) and \( 1 \leq p < \infty \). The space \( l_p \) consists of all the sequences of scalars \( \{x_1, x_2, \ldots\} = x \) for which
\[
\sum_{i=1}^{\infty} |x_i|^p < \infty.
\]

The norm in \( l_p \) is defined by
\[
\|x\|_p = \left( \sum_{i=1}^{\infty} |x_i|^p \right)^{\frac{1}{p}}
\]
and is also called classical \( l_p \) norm. The norm in \( l_\infty \) is defined as
\[
\|x\|_\infty = sup \left( |x_1|, |x_2|, \ldots \right).
\]

If we have a finite sequence \( x = \{x_1, x_2, \ldots, x_N\} \), then
\[
\|x\|_\infty = max \left( |x_1|, |x_2|, \ldots, |x_N| \right).
\]

If for all \( x \in X \) we have \( y = \theta \), then the triangle inequality (N2) is satisfied, even when \( p < 1 \).

Next, we examine the generalisation of the classical \( l_p \) norm in the form
\[
\|x\|_{p,w} = \left( \sum_{i=1}^{\infty} w_i |x_i|^p \right)^{\frac{1}{p}},
\]
where \( w_i \) (\( i = 1, 2, \ldots \)) are weight factors. If \( w_i = 1 \) \( \forall i \), then it is question of a classical \( l_p \) norm.

If all weight factors are equal to \( \frac{1}{N} \), we obtain from (7) the norm
\[
\|x\|_{p, \frac{1}{N}} = \left( \frac{1}{N} \sum_{i=1}^{N} |x_i|^p \right)^{\frac{1}{p}} = \left( \frac{1}{N} \right)^{\frac{1}{p}} \|x\|_p.
\]

In condition monitoring we also use time derivatives of displacement \( x^{(\alpha)} \), where \( \alpha \) is a real number. By using (8) we can now write
\[
\|x^{(\alpha)}\|_{p, \frac{1}{N}} = \left( \frac{1}{N} \sum_{i=1}^{N} |x_i^{(\alpha)}|^p \right)^{\frac{1}{p}} = \left( \frac{1}{N} \right)^{\frac{1}{p}} \left( \sum_{i=1}^{N} |x_i^{(\alpha)}|^p \right)^{\frac{1}{p}} = \left( \frac{1}{N} \right)^{\frac{1}{p}} \|x^{(\alpha)}\|_p.
\]
The generalised mean, also known as power mean or Hölder mean\(^{(11)}\), named after Otto Hölder (1859 - 1937), has the form

\[
M_p(x_1, x_2, \ldots, x_N) = \left( \frac{1}{N} \sum_{i=1}^{N} x_i^p \right)^{\frac{1}{p}},
\]

where \(x_1, x_2, \ldots, x_N \geq 0\). We can see that (8) and (10) have the same form. The notation \(\|x\|_p\) instead of \(\|x\|_{p, \frac{1}{N}}\) has been used in references\(^{(6,7,12)}\). This is not a confusion of the classical \(l_p\) norm, because in these references the name ‘generalised norm’ was used. Next, we consider the space \(l_p\), which Lahdelma has defined.

We suppose that the integer \(N \in [1, \infty)\). The space \(l_p\) consist of all the sequences of scalars \(\{\xi_1 = \frac{x_1}{\sqrt[N]{N}}, \xi_2 = \frac{x_2}{\sqrt[N]{N}}, \ldots, \xi_N = \frac{x_N}{\sqrt[N]{N}}\}\) = \(\bar{x}\) for which the sum

\[
\sum_{i=1}^{N} |\xi_i|^p = \sum_{i=1}^{N} \left| \frac{x_i}{\sqrt[N]{N}} \right|^p = \frac{1}{N} \sum_{i=1}^{N} |x_i|^p < \infty.
\]

Analogous to (4) we can define the \(l_p\) norm by

\[
\|\bar{x}\|_p = \left( \sum_{i=1}^{N} |\xi_i|^p \right)^{\frac{1}{p}} = \left( \frac{1}{N} \sum_{i=1}^{N} |x_i|^p \right)^{\frac{1}{p}} = \|x\|_{p, \frac{1}{N}}.
\]

By using (8) we can write

\[
\|\bar{x}\|_p = \|x\|_{p, \frac{1}{N}} = \left( \frac{1}{N} \right)^{\frac{1}{p}} \|x\|_p
\]

and for \(x^{(a)}\) we obtain

\[
\|\bar{x}^{(a)}\|_p = \|x^{(a)}\|_{p, \frac{1}{N}} = \left( \frac{1}{N} \right)^{\frac{1}{p}} \|x^{(a)}\|_p.
\]

We can call the norm \(\|\bar{x}\|_p = \|x\|_{p, \frac{1}{N}}\) as \(\frac{1}{N}\) weighted \(l_p\) norm.

### 3.3 Dimensionless vibration indices

In reference\(^{(13)}\), Lahdelma introduced the measurement index MIT for rating the condition of machinery. Dimensionless vibration indices can be combined in a measurement index.
\[ \tau MIT_{\alpha_1,\alpha_2,\ldots,\alpha_n}^{p_1,p_2,\ldots,p_n} = \frac{1}{n} \sum_{i=1}^{n} b_{\alpha_i} \frac{\|x^{(\alpha_i)}\|_{p_i}}{\|x^{(\alpha_i)}\|_{p_i}} \|_{0}, \]  

(15)

where the norms \(\|x^{(\alpha_i)}\|_{p_i}\) are obtained from the signals \(x^{(\alpha_i)}, i = 1, \ldots, n\). The index zero denotes the reference value when the machine is in good condition and \(b_{\alpha_i}\) represents a weight factor. This factor allows the rating of individual faults. The sum \(\sum_{i=1}^{n} b_{\alpha_i} = n\). Further investigations can be found in \(^{6,12}\), where a more generalised form of (15) has been introduced. Other measurement parameters, such as temperature, can also be used in the MIT index in order to obtain more information about the condition of the machine\(^{(7)}\).

4. Measurements

Measurements were carried out on the test rig (Figure 1) by moving the motor first in the horizontal plane to the position +0.50 mm. The displacement of the motor was measured with two dial gauges in order to avoid angular misalignment. During the tests the motor was moved to the position -1.10 mm in steps of 0.10 mm, and the measurements were performed in a total of 17 different offset values. The tests were carried out with 5 rotational frequencies at each position of the motor.

In this paper, signals only from one horizontal accelerometer of the bearing 1 were investigated, because the vibration caused by misalignment is clearly the strongest in this measurement point. The time signal with a sample length of 4 s was used in the calculation of features and frequency spectra, but only the first second of the time signals is shown in the figures of this paper. In the frequency domain measurements, we use the rms amplitude spectra. Signal processing, such as derivation and filtering, was performed in the frequency domain and an ideal filter was used. The frequency range was mainly from 3 Hz to 10 kHz, but also the low pass filtering of the cut-off frequency 5 kHz and 2 kHz was studied. The signals and spectra were analysed comprehensively and the number of time domain features was calculated in order to find the best sensitivity.

Figure 2 shows acceleration signals and their frequency spectra in three cases of different motor offset, when the rotational frequency was 8 Hz. In Figure 2 c), the \(x^{(2)}\) signal and corresponding spectrum are from a case where alignment is very close to the optimum (-0.20 mm). The signals b) and a) are connected to the cases, when the motor was moved from optimum alignment to 0.00 mm and +0.20 mm, respectively. The signals clearly show the types of vibrations that offset will induce.

In the signal in Figure 2 a), the offset is already quite prominent. The motor was moved from the optimum alignment about 0.40 mm. There are strong impacts in the signal, and the peak values are about 20 \(m/s^2\). The interval of the peaks in the signal corresponds to frequency, which equals four times the rotational frequency. The signal in Figure 2 b) also shows impacts caused by misalignment, but the peak
values are clearly smaller (3.8 m/s²) and impacts occur once per round. The signal in Figure 2 c) is from a case where alignment is very close to the optimum, based on the findings of this study. In that case the level of vibration is very low and the peak value is only 1.6 m/s².

![Figure 2. Acceleration signals and their frequency spectra in cases of motor displacement +0.20 mm (a), 0.00 mm (b) and -0.20 mm (c). The frequency range is 3 – 10000 Hz.](image)

The acceleration spectra in Figure 2 shows that the strongest vibration caused by offset can be seen in the frequency ranges from 1.3 kHz to 2.2 kHz and from 4 kHz to 5 kHz. The maximum amplitude of the first frequency range is 12.5 times higher in Figure 2 a) as compared with the spectrum b) and about 25 times higher than in the optimum case c). In addition, the impacts caused by offset induce vibrations over a wide frequency range, but the vibration in the frequencies over 5 kHz is very low. Therefore, can we conclude that using the upper cut-off frequency at 5 kHz does not reduce the possibility to detect misalignment of claw clutch and evaluate its severity.

5. Feature calculation

Many time domain features, which can be used to detect misalignment, were extracted from the measured signals. The values of peak, root-mean-square (rms),
crest factor, kurtosis and $l_p$ norms, when $p = 1, 1.2, 1.4, ..., 8$ and $\alpha = 0.0, 0.2, 0.4, ..., 6.0$ were calculated from all the measured signals. Table 1 contains values for some features from the frequency range $3 – 10000$ Hz, and Table 2 the same values from the frequency range $3 – 5000$ Hz. Three cases from both ends of the offset range were outlined, because vibrations were clearly stronger in these cases than in the selected range. Examination of the values in Tables 1 and 2 gives a good insight into changes in signals when offset varies. When the motor was moved to the position range between -0.10 mm and -0.20 mm from the initial state, vibrations were at the minimum. Also kurtosis values are in these cases close to 3, which is kurtosis for Gaussian noise. This means that the signal is very smooth without any special structure. Based on the values shown in Tables 1 and 2 we can say that optimum motor position is probably somewhat closer to the position -0.20 mm than the position -0.10 mm.

**Table 1.** Some powerful features calculated from the $x^{(2)}$ and $x^{(3)}$ signals in different cases of offset at rotational frequency 8 Hz using the frequency range from 3 Hz to 10 kHz

<table>
<thead>
<tr>
<th>offset [mm]</th>
<th>peak</th>
<th>rms</th>
<th>kurtosis</th>
<th>$l_4$ norm</th>
<th>$l_8$ norm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$x^{(2)}$</td>
<td>$x^{(3)}$</td>
<td>$x^{(2)}$</td>
<td>$x^{(3)}$</td>
<td>$x^{(2)}$</td>
</tr>
<tr>
<td></td>
<td>[m/s$^2$]</td>
<td>[km/s$^3$]</td>
<td>[m/s$^2$]</td>
<td>[km/s$^3$]</td>
<td>[m/s$^2$]</td>
</tr>
<tr>
<td>+0.20</td>
<td>20.4</td>
<td>319</td>
<td>1.92</td>
<td>27.2</td>
<td>17.8</td>
</tr>
<tr>
<td>+0.10</td>
<td>4.57</td>
<td>85.5</td>
<td>0.55</td>
<td>5.90</td>
<td>7.58</td>
</tr>
<tr>
<td>0.00</td>
<td>3.80</td>
<td>82.7</td>
<td>0.42</td>
<td>3.60</td>
<td>5.68</td>
</tr>
<tr>
<td>-0.10</td>
<td>1.63</td>
<td>8.12</td>
<td>0.34</td>
<td>1.36</td>
<td>3.42</td>
</tr>
<tr>
<td>-0.20</td>
<td>1.62</td>
<td>9.35</td>
<td>0.34</td>
<td>1.34</td>
<td>3.20</td>
</tr>
<tr>
<td>-0.30</td>
<td>1.63</td>
<td>19.3</td>
<td>0.35</td>
<td>1.56</td>
<td>3.32</td>
</tr>
<tr>
<td>-0.40</td>
<td>2.10</td>
<td>63.2</td>
<td>0.36</td>
<td>1.82</td>
<td>3.19</td>
</tr>
<tr>
<td>-0.50</td>
<td>1.76</td>
<td>29.8</td>
<td>0.33</td>
<td>1.76</td>
<td>3.41</td>
</tr>
<tr>
<td>-0.60</td>
<td>2.17</td>
<td>75.8</td>
<td>0.34</td>
<td>2.08</td>
<td>3.37</td>
</tr>
<tr>
<td>-0.70</td>
<td>4.26</td>
<td>71.8</td>
<td>0.40</td>
<td>3.75</td>
<td>6.07</td>
</tr>
<tr>
<td>-0.80</td>
<td>12.4</td>
<td>251</td>
<td>0.80</td>
<td>12.3</td>
<td>24.0</td>
</tr>
</tbody>
</table>

When we compare the values in Tables 1 and 2, we can see that there are no major differences between the corresponding values. The peak values of $x^{(3)}$ signals, for
example, are only about 10 – 30 percent lower when the upper cut-off frequency is 5 kHz instead of 10 kHz. The difference is nearly similar with the other features and rates of offset. Therefore, reducing the upper cut-off frequency from 10 kHz to 5 kHz is allowable for detecting misalignment of claw clutch.

5.1 Dimensionless vibration indices

The features calculated from different offset cases and rotational frequencies were compared using dimensionless vibration indices. The indices were calculated by dividing the features by the corresponding value, which was measured from the machine when it was in good condition. Both the individual relative features and their combinations were studied. This method provided a lot of information on changes in vibration when the offset of motor and rotational frequency were changed.

![Dimensionless vibration indices](image)

**Figure 3.** $x_{p}^{(3)}$ values from frequency range 3 – 10000 Hz when rotational frequency and offset changes

The relative peak values of the $x_{p}^{(3)}$ signals when the offset of motor and rotational frequency changes are shown in Figure 3. We can see that it is easier to detect the changes caused by offset when rotational frequency is relatively low. When rotational frequency increases, also the vibration induced by normal use increases, so it becomes more difficult to detect the vibration caused by offset in high rotational frequencies. This finding was also confirmed through senses during the tests. Therefore, the measurements performed at rotational frequency 8 Hz were studied more carefully in this paper. Figure 3 also shows that amplitudes and growth rate compared to the optimum alignment depend on the direction of motor movement. This can also be seen from the feature values in Tables 1 and 2.

The graphs in Figure 4 show how the order of derivative and order of $l_p$ norm influences the sensitivity of features. The rate of the offset is quite low in both the cases in Figure 4. If we analyse the signals that correspond to the graphs, we can state that there are some impacts in the signal if the order of derivative is two or higher. However, the peak values of these signals are not so high in these offset
cases. For example, the peak value of the $x^{(2)}$ signal in Figure 4 a) is $4.57\; m/s^2$ and the corresponding value in the case of b) is $1.76\; m/s^2$.

The graph in Figure 4 a) clearly shows that the best sensitivity can be obtained when $\alpha$ is between 3 and 4 and $p$ is greater than 4. For all $p$, sensitivity is very low when displacement, velocity or the other low order derivatives are used. The same finding was also made when the other features were studied. The sensitivity of the $x^{(2)}$ signal in Figure 4 a) is 2, and when the order of derivative increases, sensitivity shows a strong increase. The best sensitivity value, which is about 11, hits the values $\alpha = 3.2...3.8$. If the order of derivative is above 3.8, sensitivity is slightly lower, but in any case it is twice as high or even higher than the sensitivity of the acceleration signal. The sensitivity of the $l_p$ norm is the best when $p$ is from 5 to 8, but shows no significant increase if $p \geq 4$. In Figure 4 b), where the influence of misalignment is much smaller than in case a), the best sensitivity can be found when $\alpha \geq 3.4$. The sensitivity of the $l_p$ norm is the best in this case when $p$ is 5, but we can say that sensitivity is good when $p \geq 4$.

(a) \hspace{1cm} (b)

Figure 4. Sensitivity of the $l_p$ norm in offset cases $+0.10\; mm$ (a) and $-0.50\; mm$ (b) when the values of $\alpha$ and $p$ changes. The frequency range is $3 - 10000\; Hz$

Figure 5 shows how the sensitivity of relative kurtosis (a) and $l_8$ norm (b) changes when the order of derivative and offset change. The two selected features seem to be very sensitive in terms of detecting misalignment. The sensitivity is the best when the order of derivative is in the range from 3 to 3.6 with both these features and in almost all rates of offset. Kurtosis shows very strong changes in the low rates of the offset on both sides of optimum alignment. When the motor is moved 0.20 mm from the optimum position and the $x^{(3,2)}$ signal is used, the sensitivity value increases to 30. However, if offset is more than 0.20 mm, the sensitivity of kurtosis is clearly poorer. In the case of high offset rates, the $l_8$ norm is more sensitive. For example, in the case where offset is 0.50 mm from the optimum position, the sensitivity value is 50.
By using the kurtosis and the $l_8$ norm in the MIT index (Eq. (15)), we obtain a very sensitive indicator for offset detection in a wide range. Figure 6 shows the values of the MIT index, when the frequency range is from 3 Hz to 10 kHz and the other parameters are: $n = 2$, $\tau = 4s$, $\alpha_1 = \alpha_2 = 3.4$, $b_{\alpha 1} = b_{\alpha 2} = 1$. We can see from this figure that the MIT index is very low close to the optimum alignment (-0.20 mm) in the range of 0.10 mm, and in these cases the machine also runs very smoothly. When the motor was moved from this range 0.10 mm in either direction, the value of the index was immediately 15 – 20 times higher. The recommendation for allowable offset given by the manufacturer to the coupling of this type and size is $\pm 0.15$ mm from the optimum alignment. Based on the MIT index and the tests used in this study, we can conclude that the machine with a coupling of this type can be used best when the offset value $\pm 0.10$ mm is not exceeded. It may be that the maximum offset value given by the manufacturer induces additional vibrations.
5.2 Frequency range

Fault detection also depends essentially on the frequency range that is used in the measurements. If this range is very high, much more data storing capacity and computing power is required. It is also better for the repeatability of the measurements when magnetic mounting of a sensor is used if the upper cut-off frequency of the measurement need not to be too high.

Figure 7 shows how the upper cut-off frequency influences to the choice of $\alpha$ and $p$. In this case the offset was $+0.20$ mm and rotational frequency 8 Hz. When the upper cut-off frequency is 10 kHz (Figure 7 a)) the sensitivity is the best when $\alpha = 3.4...3.6$ and $p \geq 4$. In that case sensitivity is about 50. That same value is also obtained, when the upper cut-off frequency is only 2 kHz (Figure 7 c)), if $\alpha$ and $p$ are high enough, i.e. $\alpha = 6$ and $p = 8$. However, even better sensitivity can be obtained if the upper cut-off frequency is 5 kHz (Figure 7 b)). In that case sensitivity is altogether 93 which is nearly twice the value obtained in the case where this frequency is 10 kHz. This finding can partly be explained with the help of the frequency spectra in Figure 2, which shows that vibrations exceeding the 5 kHz limit do not increase significantly as a result of misalignment. Therefore, the upper cut-off frequency
higher that 5 kHz does not provide any advantages for the detection of the offset fault in this case. In addition, the upper limit 5 kHz provides very good sensitivity in wide ranges of $\alpha$ and $p$. Sensitivity is very close to the maximum when $\alpha = 3.4...6$ and $p = 4...8$.

Figure 8 shows signals when the frequency range and the order of derivation are optimum for detecting offset in this study. We can see from signal b) that there are very strong impacts caused by offset. The interval of the peaks corresponds to the frequency, which equals 4 times the rotational frequency. This corresponds to the number of jaws used in the claw clutch. In the case where offset was +0.20 mm (Figure 8 b)), the peak value is 15.9 Mm/s$^{3.4}$, rms value 1.42 Mm/s$^{3.4}$ and kurtosis 32.0. If we have the optimum alignment (Figure 8 a)), the corresponding values are 0.35 Mm/s$^{3.4}$, 0.043 Mm/s$^{3.4}$ and 3.64, respectively. In signal b), the peak value is 45 times and rms 33 times higher than in the optimum situation.

![Figure 8](image.jpg)

Figure 8. The $x(3.4)$ signal when alignment is close to the optimum (a) and when offset is +0.20 mm (b). The frequency range is 3 – 5000 Hz

6. Conclusions

The offset misalignment of a claw clutch was investigated in this paper using a test rig. Even the behaviour of this coupling differs from that of a conventional elastic coupling. The results of this study indicate that claw clutch misalignment can be detected reliably using vibration measurements. The study showed that if suitable features are used, it is possible to point out the best position of the motor with regard to alignment and the smoothness of running. The recommendation given by
the coupling manufacturer for allowed radial displacement is ±0.15 mm. Based on this study, can we say that offset should not be bigger than ±0.10 mm when the aim is to ensure that the machine runs very smoothly.

The best sensitivity in this case was obtained with the MIT index using the combination of kurtosis and $l_8$ norm. The kurtosis is the most sensitive feature for low offset rates and the $l_p$ norm is sensitive in cases where offset is higher. By combining these two aspects, it is possible to obtain a very powerful feature for indicating the severity of misalignment in a wide offset range. The order of derivative $\alpha$ for the signal depends on the frequency range used, but in all cases the order should be high enough for good sensitivity. Possibilities for detecting claw clutch faults using $\alpha$ lower than 2 are very small. If the measurements are performed using a wide frequency range up to 10 kHz, the best sensitivity can be obtained with $\alpha = 3.2\ldots3.8$. If the upper cut-off frequency is below 10 kHz, the benefits of higher order derivatives increase. The best sensitivity in this study was obtained using 5 kHz as the upper cut-off frequency. In that case the order of derivation should be 3.4 or higher. If $\alpha$ is high enough, the upper cut-off frequency 2 kHz can also produce a sensitivity that is equal to the case where the upper limit is 10 kHz. If we can use 2 kHz as the low upper cut-off frequency, measurements using magnetic mounting of sensor can be repeated reliably and only one fifth of storing capacity is needed.

The measurement method discussed in this paper can also be applied for aligning the claw clutch. With the method, it is possible to find an optimum alignment for the smooth running of the machine. This will clearly reduce loads and increase the undisturbed running time of the machine. It is quite simple to implement the method in practice and it can also be applied to the automatic alignment of the coupling of intelligent machines, for example.

References


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