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Using Operating Data to Locate & Quantify Unbalance in Rotating Machinery

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ABSTRACT

In a previous paper entitled ***Using Operating Deflection Shapes to Detect Unbalance in Rotating Equipment*** [1], we introduced the idea of numerically comparing currently acquired operating data with archived data to identify unbalances in rotating machinery. In a follow-up paper [2], we introduced a new metric for comparing two deflection shapes called the ***Shape Difference Indicator*** or SDI. In this paper, we introduce a refined version of the SDI algorithm, and present new results to verify its utility for locating and quantifying unbalance in rotating machinery.

We make two underlying assumptions about rotating machines; 1) all rotating machines are excited by ***inherent unbalance forces*** which cannot be directly measured, and 2) order-related vibration levels acquired from multiple locations on a machine can be ***directly correlated*** with specific unbalance conditions. We show that by comparing current with archived ODS data, specific unbalance conditions can be pinpointed.

KEY WORDS
Fourier spectrum (DFT)
Auto power spectrum (APS)
Cross power spectrum (CPS)
ODSFRF
Operating Deflection Shape (ODS)
Modal Assurance Criterion (MAC)
Shape Difference Indicator (SDI)

INTRODUCTION

Vibration measurements have been used for decades as a means of determining the health of rotating machinery. The use of vibration as a health metric is analogous to a medical doctor examining your electro-cardiogram in order to ascertain the health of your heart. Just as a doctor looks for small abnormalities in the time waveforms of the electronic signals from your chest, vibration signals also carry tell-tale signs that mechanical changes have taken place in a rotating machine.

Three of the most common health problems in rotating machine are ***unbalance*** of rotating parts, ***misalignment*** of rotating parts, and loose mountings or an overly compliant foundation, called ***soft foot***.

We believe that all three of these rotating machinery health problems can be detected using ODS data. Furthermore, we will show that by ***numerical correlation*** of current and archived ODS data, (i.e. a form of data mining), small unbalance conditions in a rotating machine can be detected and located.

In the previous paper [1], four tri-axial and two uni-axial accelerometers where attached to the rotating machine shown in Figure 1. When the peak values at the running speed (or first order) of the machine were assembled together into a “deflection shape”, it resulted in an ODS with 14 shape components (or DOFs) in it.

In this paper, only the operating data from the two tri-axial accelerometers on the bearing blocks is used, thus providing order-related ODS’s with only 6 DOFs in them. This minimal amount of data was used not only to prove the viability of ODS comparison as a method for locating and quantifying unbalances, but also to show that a minimal amount of instrumentation is required to implement this method on rotating equipment in a process plant.

Both MAC and SDI will be applied to the same seven cases of machine unbalance that were used in [1], but instead of using all of the operating data, only a minimal set of data from the two bearing blocks will be used. In addition, an extension of the SDI method will be introduced which increases its sensitivity to small differences between two shapes.

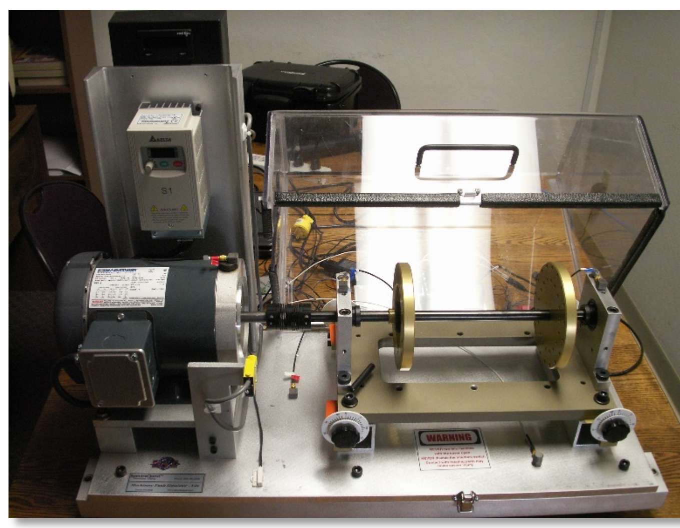

Figure 1. Rotating Machine with Accelerometers Attached

Output-Only Frequency Spectra

In operating machinery where the excitation forces cannot be measured, three types of ***output-only*** frequency spectra can be calculated from acquired time waveforms. The three types are Fourier spectra, Cross spectra, and ODSFRFs.

A **Fourier spectrum** is simply the Digital Fourier Spectrum (DFT) of a response digital time waveform. It is calculated with the FFT algorithm. A **Cross spectrum** is calculated between two simultaneously acquired responses. It is the DFT on one signal multiplied by the complex conjugate of the other. An **ODS-FRF** is the Auto spectrum of a ***roving*** response combined with the phase of the Cross spectrum between the ***roving*** response and a ***(fixed) reference*** response.

Operating Deflection Shape (ODS)

When a vibration response is measured at ***two or more points & directions*** on a machine, this data can be assembled into what is called an **Operating Deflection Shape** (or **ODS)** [5]. Three different types of ODS's are possible; ***time-based ODS's***, ***frequency-based ODS's***, and ***order-based ODS's***.

Time-Based ODS

A time-based ODS is simply the values for the same time sample of two or more simultaneously acquired or calculated time waveforms. A time-based ODS contains the responses that were simultaneously acquired at a moment of time from the machine.

Frequency-Based ODS

A frequency-based ODS is the values for the same frequency sample of two or more frequency domain functions or spectra. A frequency-based ODS is the ***true overall response*** of the machine at a specific frequency sample for which the measurement functions were calculated.

All frequency domain functions (except an Auto spectrum) are complex valued (with magnitude & phase), and consequently all frequency-based ODS's are complex valued.

Order-Based ODS

In a rotating machine, the excitation forces are dominant at multiples of the machine running speed, called orders. An ***order-based ODS*** is assembled from the ***peak values*** at one of the order frequencies in a set of output-only frequency spectra. These spectra are calculated from response data that is acquired while the machine is running. When displayed in animation on a 3D model of the machine, an order-based ODS is a convenient way to visualize distributed relative vibration levels.

The components of an order-based ODS can also be used for monitoring the health of the machine by comparing their values with pre-defined warning levels. Three commonly used warning levels are termed ***alert, alarm, & abort*** levels.

DATA ACQUISITION FROM A ROTATING MACHINE

For our previous paper [1], operating data was acquired from the machinery fault simulator shown in Figure 1. Tri-axial accelerometers were attached to the top of both bearing blocks and the motor. A tri-axial and 2 uni-axial accelerometers were also attached to the base plate. These accelerometers provided a total of 14 vibration signals, which were simultaneously acquired with a 16 channel data acquisition system.

A set of ODSFRFs was calculated between each of the channels of data and a ***single reference*** channel. An ODSFRF is a ***"hybrid"*** cross-channel measurement, derived from both an Auto and Cross spectrum. It is formed by combining the ***phase*** of the Cross spectrum between a roving and reference signal with the Auto spectrum (its ***magnitude***) of the roving response signal. The magnitude of an ODSFRF is the Auto spectrum of the response, which is a measure of the true magnitude of the machine response. The phase of an ODSFRF, which is its phase with the reference response, also provides a measure of the ***relative phase*** between its response and all other responses.

Data was acquired from the machine at an operating speed of 2000 RPM, under seven different unbalance conditions. A typical ODSFRF is shown in Figure 2. It is clear that the dominant peaks in the ODSFRF are at the running speed and its higher orders (4000, 6000 RPM, etc.).

Order-based ODS's were created by saving the peak values in the ODSFRFs at each of the first three orders.

NOTE: An order-based ODS is the ***peak values*** from a set of ODSFRFs at ***one of the machine orders***.

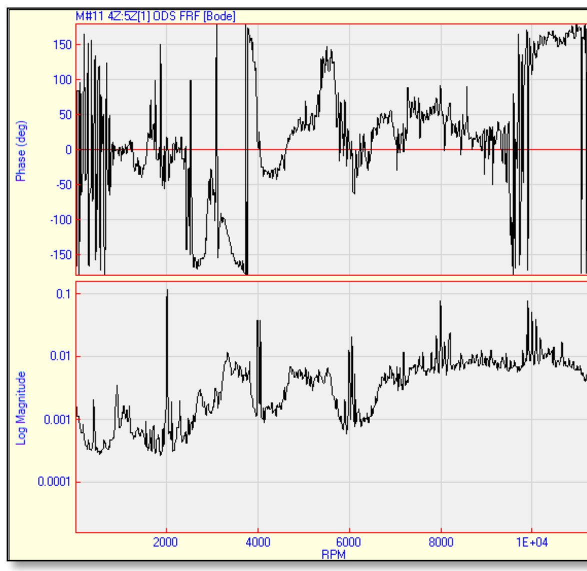

Figure 2. ODSFRF Showing Peaks at Machine Orders.

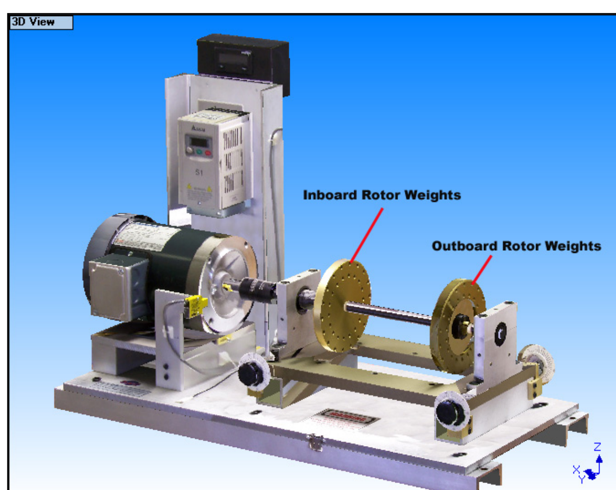

Figure 3. Unbalance Weights Attached to Rotors

SEVEN UNBALANCE CASES

Vibration data was acquired from the machine when it was considered to be in balance (the baseline condition), and under seven different unbalance conditions. Unbalance was created by adding weights to either or both of the rotors, as indicated in Figure 3. Data was acquired for each of the following unbalance conditions;

1. Small unbalance (11.25 grams) - Inboard rotor
2. Small unbalance - Outboard rotor
3. Large unbalance (22.5 grams) - Inboard rotor
4. Large unbalance - Outboard rotor
5. Two large unbalances - 0 degrees apart
6. Two large unbalances - 90 degrees apart
7. Two large unbalances - 180 degrees apart

For case 1, a small unbalance weight (11.25 grams) was added only to the inboard rotor, closest to the motor. For case 2, the same small unbalance weight was added only to the outboard rotor, farthest from the motor. Cases 3 & 4 were the same as cases 1 & 2, but a larger unbalance weight (22.5 grams) was used.

In cases 5, 6 & 7, the same large unbalance weight was added to both rotors, but the weights were added in different positions. In case 5, they were added at the same radial position on both rotors (with 0 degrees difference between them). In case 6, they were added at 90 degrees apart from one another, and in case 7 they were added at 180 degrees apart.

ODS data for the unbalance cases previously used [1] was also used for this paper, but only data from the accelerometers ***on the two bearing blocks*** was used. This will illustrate the use of a ***minimal set of data*** for detecting and identifying each of the seven cases.

MODAL ASSURANCE CRITERION (MAC)

One might ask, ***Isn't the Modal Assurance Criterion (MAC) used for numerically correlating two shapes? Why introduce another correlation method?*** MAC [3], [4] is useful for comparing two shapes but it has two limitations,

1. It only indicates the ***co-linearity*** of two shapes, not their difference.
2. It can only be applied to shapes with ***two or more*** shape components. Its value for two scalars is ***always* 1**.

MAC is calculated with the formula,

$$\mathrm{MAC} = \frac{\left\|\{u\}^h\{v\}\right\|^2}{\{u\}^h\{u\}\{v\}^h\{v\}} \qquad (1)$$

{u}= complex comparison shape (m-vector)
{v}= complex baseline shape (m-vector)
m = number of <u>matching DOFs</u> between the shapes
h - denotes the <u>transposed conjugate</u> vector

MAC measures the ***co-linearity*** of two shapes, so if they lie together on the same straight line, **MAC = 1**. Another way of understanding MAC is that it is the ***dot product*** of the two shapes squared, ***normalized*** by each of their magnitudes squared. MAC is not sensitive to the difference in the actual values of the shapes themselves, only to the difference in their ***"shapes"***. If two shapes do not lie on the same straight line, then **MAC < 1**.

MAC does not answer the question, ***"How different are the shape component values of one shape from another?"*** To answer that question, a new measure of the difference between two shapes was introduced in [2]. SDI has proven to be more useful than MAC for comparing ODS's to detect machine faults.

SHAPE DIFFERENCE INDICATOR (SDI)

The Shape Difference Indicator is defined with the formula,

$$\mathrm{SDI} = \left(1 - \frac{\|\{u\}-\{v\}\|^2}{\{u\}^h\{u\}+\{v\}^h\{v\}}\right)^2 \qquad (2)$$

or

$$\mathrm{SDI} = \left(\frac{2\,\mathrm{real}(\{u\}^h\{v\})}{\{u\}^h\{u\}+\{v\}^h\{v\}}\right)^2 \qquad (3)$$

$\mathrm{real}\left(\{u\}^h\{v\}\right)$ = the real part of the vector dot product
{u}= complex comparison shape (m-vector)
{v}= complex baseline shape (m-vector)
m = number of <u>matching DOFs</u> between the shapes
h - denotes the <u>transposed conjugate</u> vector

SDI values also range between **0 & 1**. If two shapes have ***identical shape components***, **SDI = 1**. If two shapes have ***different shape components***, **SDI < 1**. Several examples illustrate typical SDI values.

- If {v} = {u}, SDI = 1
- If {v} = 0 *or* {u} = 0, SDI = 0
- If {v} = 2{u}, SDI = 0.64
- If {v} = 10{u}, SDI = 0.04

APPLYING MAC & SDI TO ORDER-BASED ODS'S

The following Figures 4 through 9 are bar charts of the MAC and SDI values between order-based ODS pairs for the baseline and seven unbalance cases.

Each bar chart depicts an 8 by 8 matrix of MAC or SDI values. Each diagonal bar of value **1** is the MAC or SDI value of each ODS correlated with itself. Each bar chart also shows the ***worst case*** of a MAC or SDI value in the box at the top. Shape #1 is the baseline (balanced) case. Shapes #2 through #8 are the seven unbalance cases in order.

A MAC or SDI value ***less than* 1** indicates that a pair of ODS's are different from one another. A bar value ***close to zero*** is a clear indication that two ODS's are different.

NOTE: If all of the ***off-diagonal*** bars in these bar charts are ***close to zero***, the metric can be used to ***uniquely identify*** each unbalance condition.

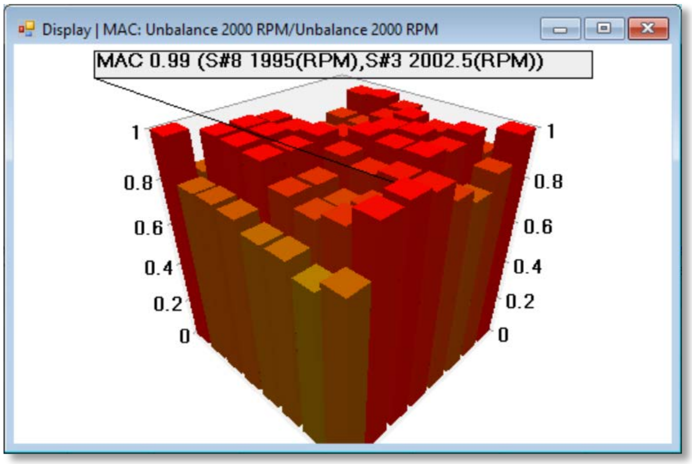

Figure 4. MAC values (First Order)

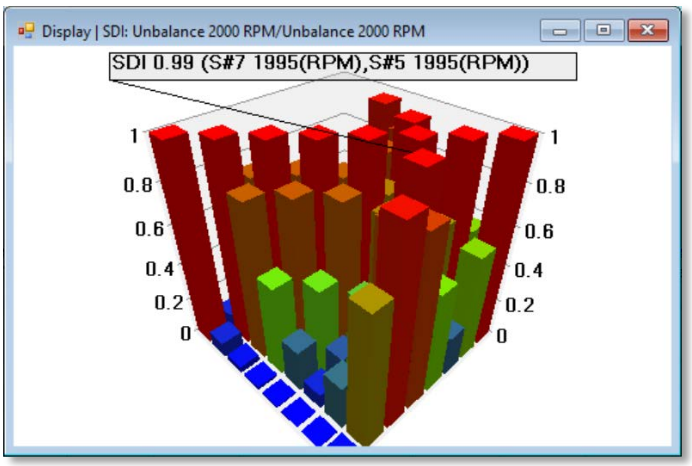

Figure 5. SDI Values (First Order)

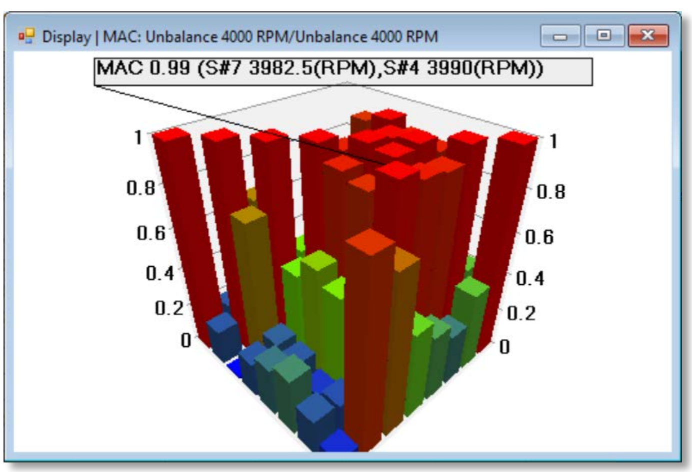

Figure 6. MAC Values (Second Order)

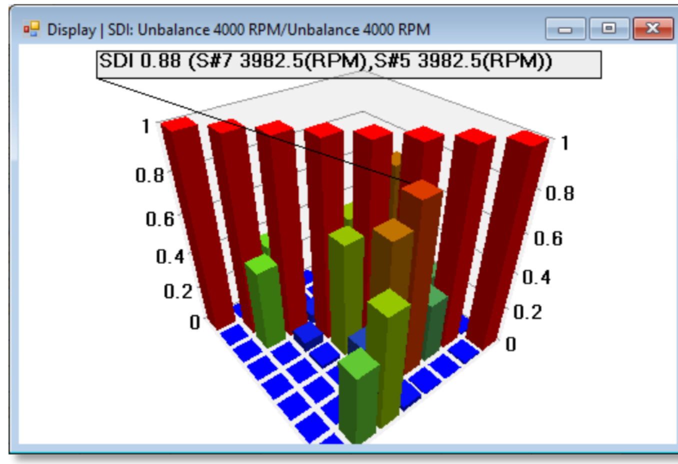

Figure 7. SDI Values (Second Order)

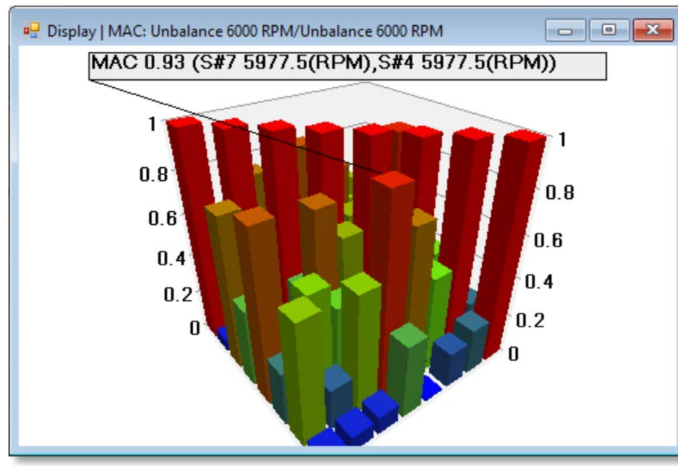

Figure 8. MAC Values (Third Order)

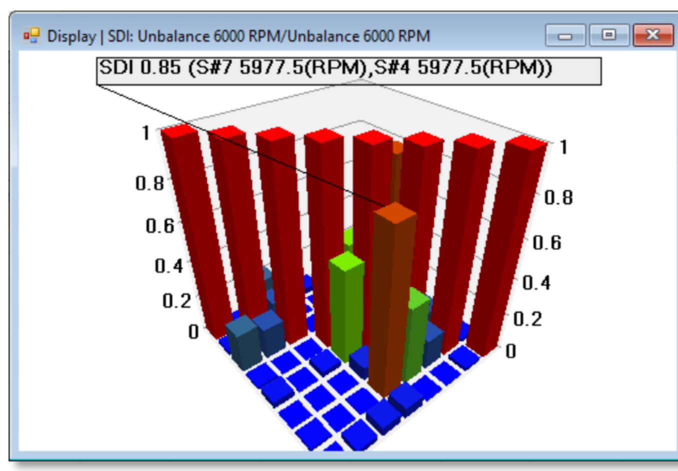

Figure 9. SDI Values (Third Order)

Figure 4 shows the MAC values for the first order ODS data. Many of the MAC values for the off-diagonal pairs are ***close to* 1**. This bar chart shows that MAC values cannot be used on first order ODS data to uniquely identify each unbalance case.

Figure 5 shows the SDI values for the first-order ODS data. Overall, these values are closer to zero than the MAC values, but the ODS's for the worst case pair (cases 2 & 7) are still closely correlated (**SDI = 0.93**). Hence, SDI values cannot be used on first order ODS data to uniquely identify each unbalance case

Figure 6 is the MAC values for the second order ODS's. This bar chart still shows that the MAC values cannot be used on second order ODS data to uniquely identify each unbalance case. Figure 7 is the SDI values for the second order ODS's. It shows that the worst case pair (cases 4 & 6) has an **SDI = 0.88**. This bar chart also shows that SDI values cannot be used on second order ODS data to uniquely identify each unbalance case.

Figure 8 shows that the worst case pair (cases 3 & 6) has a **MAC = 0.93** for the third order ODS's. Even though overall these MAC values are closer to zero than for the first and second orders, these values still cannot be used to uniquely identify each unbalance case. Figure 9 shows that a worst case pair (cases 3 & 6) has an **SDI = 0.85**. Again SDI cannot be used on third order ODS data to uniquely identify each unbalance case.

Even though SDI is a stronger indicator of shape differences than MAC, it would still be an unreliable method for discriminating among the seven unbalance cases and the balanced case, regardless of which order of ODS data were used.

SDI SENSITIVITY

Figure 10 is a plot of three SDI curves for scalar values of {u} & {v}. In general, {u} & {v} are vectors, but in this case each vector only has one real component. Three curves are plotted for the baseline shape {v} = 1, 10, 100.

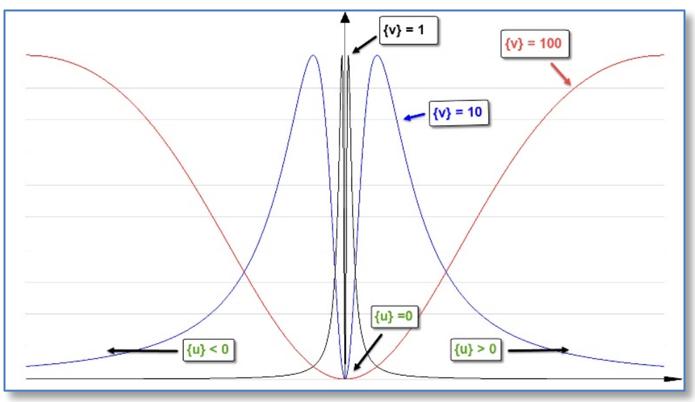

Figure 10. SDI Values for Scalars {u} & {v}

These SDI curves have two unique properties,

1. When {u} = 0, SDI = 0
2. Each SDI curve ***flattens out*** as it transitions from zero to its ***peak value*** (**SDI =1**), which occurs when {u} = {v}

Another way of interpreting this is that the ***sensitivity*** of SDI becomes greater as {v} approaches zero. In order to increase the sensitivity of SDI, the vectors {u} & {v} can be replaced with the following vectors before calculating their SDI value.

$\{\underline{\mathbf{v}}\}$ = {sensitivity} where (sensitivity > 0)

$\{\underline{\mathbf{u}}\}$ = {u} – {v} + $\{\underline{\mathbf{v}}\}$

Replacing {u} & {v} with $\{\underline{\mathbf{u}}\}$ & $\{\underline{\mathbf{v}}\}$ makes the SDI calculation more sensitive to the difference between {u} & {v}.

In order to distinguish the difference between a pair of vectors, a sensitivity should be chosen which drives their SDI value as close to zero as possible.

The following Figures 11, 12, & 13 contain bar charts of the SDI values for the same order-based ODS data as Figures 5, 7, & 9, but with ***sensitivity* = 0.1**.

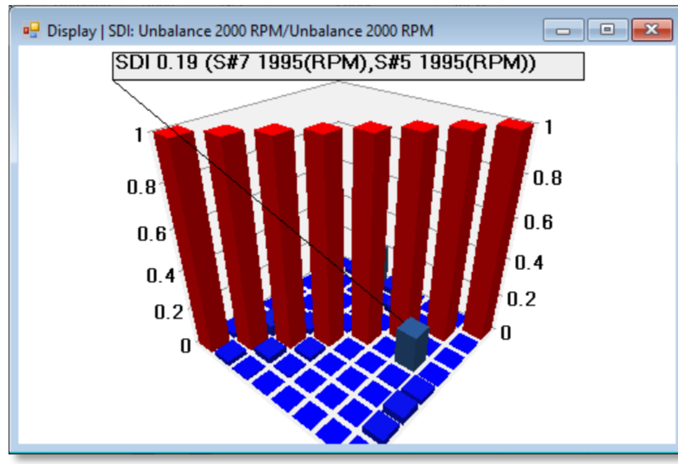

Figure 11. SDI Values (First Order)

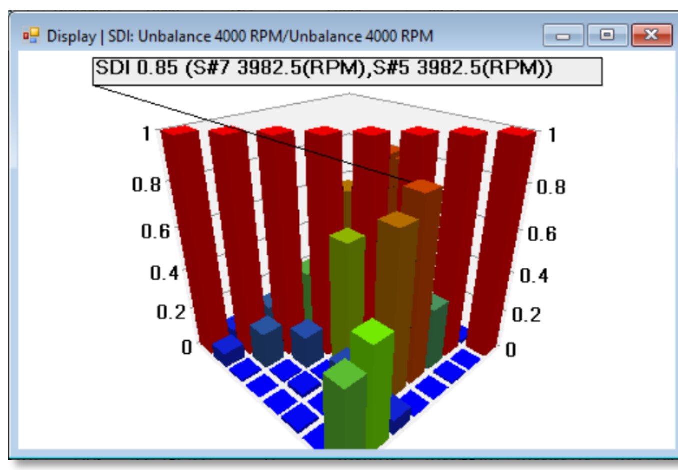

Figure 12. SDI Values (Second Order)

Figures 11, 12, & 13 are the graphic evidence that the SDI algorithm, with modifications to a pair of order-based ODS's to make it more sensitive to their difference, can be used as a discriminator between different unbalance conditions in a rotating machine. This algorithm has been implemented in the ME'scope software, a product of Vibrant Technology.

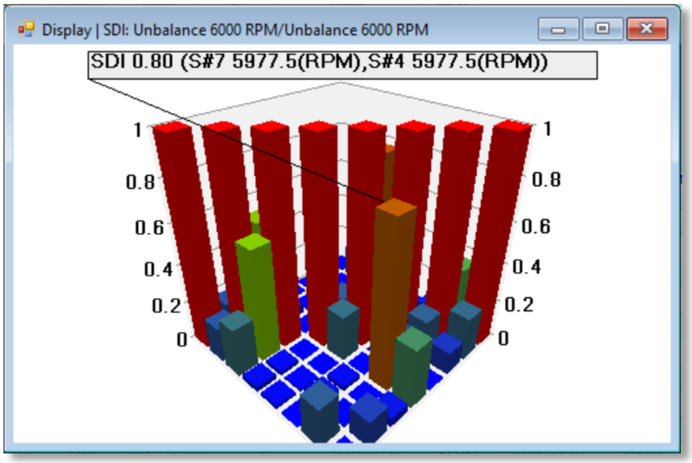

Figure 13. SDI Values (Third Order)

FAULT CORRELATION TOOLS (FaCTs)

When SDI is used together with an archival database, where archived ODS's have been associated beforehand with known unbalance conditions, SDI bars can be used to identify specific unbalance conditions. This capability has been branded as **FaCTs™**, an acronym for **Fault Correlation Tools**, in the ME'scope software.

FaCTs can be used in a number of ways as part of the post-processing software in an online machine health monitoring system. In addition to correlating current ODS data with archived data that has been associated with a known unbalance condition, FaCTs can also be used to graphically indicate any change in a machine operating condition by providing a real-time comparison of current versus baseline ODS data.

FaCTs can also be used as a pass/fail indicator as part of a qualification testing system where vibration data, or any other type of engineering data, is acquired from the machine or test article. Any type of engineering data can be added as components to a shape vector, and consequently can be used in an SDI calculation as part of FaCTs.

CONCLUSION

The purpose of this paper was to show that ODS data taken from the bearing blocks on a rotating machine can be post-processed to detect and identify various unbalance conditions of the machine. The idea behind this approach is to correlate currently acquired data with data that has been previously archived in a data base, and which has been associated with particular unbalance conditions.

We applied two different measures of shape correlation to the ODS data, MAC & SDI. Both measures indicate the likeness of a pair of shapes by giving values between 0 & 1. A value of 1 means that the shapes are the same, and a value less than 1 means that they are different. Both measures could be referred to as ***correlation coefficients***.

MAC indicates whether or not two shapes are ***co-linear***, lying together on the same straight line. SDI measures the ***true difference*** between two shapes. When both measures were applied to the bearing block ODS data, the SDI bar charts showed that the shape difference was stronger than shape co-linearity for discriminating between the unbalance cases. However, even SDI didn't provide a clear distinction between all cases.

Therefore, it was also shown that the sensitivity of SDI can be increased by inputting two ***modified shapes*** to the SDI algorithm which are derived from the original shapes. By increasing its sensitivity, SDI was able to clearly discriminate between all of the unbalance conditions and the balanced condition of the rotating machine.

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