VIATC TRAINING CONFERENCE & EXPO
NEWPORT NEWS, VIRGINIA | AUGUST 6-8, 2025

USING MODE SHAPES FROM CELL PHONE VIDEOS FOR MACHINERY HEALTH MONITORING

Shawn Richardson & Mark Richardson
Vibrant Technology, Inc.

[Click here](#) for the Power Point presentation.

Shawn Richardson is manager of Special Projects at Vibrant Technology. Mark Richardson is a co-founder and President of Vibrant Technology. Vibrant sells and supports the MEscope family of post-test noise and vibration analysis software tools.
Mark joined Hewlett Packard Co., Santa Clara, California in 1973, where he directed the development of the first commercially available FFT-based modal testing system. Following that, he directed the development of the first modal testing instrument, the Hewlett Packard 5423A Structural Dynamics Analyzer.
In 1979, Mark co-founded Structural Measurement Systems, Inc. SMS developed and marketed the popular StarModal and StarStruct software packages.

Abstract

Use of a cell phone video provides a low-cost complement to traditional accelerometer-based methods for monitoring the health of plant operating equipment. The video enhancement technology in modern-day cell phones renders them ideal for use as a convenient measurement device for use in a plantwide route-based machine monitoring program.

To demonstrate the use of this technology, several unbalance cases were created in a rotating machine by adding screws to its rotors. Then while the machine was running, a cell phone video was recorded during each unbalanced condition. Mode shapes were extracted from each video, labeled with their unbalanced condition, and stored into an archival database. Then a database search method called **FaCTs™** was used to uniquely identify each unbalance condition based on the **OMA** mode shapes of the first three orders of the machine.

Key Words

Time Waveform (**TWF**), Digital Fourier Transform (**DFT**), Auto Spectrum (**APS**), Cross Spectrum (**XPS**), **ODS-FRF**, Operating Deflection Shape (**ODS**), Operational mode shape (**OMA** mode shape), Degree of Freedom (**DOF**), neural network (**NN**), Fault Correlation Tools (**FaCTs™**), Frames Per Second (**fps**)

Rotating Machine

In this paper, **FaCTs™** is used to uniquely identify ***five different unbalance cases*** of the rotating machine shown in Figure 1. The machine has a variable speed motor connected to the rotor with a coupler. The motor speed was adjusted to ***approximately 1000 RPM*** and remained there throughout all the cell phone video recordings.

Figure 1. Rotating Machine Showing Unbalance Screws Added to Its Rotors

Introduction

Most manufacturing plants worldwide have implemented route-based monitoring programs for accessing the health of their rotating machinery and associated equipment. Digital vibration signals are the primary data used for machinery health monitoring.

Traditionally, machine monitoring has been done by attaching accelerometers to the surfaces of the operating equipment and acquiring signals from the accelerometers with a portable digital spectrum analyzer. Compared to recording a cell phone video, using accelerometers for data acquisition is more expensive and time-consuming to implement. Furthermore, because it is non-contacting, a cell phone can record vibration of machine parts that are too hot, too dangerous, or are inaccessible for attaching accelerometers.

In previous papers [1] to [4], traditional signal processing methods were applied to the **TWFs** extracted from the frames of a video. Both **TWFs** and their associated **DFTs** can be used to display either **time-based** or **frequency-based ODS**'s allowing vibration to be visualized at slower speeds with higher amplitudes.

A new database search method called **FaCTs™** was introduced in a previous paper [2]. In this paper, **FaCTs™** is used to identify different unbalance conditions of a rotating machine using only its mode shape **DOFs** from two points on the motor and the tops of its two bearing blocks. **FaCTs™** uniquely identified all five unbalance conditions using only the **OMA** mode shapes of the first two machine orders.

FaCTs™ functions in the same manner as a trained neural network. It uses the current mode shapes of a machine together with a shape correlation coefficient, called the shape difference indicator (**SDI**), to search in an archival database for labeled mode shapes that ***closely match*** the current mode shapes. Each mode shape in the database is labeled with the machine condition and a time stamp when it was archived.

FaCTs™ displays a bar chart of the **SDI** values of the current mode shapes with the ***closest matching*** archived mode shapes, thereby defining the most likely current mechanical condition of the machine based on its current mode shape values.

Artificial Intelligence (Machine Learning)

Artificial Intelligence, popularly known as **AI**, uses a ***trained*** neural network (**NN**) to interpret the meaning of a set of data. However, to accurately diagnose a mechanical fault, an **NN** must be trained with a ***lot of vibration data***.

A neural network is a machine learning model that uses a network of interconnected nodes, or artificial neurons, to process data in a way that mimics the human brain. It uses a machine learning (ML) process of many interconnected nodes in a layered structure that resembles the human brain. A neural network is depicted in Figure 2

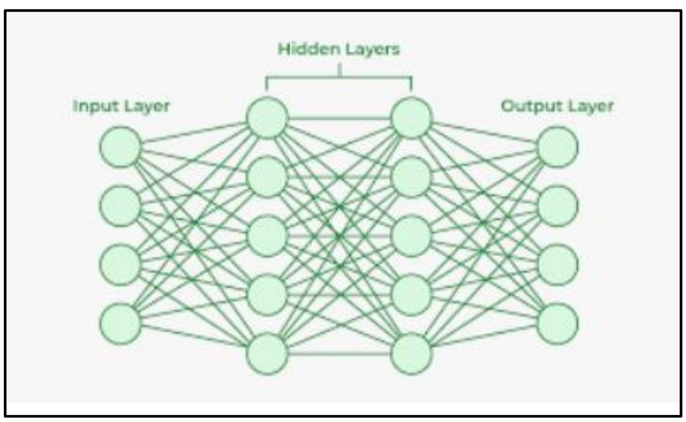

Figure 2. A Neural Network

To diagnose mechanical faults, an **NN** must be trained with data that is ***uniquely associated*** with a mechanical fault. Then when vibration data is input to a trained **NN,** called an Inference Engine, it diagnoses a mechanical fault, as shown in Figure 3. But a drawback of using a trained NN is that ***lots of labeled vibration data*** is required to train an **NN**.

Vibration data in the form of **TWFs**, **DFTs**, **ODS-FRFs**, **ODS's** or **Mode Shapes** can be used to characterize machinery vibration. Using **OMA** mode shapes obtained from a cell phone video together with **FaCTs**, machine health monitoring can be done in a much more efficient manner.

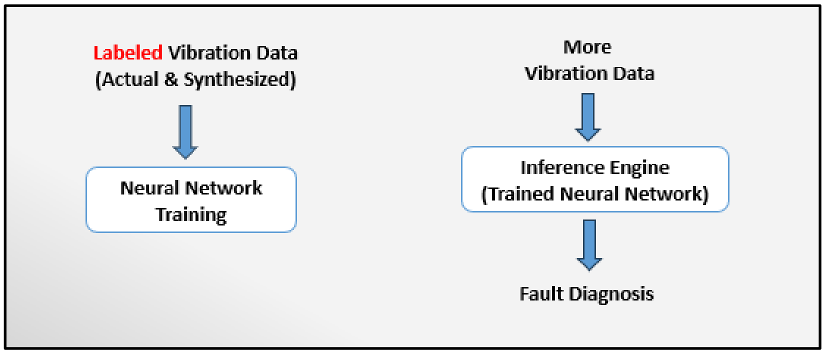

Figure 3. NN Training & Inference Engine

FaCTs™

FaCTs™ [4] is a database search algorithm used in MEscope [10]. It searches for ***labeled*** mode shapes; each mode shape labeled with ***a particular machine condition or mechanical fault***. **FaCTs** then displays a bar chart of **FaCTs** values for those mode shapes that ***closely match*** a current set of mode shapes. The bar chart displays the ***mechanical fault and time stamp*** associated with the archived shapes that ***most closely match*** the current mode shapes.

FaCTs™ uses an algorithm called the Shape Difference Indicator **(SDI)** [8]. **SDI** calculates a correlation coefficient between ***two complex-valued*** shape vectors. **SDI** is used to search the archival database for the mode shapes that have the ***highest* SDI *value*** with each current mode shape.

- **FaCTs** values are between **0.0 & 1.0**
- **FaCTs = 1.0** ➔ two mode shapes are ***identical***
- **FaCTs >= 0.9** ➔ two mode shapes are ***similar***
- **FaCTs < 0.9** ➔ two mode shapes are ***different***

Using Mode Shapes with FaCTs

To use mode shapes with **FaCTs**, each set of mode shapes in the archival database must be labeled with a machine condition, (balanced, bearing replacement, unbalance, aligned, passed inspection, etc.). Each set of shapes is also given a time stamp when it is stored into the database. Like an **NN**, **FaCTs** will also become more accurate as more labeled mode shape data is stored in the archival database.

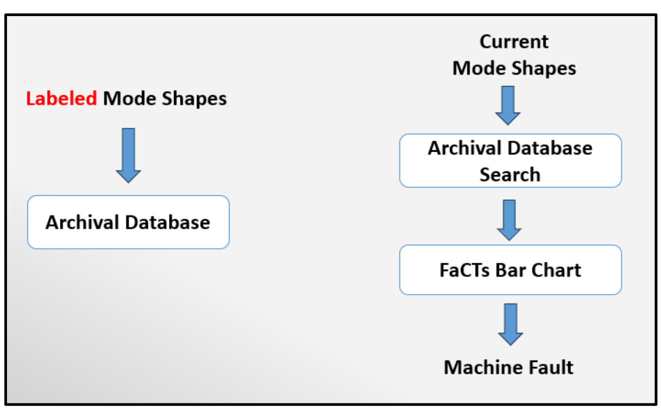

*Figure 4. **FaCTs** Archival Database Search*

Then when a new set of mode shapes is acquired, **FaCTs** is used to search the archival database and display a **FaCTs** bar chart, ordered from the ***closest matching*** mode shapes to the ***least matching*** mode shapes. The shapes with the ***highest*** **FaCTs** ***values*** have the ***highest correlation*** with the current mode shapes. This search process is depicted in Figure 4.

FaCTs Bar Chart

A **FaCTs** bar chart shows the ***closest matches*** of a set of ***current*** mode shapes with sets of ***labeled*** mode shapes already stored in the archival database. The search method uses a correlation coefficient called the **Shape Difference Indicator** (**SDI**) [8] which measures the difference between two mode shapes. A typical **FaCTs** bar chart is shown in Figure 5.

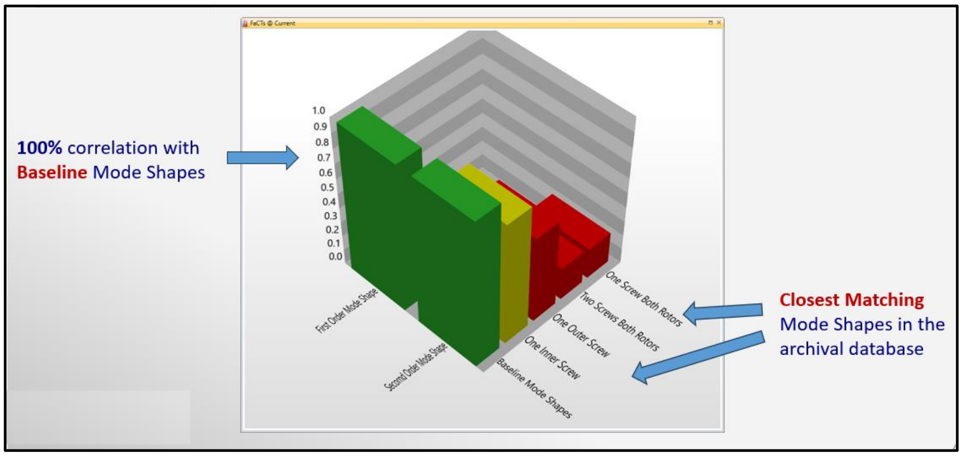

*Figure 5. **FaCTs** Bar Chart*

TWFs & DFTs

When a video is processed in MEscope [8], a rectangular grid of points with rectangular surfaces between them is created. Frames of the video are attached to the rectangular surface during an animated display of the **ODS's** extracted from the video.

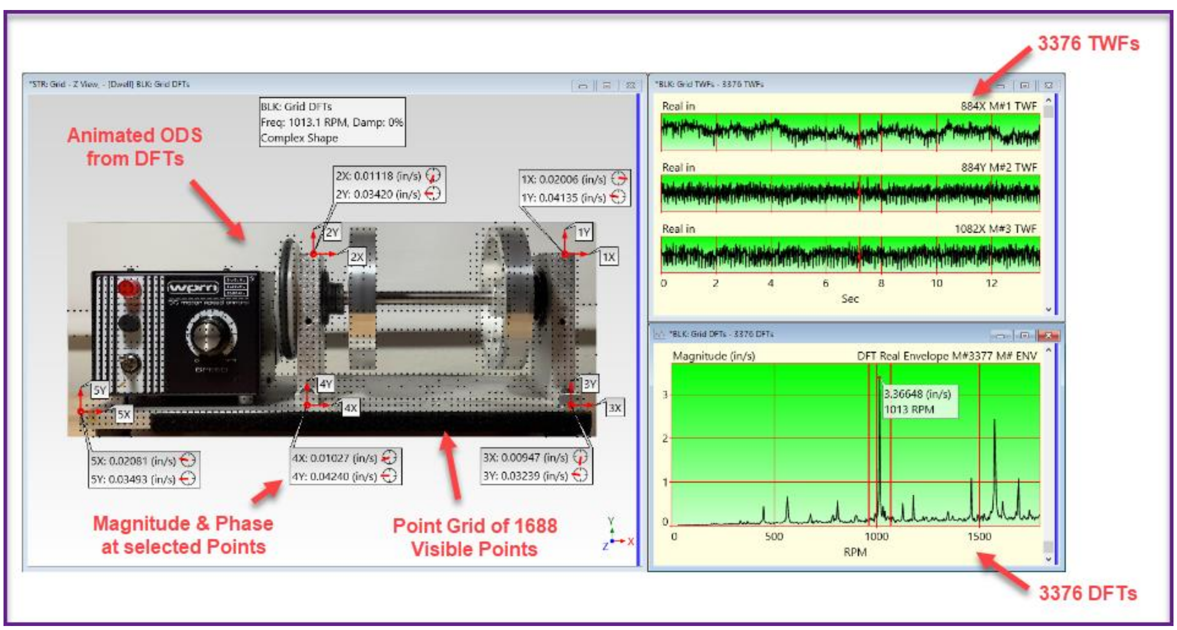

*Figure 6. First-Order Frequency-based **ODS** Animated from **DFTs***

Using a rectangular point grid, the displacements of ***millions of pixels*** per video frame are processed to extract the **TWFs** of the horizontal & vertical motion of ***thousands of points*** in the point grid.

Grid points with ***little or no motion***, (like background points), are hidden and their **TWFs** are removed from further analysis. A point grid with background points hidden is shown in Figure 6.

Time-based **ODS**'s are displayed in animation from the **TWFs** using a sweeping Line cursor. Each frame of the raw video corresponds to a sample of the **TWFs**, so frames of the raw video are displayed on the point grid during sweep animation through the **TWFs**.

A **DFT** is calculated for each **TWF** that is extracted from the video. The frequency-based **ODS** at the cursor position in the **DFTs** is displayed in animation using sinusoidal modulation of the **ODS** values. The magnitude & phase of the **ODS** at selected points on the point grid can also be displayed during **ODS** animation, as shown in Figure 6. This feature enables the examination of ***magnitude & phase differences*** between various points on the test article during **ODS** animation.

Scaling the TWFs

During extraction of **TWFs** from a raw video, the **TWFs** are scaled to displacement units by choosing two points ***in or close to*** the plane of the video and entering the distance between them in length units, The **TWFs** are then scaled to the chosen displacement units. When scaled into displacement units, both **TWFs** and **DFTs** can be accurately ***differentiated*** to velocity units or ***double differentiated*** to acceleration units.

ODS-FRFs

A unique frequency domain function, called an **ODS-FRF,** can be calculated from each response **TWF** extracted from a video. A set of **ODS-FRFs** calculated from the **TWFs** is typically more accurate than their **DFTs** because ***spectrum averaging*** can be used to reduce extraneous noise, and a Hanning window applied to reduce leakage in the **ODS-FRFs**.

The ***magnitude*** of an **ODS-FRF** is the value of the **APS** of the response **DOF** at a grid point. The ***phase*** of the **ODS-FRF** is the phase of the **XPS** between the response **DOF** and the **DOF** of a **reference** grid point.

ODS-FRFs carry the ***same displacement units*** as the response **TWFs** from which they are calculated. A typical **ODS-FRF** in displacement units is shown in Figure 7. Because it is a frequency domain function, an **ODS-FRF** can be ***accurately differentiated*** to ***velocity units*** by multiplying it by the frequency variable.

Vibration levels in ***velocity units*** are commonly used by vibration analysts to assess potentially harmful vibration levels in rotating equipment.

Law of the FFT

One of the laws of the **FFT** algorithm is that **Δf = 1/T**, where **Δf** is the ***frequency difference between samples*** of an **ODS-FRF**, and **T** is the ***time length*** of **TWF** data from which the **ODS-FRF** was calculated. For example, if an **ODS-FRF** is calculated from **TWF** samples that span a **15 second** period, the frequency resolution (**Δf**) of the **ODS-FRF** is **60/15 = 4 RPM**.

To increase the frequency resolution of **ODS-FRFs**, **TWF** data ***over a longer time period*** is required. Therefore, the video from which the **TWFs** are extracted must be recorded over a ***longer period*** **T**.

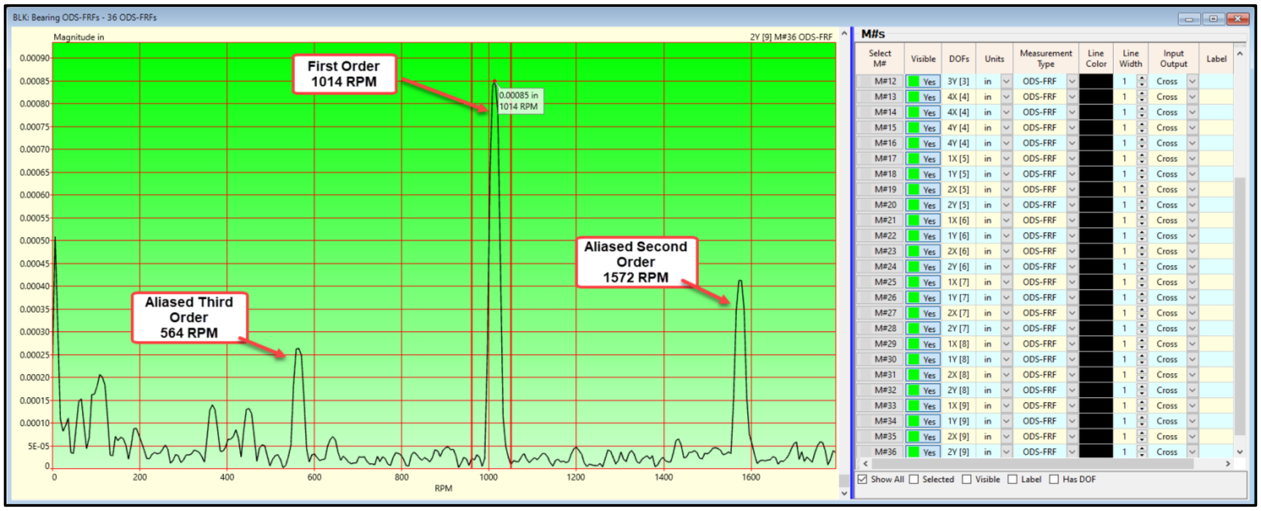

Figure 7. ***ODS-FRF*** *Showing First Three Order Peaks.*

Aliased Order Peaks

A limitation of any video recording is that ***anti-alias filtering cannot be used*** to remove high-frequency signals from the video.

Without anti-alias filtering, machine order peaks ***greater than one-half the sampling frequency***, (called **Fmax**), are ***folded around*** **Fmax** and appear at lower frequencies in the **ODS-FRFs**, as shown in Figure 7.

All order-related resonance peaks between **Fmax & 2 x Fmax** are folded around (***wrapped around***) **Fmax** and appear at a lower frequency in the frequency band **(0 to Fmax).** Aliasing of these higher frequencies to lower frequencies occurs in both **DFTs** and **ODS-FRFs**.

The **ODS-FRF** shown in Figure 7 was calculated from a **TWF** that was extracted from a video that was sampled at **60 fps**, or **3600 RPM**. Therefore, **Fmax** of the **ODS-FRF** is **1800 RPM**.

The first-order peak is at the machine running speed and is visible at **1014 RPM**. The second order resonance peak should be at **2028 RPM** and third order resonance peak should be at **3042 RPM**, but they are both ***folded around*** **1800 RPM** and are clearly visible ***at lower frequencies*** in the **ODS-FRF**.

The aliased frequency of an order with frequency between **Fmax** & **2 x Fmax** can be calculated from the expected order frequency and **Fmax**.

- **Second order** aliased frequency ➔ 1800 - (2028 - 1800) ➔ **1572 RPM**
- **Third order** aliased frequency ➔ 1800 - (3042 - 1800) ➔ **558 RPM**

The **ODS-FRF** in Figure 7 was calculated from a **TWF** with ***a 10-second time length*** **T**. Therefore, **Δf = (1/10) Hz or 60/10 = 6 RPM**. So, the third order aliased frequency peak at **558 RPM** ***is within one*** **(Δf)** of its calculated value.

Spectrum Averaging

ODS-FRFs are calculated using spectrum averaging. The advantages of spectrum averaging are listed in Figure 8.

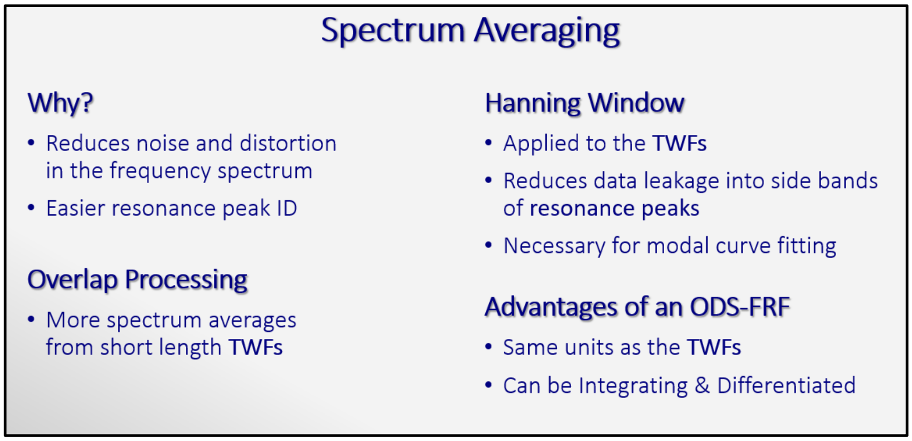

Figure 8. Spectrum Averaging

Experimental Mode Shapes

Experimental Modal Analysis (**EMA**) is used to define the resonances of a mechanical structure in terms of its modal parameters. Modal parameters are used to define each resonance, as shown in Figure 9

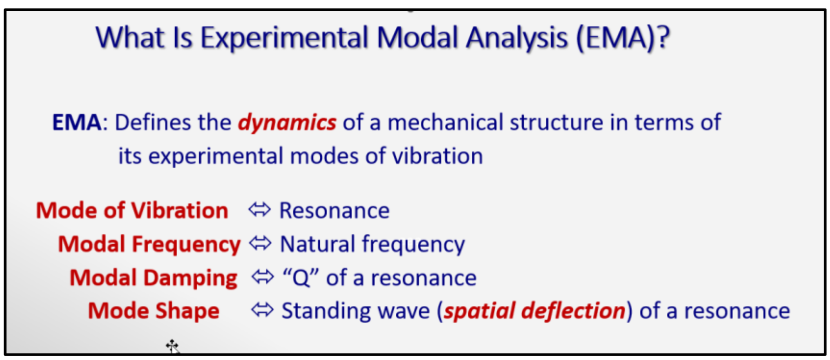

Figure 9. What is EMA?

Resonant vibration follows the rules of modal analysis, as shown in Figure 10.

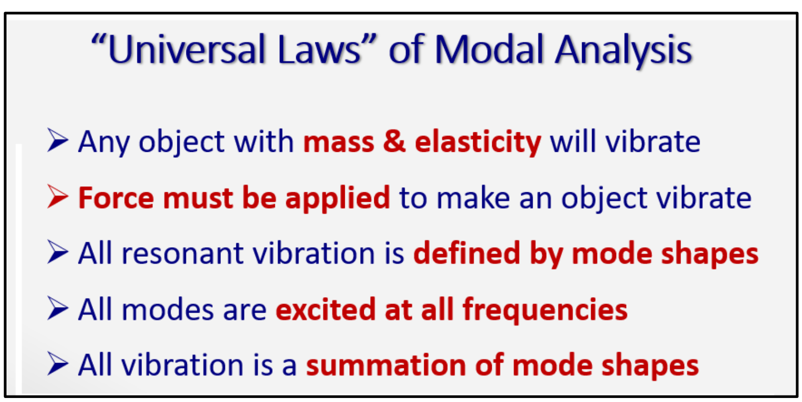

Figure 10. Laws of Modal Analysis

An **ODS** is different from a mode shape, but the two are related to one another, as shown in Figure 11. An **ODS** is the overall deflection of a mechanical structure due to applied forces, while a mode shape is the spatial deflection of a structural resonance. All FRF-based curve-fitting assumes that all **ODS** data is a ***summation of mode shapes***.

A set of **ODS-FRFs** is a set of **ODS's** defined over a span of frequencies.

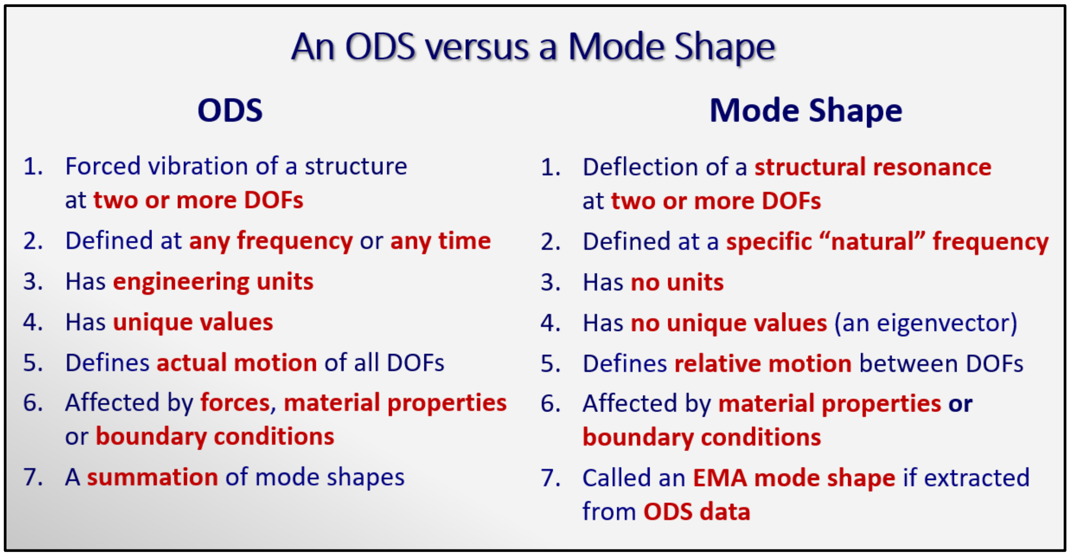

*Figure 11. **ODS** versus a Mode Shape*

Using Mode Shapes for Machine Monitoring

The steps required to use mode shapes calculated from a cell phone video for machinery monitoring are listed in Figure 12.

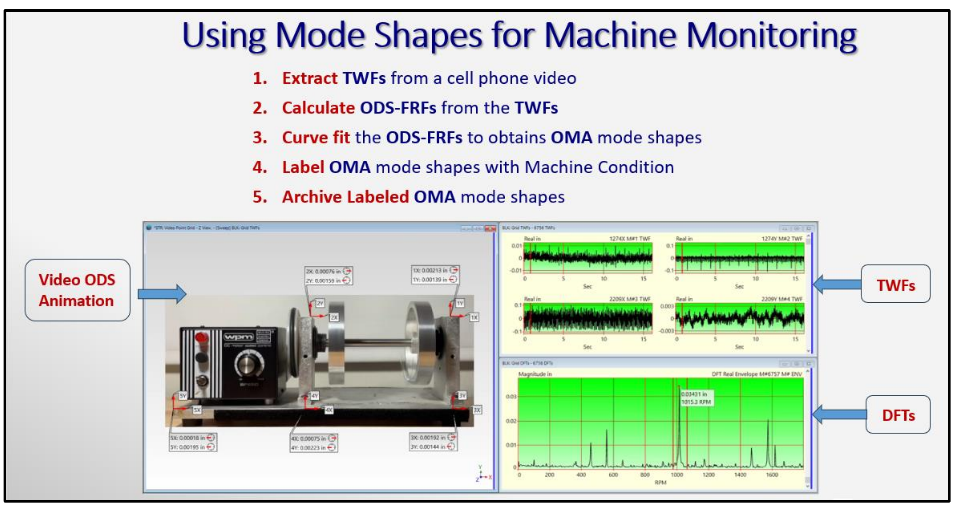

Figure 12. Steps Required to Use Mode Shapes

Curve Fitting ODS-FRFs

FRF-based curve fitting methods are commonly used on a set of **FRFs** that have been calculated from accelerometer-based **TWFs** acquired during a modal test. However, to calculate an **FRF**, the forces which cause the resonant vibration must be ***simultaneously acquired*** with the response.

When the excitation forces cannot be measured, then either Cross Spectra (**XPS's**) or **ODS-FRFs** can be calculated from the response **TWFs**, and curve fit using FRF-based curve fitting to extract **OMA** mode shapes.

FRF-Based Curve Fitting

For this paper, FRF-based curve fitting was applied to a set of **ODS-FRFs** calculated from the **TWFs** extracted from a cell phone video to obtain **OMA** mode shapes of a rotating machine. A typical FRF-based curve fit of several **ODS-FRFs** is shown in Figure 13.

Then the mode shapes were labeled with their associated machine unbalanced condition and archived into a database. Mode shapes were archived for five different unbalanced conditions on the rotating machine shown in Figure 1.

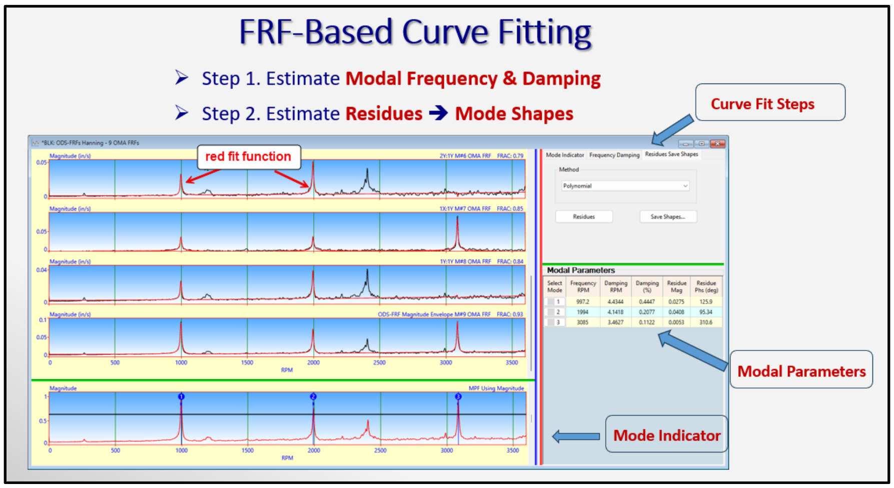

Figure 13. FRF-based Curve Fit of ODS-FRFs

Animated Mode Shape Display

After obtaining **OMA** mode shapes from a cell phone video, it is useful to animate the mode shapes on the point grid to spot errors that might have occurred from the curve fitting step.

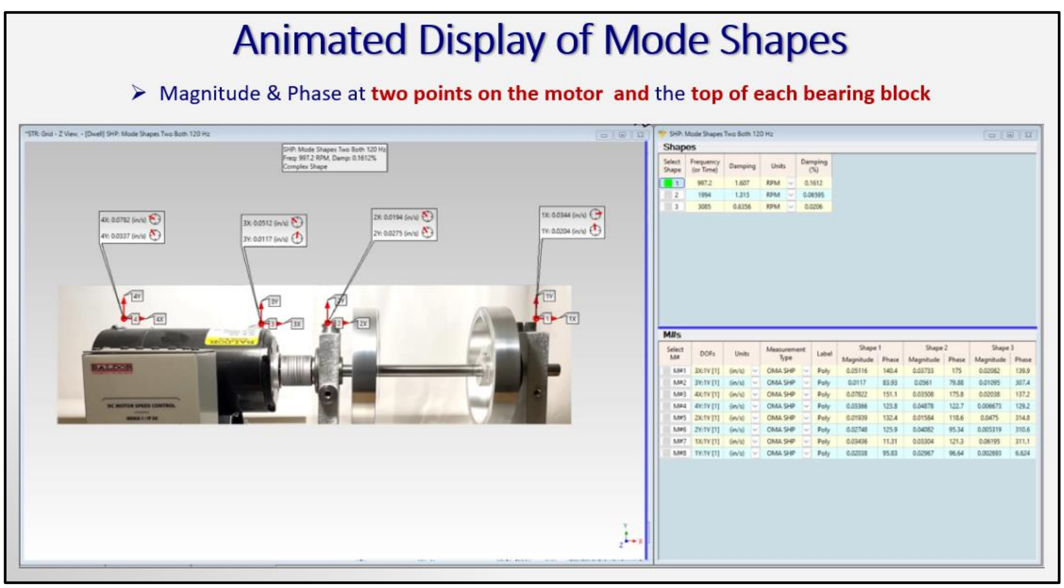

Figure 14. Mode Shape Display Showing Magnitudes & Phases

The other advantage of the mode shape animation is that the ***magnitude & phase*** of the two points on the motor and one on each bearing lock can be used to identify a particular machine fault. A typical display of ***magnitude & phase*** during mode shape animation is shown in Figure 14.

Baseline Case

When no screws were added to either rotor of the machine in Figure 1, its mode shapes were labeled as the Baseline case. When the Baseline case is archived into the database, the **FaCTs** bar chart in Figure 15 clearly identifies it by its unique **OMA** mode shapes compared to the mode shapes of other unbalanced cases. The **FaCTs** bars of the Baseline case with all the other unbalanced cases are ***much less than*** **1.0**.

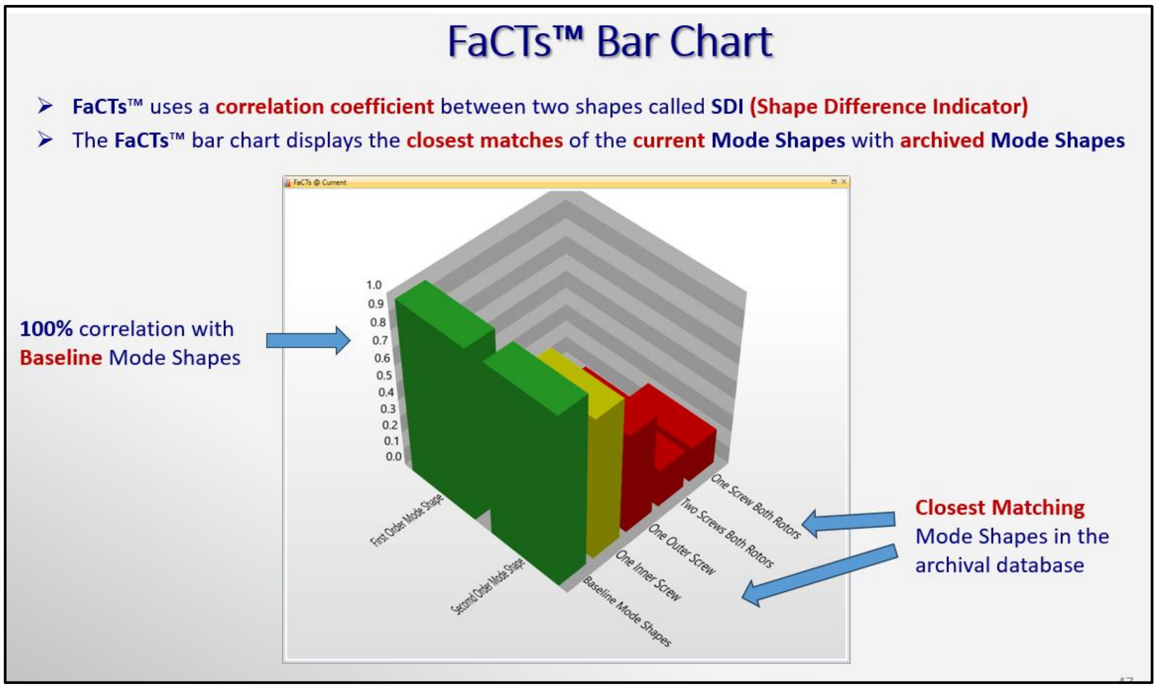

Figure 15. Baseline OMA Mode Shapes Versus Other Unbalance Cases

Cases With Unbalance Screws Added

Figures 16 and 17 show the **FaCTs** bar charts for the ***four unbalanced cases*** where screws were added to either the inner or outer rotor, or to both rotors. Each unbalance case was ***uniquely identified*** by **FaCTs** because its corresponding mode shapes were unique when compared to the mode shapes of the other unbalance cases.

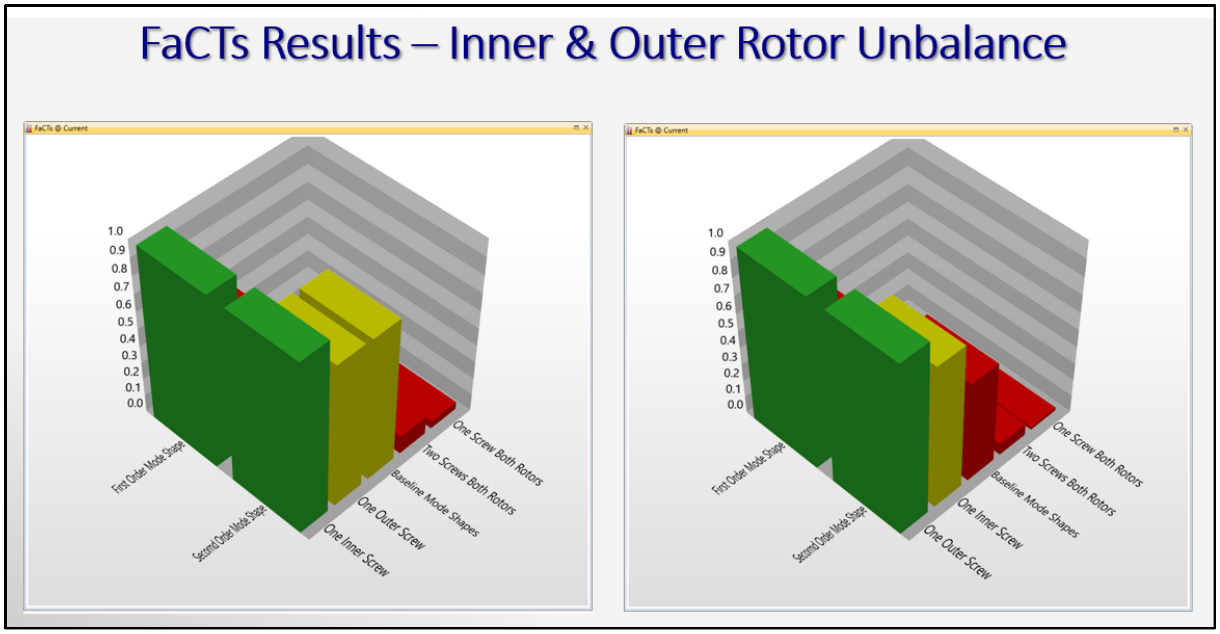

Figure 16. One Inner Screw and One Outer Screw

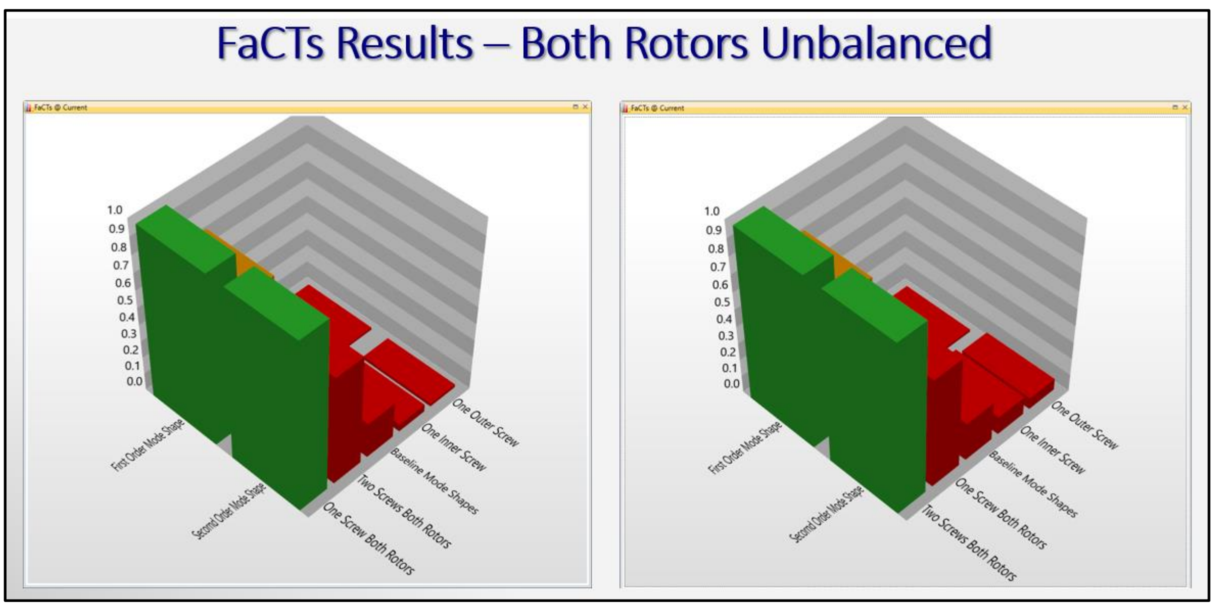

Figure 17. One Screw Both Rotors and Two Screws Both Rotors

Conclusions

Five different unbalance cases were created on a rotating machine by adding screws to its ***inner*** and ***outer*** rotors. The first case with ***no screws added*** was labeled as the **Baseline** case. In each case, a **30 second** cell phone video was recorded, with the machine running at approximately **1000 RPM**.

Using MEscope [10], **TWFs** were extracted from each cell phone video and **ODS-FRFs** were calculated from the **TWFs** for each unbalance case. To reduce noise in the **ODS-FRFs**, ***spectrum averaging*** and ***overlap processing*** were used to calculate the **ODS-FRFs**. A Hanning window was also applied to each **TWF** during the calculation of each average to enable curve fitting of the **ODS-FRFs**.

Then the **ODS-FRFs** were curve-fit using **FRF-based** curve fitting and the **OMA** mode shapes for the ***first two machine orders*** were labeled and stored in an archival database. Each set of mode shapes was labeled with its ***corresponding unbalance case***.

Then, when the mode shapes for each unbalanced case were again stored into the archival database, **FaCTs** correctly identified each case by calculating their **FaCTs** value with each ***labeled*** set of mode shapes in the database.

This numerical comparison of a ***current set*** of mode shapes with sets of ***labeled*** mode shapes in the database uniquely identified each of the unbalance cases using only ***eight mode shape components***, X & Y **DOFs** for two points on the motor and one point on the top pf each bearing block.

This simple non-contacting approach using cell phone videos and **FaCTs** could be used by any plant maintenance department for monitoring the condition of its rotating equipment and accurately identifying common machine faults such as unbalance, misalignment, soft foot and loose parts.

These results demonstrate the reliability of using mode shapes extracted from cell phone videos for machine health monitoring.

References

[1] - S. Richardson, M. Richardson "Extracting 3D Mode Shapes from a Cell Phone Video" IMAC XLII, February 10-13, 2025, Orlando, FL

[2] - B. Schwarz, S. Richardson, P. McHargue, M. Richardson "Using Modal Analysis and ODS Correlation to Identify Mechanical Faults in Rotating Machinery" IMAC XLII, January 29 - February 1, 2024, Orlando, TX

[3] - D. Ambre, B. Schwarz, S. Richardson, M. Richardson, "Using Cell Phone Videos to Diagnose Machinery Faults" IMAC XLI, Austin, TX, February 13-16, 2023

[4] - B. Schwarz, S. Richardson, M. Richardson, "Using a Cell Phone Video and ODS Correlation to Diagnose Unbalance in Rotating Machinery" IMAC XLII, January 29 - February 1, 2024, Orlando, FL

[5] - M.H. Richardson, "Is It a Mode Shape or an Operating Deflection Shape?" Sound and Vibration magazine, March 1997

[6] - B. Schwarz, M.H. Richardson, "Measurements Required for Displaying Operating Deflection Shapes" Proceedings of IMAC XXII, January 26, 2004

[7] - B. Schwarz, M.H. Richardson, "Introduction to Operating Deflection Shapes" CSI Reliability Week, Orlando, FL, October 1999

[8] - S. Richardson, J. Tyler, P. McHargue, M. Richardson "A New Measure of Shape Difference" IMAC XXXII February 3-6, 2014

[9] - S. Richardson, J. Tyler, B. Schwarz, P. McHargue, M. Richardson "Using Modal Parameters for Structural Health Monitoring" IMAC-XXXV January 30–February 2, 2017, Garden Grove, CA

[10] - MEscope™ is a trademark of Vibrant Technology, Inc. www.vibetech.com