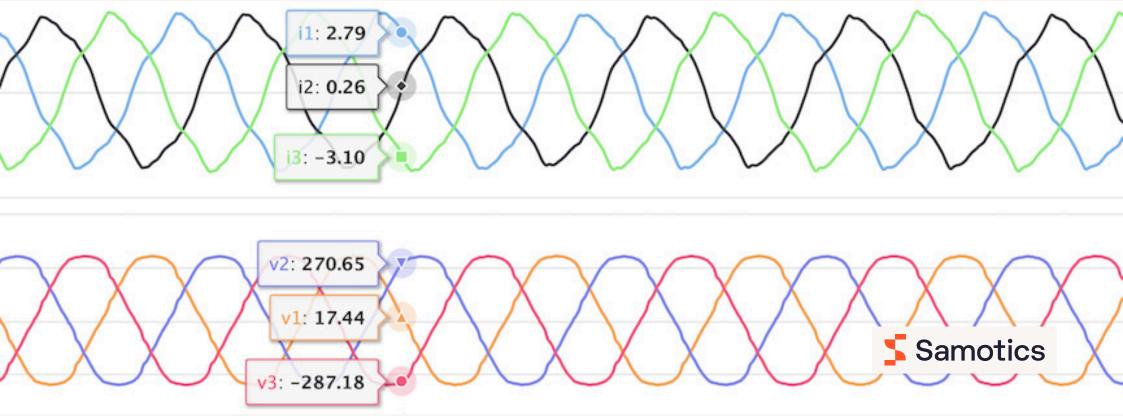
E-BOOK

Electrical signature analysis explained

Find out how the ESA condition monitoring technique uses current and voltage to detect upcoming failures at an early stage, and what makes it stand out from other technologies.





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ESA for smart industry



ESA stands for electrical signature analysis. Where other condition monitoring technologies analyze vibrations or oil or temperature, ESA analyzes current and voltage.

It's a close cousin to motor circuit analysis, or MCA. The difference is that ESA is performed while the machine is running (or "online"), while MCA is performed while the machine is deenergized ("offline").

Electrical signature analysis is based on the fact that subtle changes in a machine's operation affect the connected motor's magnetic field, which then affects the supply voltage and operating current. (For this reason, ESA works equally well on generators.) Using a variety of analytical techniques, ESA can provide a detailed picture of what's going on across the entire drive train, from motor to transmission to load.

The technique has a long track record, dating all the way back to 1985. Today, companies in diverse industries use electrical signature analysis to reduce the risk of machine failure, improve reliability and efficiency, save energy and decrease costs.

ESA can't do everything, but it can do a lot—and there are things only ESA can do. That makes it a condition monitoring technique every 21st-century company should have in its maintenance toolkit.

IT ALL BEGAN WITH MCSA

In 1985, the Oak Ridge National Laboratory (ORNL) launched a project to assess the age of motor-operated valves in nuclear power plants, at the request of the US Nuclear Regulatory Commission. One focus of this work was to extract useful information from a motor's running current, which had the advantage that it could be acquired remotely and non-intrusively. That work resulted in several motor current signature analysis (MCSA) techniques that could be used to detect damage and upcoming failure. ORNL then added in voltage and power monitoring to develop additional methods, and coined the term electrical signature analysis for the full group of resulting techniques.

How ESA works: data capture



The first step in any smart condition monitoring program is to install permanent sensors to continuously capture high-frequency data.

Vibration-based systems might stick accelerometers on the equipment to measure how it's jostling around; temperature-based systems might hang infrared cameras near the equipment to take pictures of the heat coming off it.

ESA systems are different from all these other systems in that electrical sensors do not need to be near the actual machine. ESA uses current transformers and voltage taps that install in the motor control cabinet, where they capture all three phases of the current and the voltage at a high frequency around the clock.

So, right there you have ESA's first major advantage. It doesn't matter whether your pump is submerged in wastewater or you're running 2,000-degree molten steel over your rollers; MCSA sensors are easy and safe to install, and they're shielded from operational hazards.

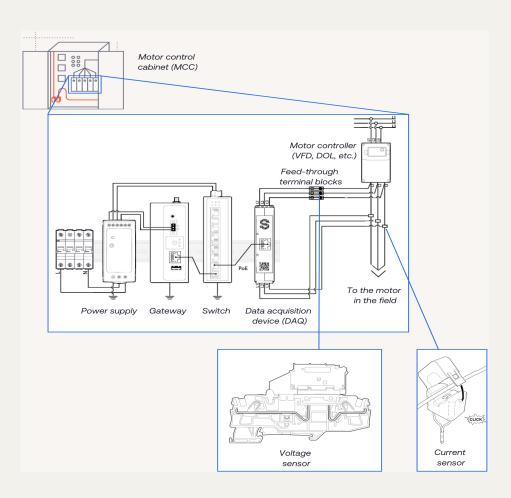


Figure 1. ESA sensors attach to the electrical wires in the motor control cabinet, protected from the hazards of the production floor.

How ESA works: data analysis



There are several ways that ESA systems use current and voltage data to provide machine insight. For example, spectral analysis maps out the strength of different frequencies in the incoming signal. Lateral and torsional analysis give you insight into the machine's back-and-forth and rotational vibrations, respectively. Power analysis reveals signal irregularities such as voltage unbalance and harmonic distortion.

Each of these categories uses several algorithms—specific recipes for processing the data. Examples include the continuous wavelet transform, the Hilbert transform and the extended Park's vector approach. Each algorithm reveals something different about the machine, and together they provide a comprehensive view. By repeatedly performing these algorithms as new data comes in, ESA can identify changes that reveal developing faults. It can also reveal system behavior that will eventually cause faults to develop, such as pump cavitation.

Electrical signature analysis also performs basic calculations on the raw current and voltage to get the RMS current and voltage, the supply frequency, the power factor, the number of machine starts and stops, the machine's running time, and so forth. These metrics are used to provide energy and performance insights. We'll talk more about these insights on pages 14–18. But first, let's take a closer look at one of ESA's most fundamental algorithms: the fast Fourier transform.

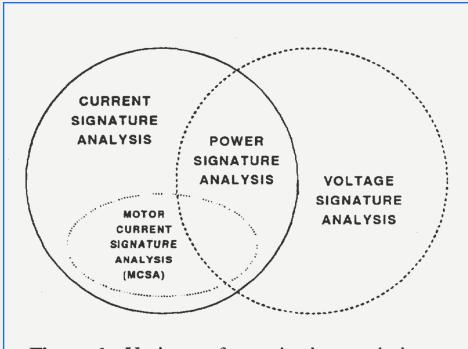


Figure 1 Variety of monitoring techniques included under the name Electrical Signature Analysis (ESA).

Figure 2. From ORNL's 1995 paper describing 10 years of work to develop electrical signature analysis.



The fast Fourier transform



The first step in spectral analysis is to convert the captured data from the time domain to the frequency domain.

This breaks down the incoming signal into its constituent frequencies. You can think of the resulting graph as the signal's frequency "signature"—the S in ESA.

The incoming data can be any space- or time-dependent signal: voltage, vibration, temperature, speech... Whatever the source, spectral analysis starts with this conversion. There are different ways to convert the data, but the most common way is called the fast Fourier transform, or FFT. It's a hugely valuable tool: the world's largest association of engineers voted it one of the top 10 algorithms of the 20th century, and it's even been called "the most important numerical algorithm of our lifetime." It's based on Joseph Fourier's 1822 discovery that if you add together enough sine waves, you can mimic pretty much any function.

The FFT tells you how much of each sine wave you need to build the signal you gave it. A longer time window means a different signal, and thus a different answer. If your sampling window is too long, you get an answer that doesn't reflect the machine's actual state at any point. You might hear the term short-time Fourier transform to describe using tiny enough windows to accurately capture machine behavior.



Figure 3. ESA uses the fast Fourier transform to convert the current and voltage samples into a frequency spectrum. In the bottom graph, the height of each point tells us how much energy that frequency contributes to the corresponding sine wave in the top graph during a short period of time.



Once you've converted enough incoming data, you can create what's called a heat map.

You may also hear the words *spectrogram* or *waterfall*. It's a way to look at all the graphs from a longer period of time, to see how things have changed.

(Obviously condition monitoring software doesn't need to look at graphs, but they're pretty darn nice for us humans.)

Like an FFT graph, a heat map plots frequency on the x-axis, but instead of energy it plots time on the y-axis. Now, if that were it, we'd just have a big black square, because every frequency is present in the current signal whenever a machine is running. We also need to see the *amount* of each frequency. For that, heat maps use color. In the heat map shown here, blue means low energy and red means high, with yellow in the middle. Thanks to this all-in-one format, with the older situation at the top and the latest situation at the bottom, you can see at a glance that something's changed in this machine.

Now let's see how ESA determines what it is that's changed, continuing with FFT-based spectral analysis as our example.

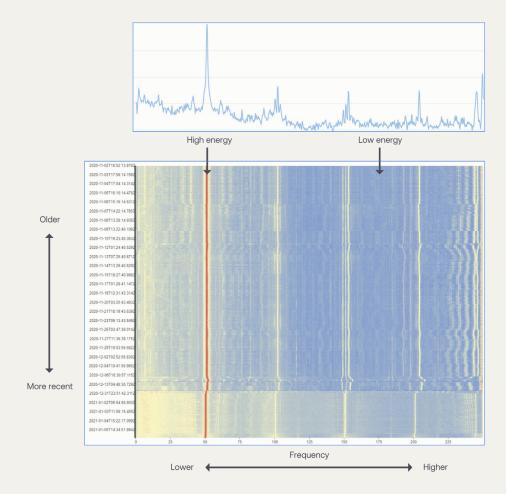


Figure 4. A heat map showing the energy at each frequency over a longer period of time. The overall rise in energy near the bottom indicates a clear change, possibly fault-related. (In this case, there was an electrical short in the VFD driving this machine.)

Model-driven analysis



In the graph below, we've drawn a particular motor's current frequency signature at two different points in time: the newer one in blue, the older one in black. You can see they don't precisely line up. That tells you that something has changed.

Now sometimes that will be a normal process change—maybe you're running the motor faster, or you're pumping a thicker fluid. But you'll also see changes when something inside the equipment changes: a bearing starts to wear out, for example, or a coupling starts to loosen, or the insulation covering the windings in the motor's stator starts to degrade.

So the first way that spectral analysis helps detect developing problems is to track these changes over time and compare them with a library of known failure mechanisms. We call these "fingerprints of failure." In the graph we're looking at here, the blue peaks at multiples of this motor's rotational frequency are the hallmark of a broken rotor bar.

(There's nothing unique going on here—this is what every condition monitoring technology does. There are identifiable fingerprints of failure for oil, heat, vibration, sound, and so on. MCSA just uses this established technique on a different source of data, with different "fingerprints.")

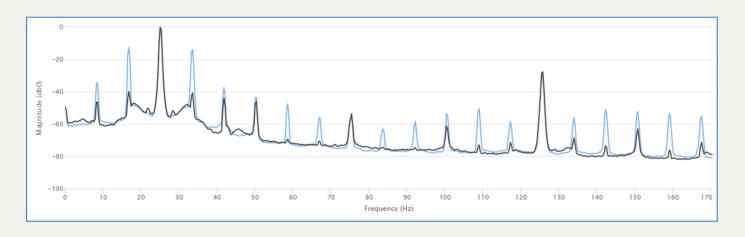
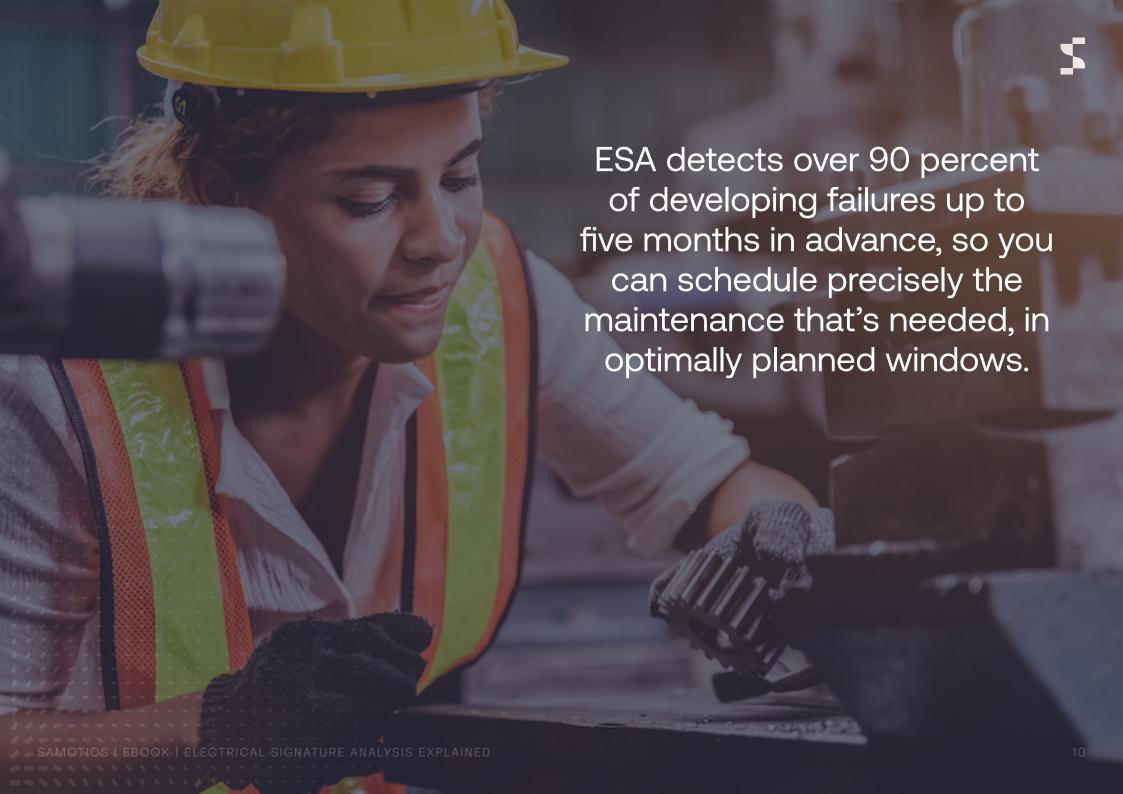


Figure 5. Comparing the spectral energy for a healthy motor (black) and that same motor with a broken rotor bar (blue).



Data-driven analysis



Here's a second machine, whose current signature in the frequency domain is quite different from the one on page 7. So part of the challenge in spectral analysis (no matter what kind of data you're using) is to identify what a "fingerprint of failure" looks like for each unique machine.

That's why a good condition monitoring system also performs data-driven analysis, and not just modelbased analysis.

"Data-driven" means the system learns what healthy behavior looks like for that specific equipment, so when changes start to happen, the system can distinguish right away between normal variation and changes that signify a problem.

This is where you absolutely have to have a system based on artificial intelligence. There's no way any human being, no matter how expert, can keep up with the volume of information this depth of analysis requires.

But machine learning algorithms havev three superpowers: first, they're at work 24/7/365, processing terabytes of data without cease. Second, they're able to detect tiny changes the human observer would miss.



Figure 6. Every motor and machine has a different healthy pattern, which the condition monitoring system must learn if it's going to detect developing faults early enough to help. Recent advances in machine learning have brought this level of detection within reach.



Third, they're constantly improving their predictions based on new data. All this means that Al-based systems consistently close in on perfection—catching all true positives and flagging no false positives—the longer they run. Al systems never have a bad day, go on vacation or forget what they've learned.

This is what makes 21st-century condition monitoring systems so scalable.

The AI software does all the heavy lifting, only alerting the system's data scientists when there's an actual fault that needs to be reviewed and communicated to the customer.

Now let's look at a specific industrial asset for some concrete examples of FFT-based analysis using electrical signals.

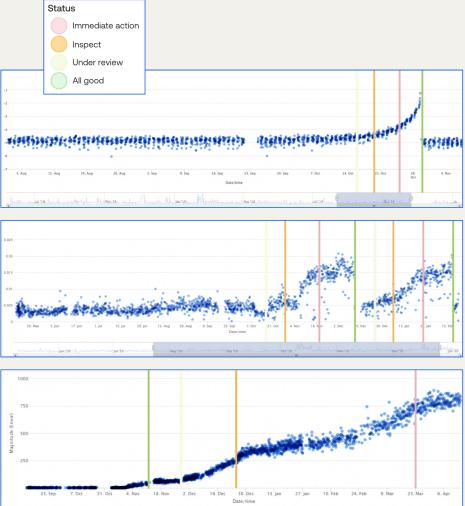


Figure 7. Three graphs tracking changes at a specific fault frequency over time, for three different situations: bearing damage, an elevator guide rail failure, and a broken rotor bar. The colored vertical lines show where the Al flagged a new status (see legend). A return to green indicates the customer resolved the problem through maintenance.

Mechanical faults



Here we see some potential failures in a specific industrial asset—a pump that's cavitating, a misaligned coupling, some damage to a bearing. These changes cause vibrations that influence the air gap between the motor's stator and rotor, causing the magnetic field disturbances we mentioned on page 3. Each disturbance has a specific effect on the current and voltage frequency signatures.

For example, when a bearing starts to degrade, the energy will start to rise at one or more of the frequencies associated with the bearing's physical dimensions: the fundamental train (or cage) frequency, the ball pass inner and outer race frequencies, and the ball spin frequency.

These "frequency fingerprints" in the current and voltage data, combined with knowledge of the machine's geometry, help ESA systems detect and localize mechanical faults throughout the drive train.

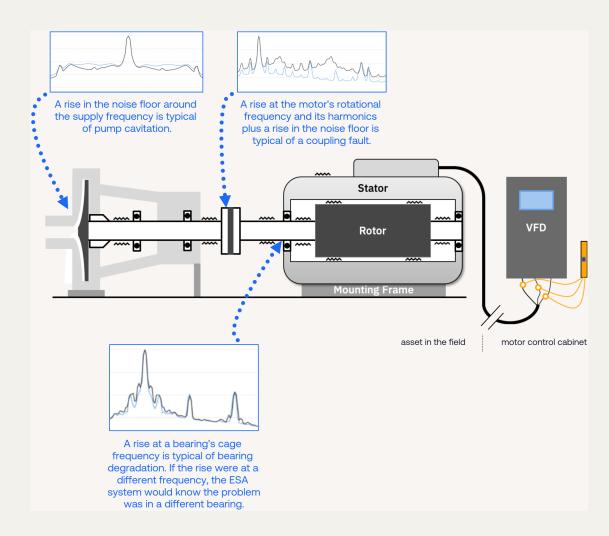


Figure 8. ESA can detect and localize mechanical faults in diverse parts of the connected asset.

Electrical faults



So far, so good: electrical signature analysis is great at detecting and localizing mechanical faults. Now what about electrical faults, which are responsible for roughly 30% of industrial motor failures?

Here's where ESA really stands out. ESA systems will detect electrical faults earlier than any other condition monitoring technology. This includes broken rotor bars, bearing currents, stator faults and power quality issues.

That's because electrical changes directly affect the motor's magnetic field. By measuring current and voltage, electrical signature analysis has direct access to the very first sign that damage is starting to occur.

Now let's look at ESA's extra features, beyond fault detection.

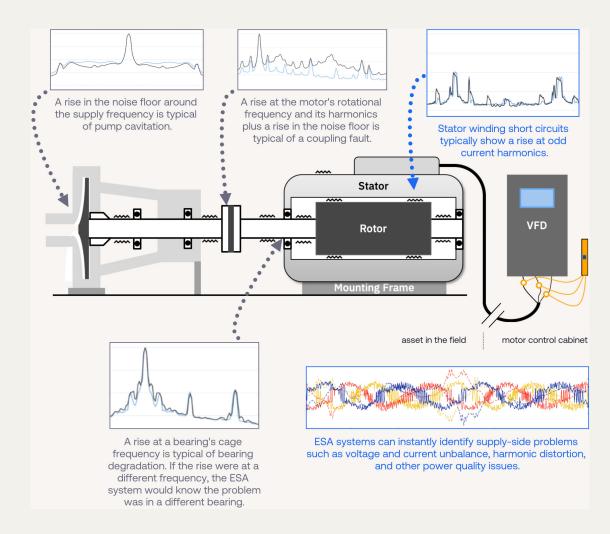
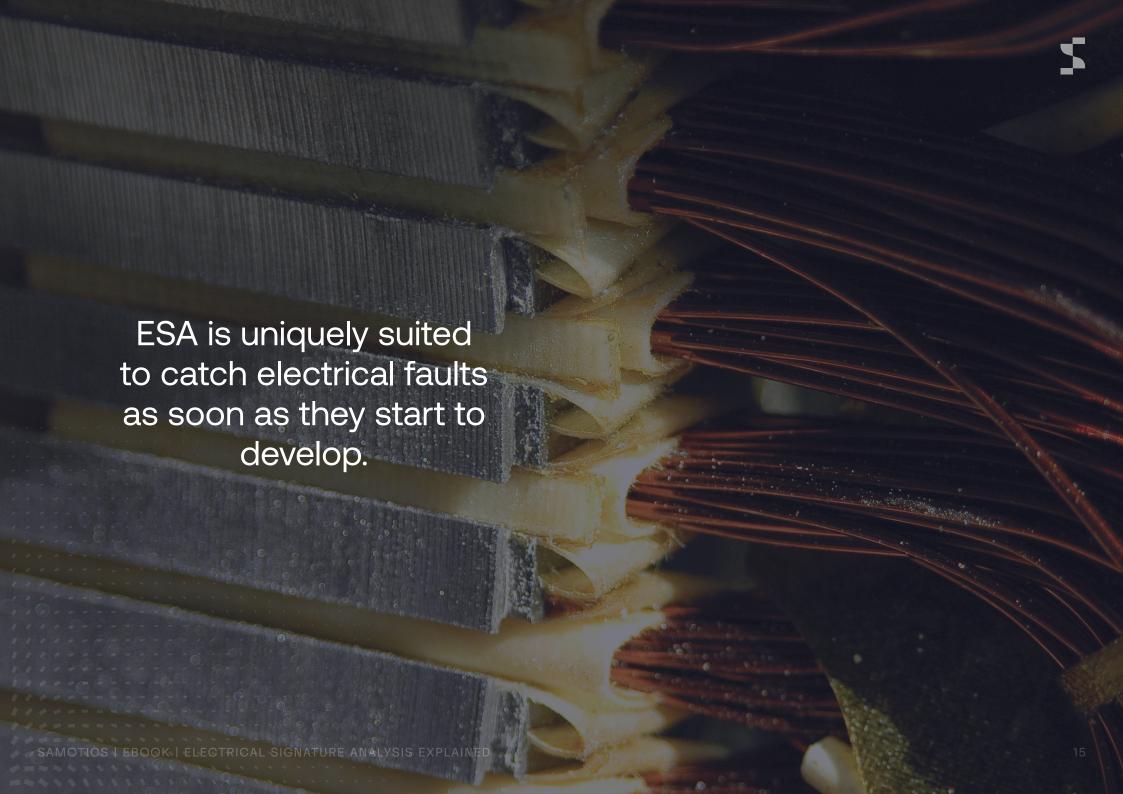


Figure 9. MCSA will detect electrical faults sooner than other techniques.



Automatic operating point classification



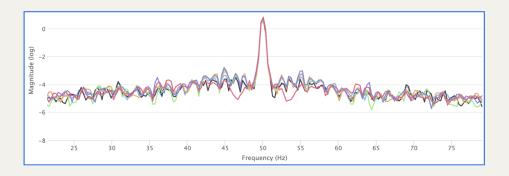
Many industrial assets run at different operating points. These changes can run the gamut from occasional and planned (a fan that runs faster when more ovens are in production) to constant and unpredictable (a wind turbine subject to changing wind speeds and directions).

Changes in load and speed distort pretty much every kind of data you can use to monitor asset health. That makes it important to know whether a change in the incoming data reflects a developing problem, or just a change in operational parameters. Most condition monitoring techniques must get this information elsewhere: from the customer's production schedule, for example, or from a separate system of devices that can track the relevant data.

With ESA, load and speed are built into the box.

ESA systems directly measure the frequency supplied to the motor—which means you automatically have the speed for every data point you collect. The measured current and voltage give you the system's active power, which tells you the relative load for each data point.

The AI software does the rest, automatically comparing each new measurement with the right set of data: the asset's history of healthy behavior for that specific combination of speed and load.



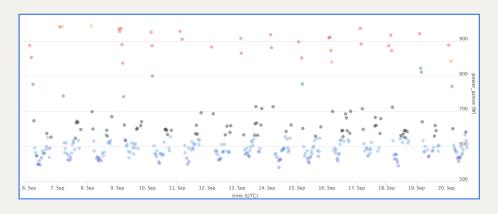


Figure 10. Each color represents this machine's frequency signature (top) at a different load (active power, bottom). Note how much the signatures vary—if we didn't know they represented different situations, we would either flag nonexistent damage (because behavior has visibly changed) or miss real damage (because our definition of "healthy behavior" is too broad). Only systems that measure current + voltage can automatically eliminate these risks.

Real-time performance & energy metrics

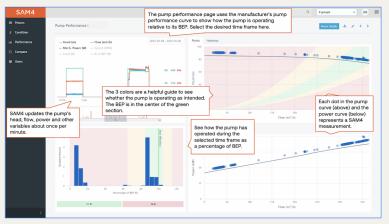


ESA systems can track a host of additional metrics* that help you raise efficiency, lower costs and shrink your company's environmental footprint.

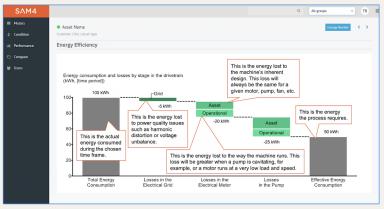
Examples:

- a real-time pump monitor to help you steer a pump back to its best efficiency point, reducing cavitation and raising bearing and seal life. Over time, the data can tell you where redesign or replacement would score major cost and efficiency gains.
- an energy monitor to track an asset's operational efficiency.
 Over time, the data can tell you where redesign or replacement would score major cost and efficiency gains. (Read more in our sustainable industry white paper.)
- a power quality monitor to identify and solve supply-side issues such as voltage unbalance and harmonic distortion.

All these metrics require current and voltage information; they can't be calculated from vibration, thermal, acoustic or oil-based data.



(a) sample real-time pump curve and performance metrics



(b) sample power quality and energy efficiency metrics

Figure 11. Only an ESA system has the necessary data to calculate extras such as quality, performance and energy efficiency metrics.

^{*} Since these metrics are extras that go beyond monitoring for developing failures, not every ESA vendor will provide them. Be sure to compare features across different systems.



Conclusion

So there's a brief peek under the hood of electrical signature analysis! We hope this explainer has given you useful insight into this condition monitoring technique and how it can strengthen your predictive maintenance strategy for critical AC motors and rotating equipment.

If you're ready to start comparing apples to apples, we'd be happy to tell you more about our ESA solution, SAM4. Just drop us a line to book a no-obligation demo at your convenience.

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