Knowing your asset

Condition based maintenance at Outokumpu Steckel Mill

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Unplanned downtime can be extremely costly for a production facility that runs 24 hours a day, seven days a week. It goes without saying then that proper maintenance has a very strong influence not only on production output but also on product quality. A clear strategy for maintenance to ensure a reliable process with high availability is therefore of the utmost importance.

The key to improved maintenance planning is knowing the "health" of each asset in real time, as well as the estimated time to failure. Getting this information in a complex system is not straightforward. Several systems that monitor the condition of a system as well as predict remaining lifetime do exist, but what has been missing in today's market is a complete solution package that can be applied to any type of asset and which is based on some kind of industrial software platform.

One such system now exits. It is the result of a close collaboration between ABB and Outokumpu Steckel Mill in Avesta, Sweden. The system provides the necessary information on asset wear as well as the residual lifetime for critical assets, such as bearings in the production line. It can predict the time-to-failure of an asset and significantly improve overall maintenance planning.

Sensing and controlling

For many years, optimization and fine-tuning in process control and automation was the norm. Because of this practice, very low margins now exist for improvement within these areas. Increased OEE[1)] has quickly become a key element for most industrial manufacturing units. As unplanned downtime is extremely costly for any production facility, the focus naturally turns to asset optimization and maintenance planning. A well functioning maintenance organization is vital when it comes to increasing Return on Investment (ROI).

> The residual lifetime calculated from the accumulated wear value is only a rough guide as to how the asset is worn on a day-to-day basis.

Condition-based maintenance is an automatic process that strives to identify incipient faults before they become critical. This in turn leads to more accurate planning of preventative maintenance. Several conditioning monitoring systems are available. They differ in that some are based on statistics from historical failures and others on first principles modeling.

For Outokumpu[2)] Steckel Mill in Avesta 1, however, these solutions did not address its need for a complete packaged online condition monitoring system that could be applied to any asset in a production facility to provide information on its status, accumulated wear and residual lifetime. This system should also significantly improve maintenance planning to avoid costly unplanned downtime or unnecessary preventative maintenance. The company teamed-up to ABB and together they developed a system that not only meets all of the above requirements, but which is also fully generic for any industrial plant.

The ABB/Outokumpu solution is based largely on ABB's Industrial^{IT} Extended Automation System 800xA[3)], which allows an efficient, seamless integration of ABB proprietary solutions and non-ABB solutions like Computerized Maintenance Management Systems (CMMS). The 800xA control platform provides the basic functionality needed for the efficient development and integration of solutions for automatic condition monitoring as a complement to the traditional process control.

The following paragraphs describe this asset optimization and condition monitoring solution in greater detail.

System overview

The overall solution consists of a suite of applications listed in Factbox. As well as including existing ABB software tools, new ones were developed to determine asset wear and lifetime. This solution suite allows: accumulated bearing wear calculation; bearing fault detection; residual lifetime estimation; anomaly detection from normal behavior; sensor diagnostics; and SMS and email messaging.

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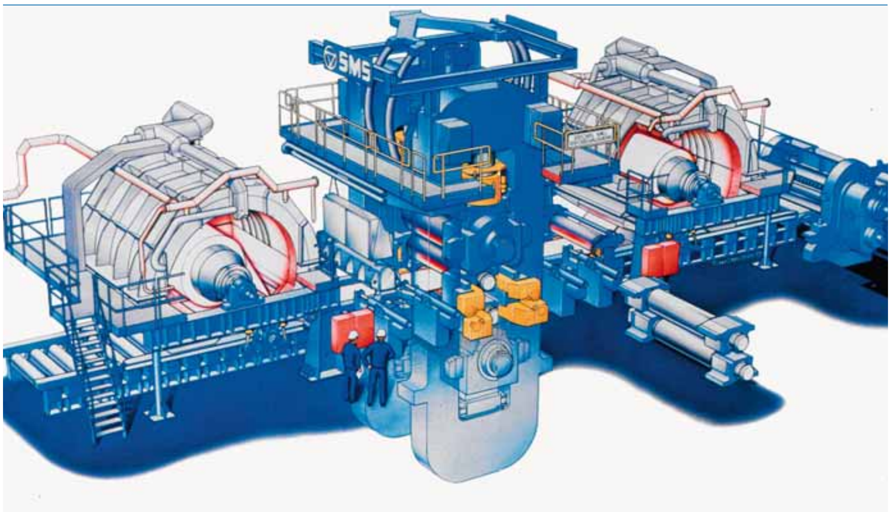
A typical asset status screenshot (a sublevel view) is shown in 2. All diagnostics are based on green (status satisfactory), yellow (warning) or red (alarm) signals, and remaining asset lifetime is given in runtime hours. If a problem occurs, the data can be viewed and analyzed by venturing into various sublevels containing more detailed information. One noteworthy feature of this system deals with accumulated wear. This is particular to parts – such as pinch rolls – that are removed for one reason or another, and replaced at different positions. A storage identification (ID) function is manually activated from the wear aspect system by the operator for each asset 3. If an old asset is installed in a new position, the previous wear will be retrieved and the calculation of wear will continue from where it stopped.

1 The Outokumpu Steckel Mill in Avesta



Factbox Outokumpu Steckel Mill installed system components

- 800xA SV 3.1
- Asset Optimizer with Asset Monitors
- Inform^{IT}
- Wear Aspect System (New)
- Condition Severity Aspect System (New)
- DriveMonitor for bearing diagnostics
- Argus CC4 for data collection
- Argus OPC Server (New)
- PCA Model Builder Tool (New)

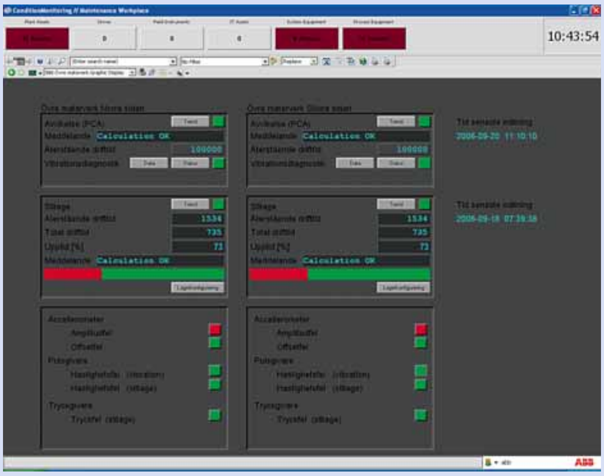
It is important to understand how the lifetime of an asset is determined. There are several different ways of doing this, but a crucial factor is the definition of failure. Failure is defined as the point at which the asset is normally replaced because of noise, vibrations or poor performance, but prior to mechanical breakdown.

Residual lifetime can be calculated if the rate of wear per run-time is known. When estimating the lifetime of a bearing with a specific load, the well established L10 theory [2] of bearing wear from SKF is used. The tricky part is to keep track of the variations in load and rotation speed and integrate the totally accumulated wear over time.

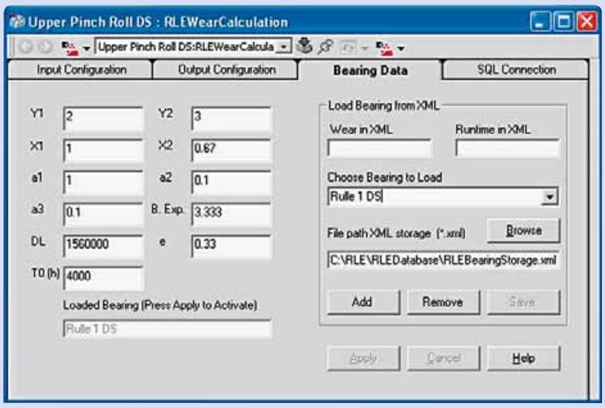
Firstly, load and rotational speed samples are continuously collected by a data logging system called Argus[4]. These data are then delivered as OPC values to ABB's System 800xA. The residual lifetime calculated from the accumulated wear value is only a rough guide as to how the asset is worn on a day-to-day basis. This is because the absolute value of the bearing wear may not be very accurate as it depends on environmental variables such as misalignment, bearing currents, cracks and looseness.

For practical reasons, the bearing wear calculation needs to be split into four intervals: prehistoric, old, new and prediction 4. The prehistoric interval is defined as the time before logging starts, and is particular to old bearings thar were in use long before the system was installed. If a new bearing is installed while the logging system is active, the prehistoric time is then zero. The old interval starts at the moment of logging right up to the second last batch, the new interval is the latest batch and finally, the prediction interval is used to estimate the future wear from moving averages of the current wear.

2 A sublevel view of the upper pinch roll with simulated bearing fault detection, anomaly detection, wear calculation and sensor monitoring



3 A screenshot showing bearing configuration and ID selection



Prehistoric wear

It is highly likely that many bearings will have been in operation for several months before the data logging system for wear calculations is implemented and this must be considered in the wear calculations. In the ABB/Outokumpu system, the time in operation prior to logging is represented by the parameter T0 in 3. Future and prehistoric wear is then estimated using averages from the old interval. The reason for this is that wear can vary significantly from batch to batch and it needs to converge towards a reasonable average rate. The averages used are: run-time per total time, wear per revolution, and revolution per runtime. As the data are collected in the old interval, the averages are continuously updated online and will converge after a few weeks[5]. The total accumulated wear is calculated as the sum of all the different intervals. The residual runtime and the residual total time can now be calculated using the converging averages from the old interval.

Anomaly detection

Sensors are the eyes and ears of process control and modern manufacturing plants are alive with them, observing every aspect of plant activity. However, faults do occur that are very rare and problems arise when these new or extremely rare faults are not spotted in time and to sufficient accuracy. This has to be considered in any new system design.

Footnotes

1) OEE – or Overall Equipment Effectivesness – is the industry accepted tool to measure and monitor production performance.

2) Outokumpu is an international stainless steel and technology company. Its headquarters are in Espoo, Finland.

3) System 800xA is an automation platform that integrates the core automation system in a plant (the process control system) with all the other applications essential to plant productivity and efficiency – such as engineering, documentation, quality control,safety, smart instrumentation, asset optimization and maintenance management. For more information, see http://www.abb.com. Select Product Guide. Under Control Systems select 800xA

4) Argus was developed by ABB Service.

5) A short stop at the beginning of production will significantly lower the runtime per total time average and effect the calculations. After a few weeks, however, this effect will not be seen.

Sensing and controlling

The preferred method of detecting deviations is to train the system using normal data. The chosen method for the modeling of normal behavior is a linear variable reduction method called Principal Component Analysis, (PCA)[6]. The PCA model tool developed within the project is generic and can be applied to any kind of process data. For the Outokumpu mill it has been applied to vibration data. As a fault evolves over time, the deviation from normal behavior – in PCA space – is seen in the residual Q of the new data projected onto the PCA model. As the Q value increases, the rate of change can be used to predict the time before a preset alarm limit is reached.

This system should also significantly improve maintenance planning to avoid costly unplanned downtime or unnecessary preventative maintenance.

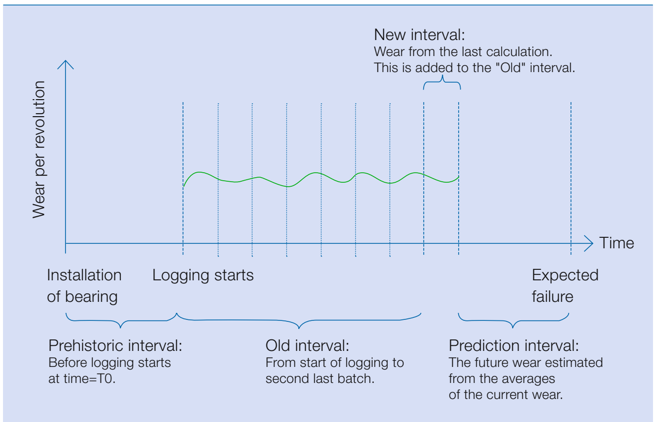
If the PCA model is applied to a new bearing with no defects, the residual lifetime will be determined as infinite. Therefore the residual lifetime calculated using the accumulated wear value is taken as the guideline. The PCA model will determine a realistic value only when a fault has been detected. When this does happen, the PCA residual lifetime value is considered more reliable because the PCA model is deemed a better estimator of fault evolution.

Asset state detection

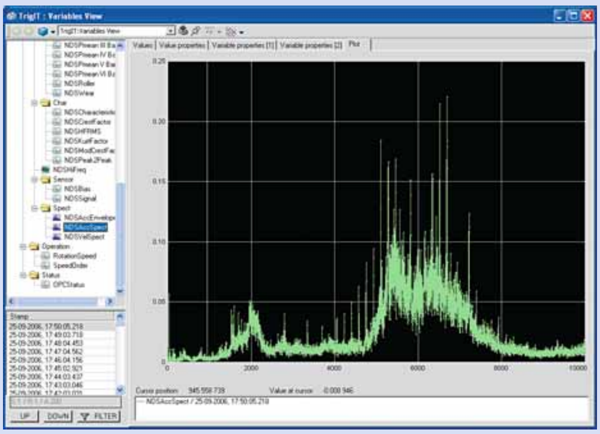
Each bearing must be configured, and the specific bearing fault frequencies are calculated using material from the manufacturer. The current and actual state of the bearings (healthy or broken) is detected by a diagnostic module called DriveMonitor[1]. The DriveMonitor solution detects outer race, inner race and roller faults online. Fault detection algorithms for other assets can also be configured using this tool. For example, to detect sensor fault in the accelerometers 5, the bias and standard deviation of the signal are calculated. Depending on the result, an alarm is issued if a preset threshold level is exceeded. Asset Monitors are applied directly to some signals outside the scope of the DriveMonitor tool (such as load and speed sensors signals used for wear calculation) to ensure that alarms are triggered if threshold levels are exceeded.

Finished roll of metal sheet.

4 The different wear intervals



5 DriveMonitor displaying an Acceleration FFT spectrum from the exhaust fan with a likely outer race bearing fault in the blade side bearing



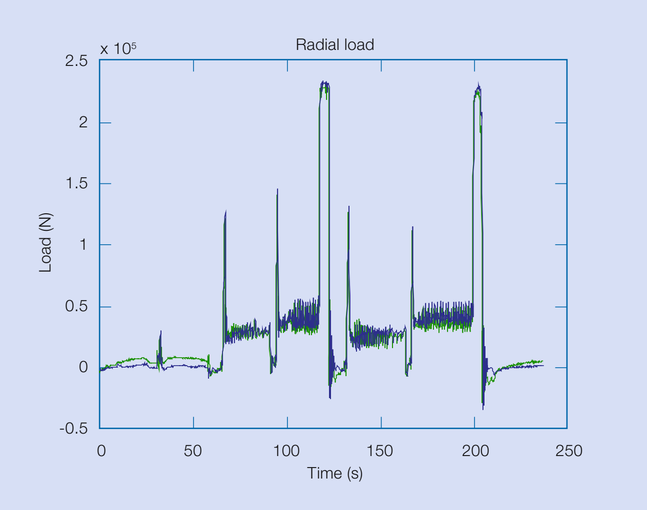
Faults do occur that are very rare and problems arise when these new or extremely rare faults are not spotted in time and to sufficient accuracy.

Experimental results

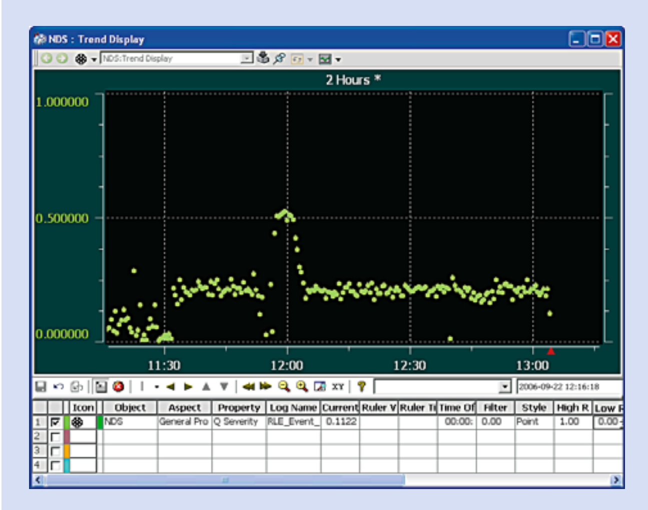
The asset optimization and condition monitoring system has been installed on the following four rolling mill assets: upper pinch roll; lower pinch roll; three-roller table; and the exhaust fan[7]. The following paragraph looks at data acquired (using the Argus PC) from the upper pinch roller bearings.

The process duration for each slab of material is normally of the order five to seven min-

6 Radial load on the upper pinch roll bearings for driving side (—— DS) and non-driving side (—— NDS).



7 A Q trend – using the PCA model tool – on the vibration data from the fan.



utes. For the slabs in this example, the bearing loads, as shown in 6, and rotational speeds were measured by the Argus unit and stored in a file. The file data were then converted to an OPC array by the Argus OPC Server. The sharp load spikes seen in 6 occur because each slab end hits the pinch roll when the side that is hooked has been released from the coiler. Engineers calculated that if these spikes were halved to 1.2×10^5N, the bearing lifetime could be extended by a factor of five! The accumulated wear calculation shows the difference in wear for different slabs. This is most likely due to the slab thickness, the time it takes to roll it, and the specific material used. The more detailed influence of different variables remains to be studied.

From the results obtained so far, it would be reasonable to extend the time between maintenance stops and have more up-time for the production. The algorithm was tested on the upper pinch roll driving side (DS). The wear per batch is significantly different, and can vary by as much as a factor of five. This linearly affects the remaining runtime. 7 shows the Q trend, using the PCA model tool, on the vibration data from the fan.

This asset optimization and conditioning monitoring system is fully generic for any industrial plant.

Everyone's a winner

Asset optimization and condition monitoring solutions are providing ABB with new and exciting business opportunities. However if the system is marketed and sold only within the rolling mill segment, the development payback time for ABB is estimated at six years. Anders Bohlin, senior project manager at Outokumpu, reckons that if the system performs to expectations the pay back time for Outokumpu could be very short.

As was previously stated, this system is extraordinary in that it is fully generic for any industrial plant, not just rolling mills. This means the true business potential will be significantly greater if the system is marketed within many other industries such as pulp and paper, petrochemicals, mining, cement, food and beverage, and pharmaceuticals.

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Footnotes

6) Principal Components Analysis (PCA) is a powerful way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. Once a pattern is found, the data can be compressed without much loss of information.

7) With driving side and non-driving side on all.

References

[1] Wnek, Maciej; Orkisz, Michal; Nowak, Jaroslaw; Legnani, Stefano; DriveMonitor: Embedded product intelligence that enhances lifecycle management and performance in drive systems; http://www.abb.com

[2] SKF product documentation "SKF spherical roller bearings – setting a new standard for performance and reliability"