AN AI TAKEOVER?

Mike Hastings, Brüel & Kjær Vibro, Denmark, outlines and evaluates the expanding role of artificial intelligence in condition monitoring.

The profitability of LNG plants, like many other process industry plants, depends heavily on how production machines are operated and maintained. For many years, condition-based maintenance, together with machine condition monitoring (CM) systems and services, has played a key role in optimising production uptime and reducing the lifecycle costs of critical machines and much of the balance-of-plant. In fact, CM has become a vital part of asset management. Over time, the technology for CM has further improved to provide even greater added value. In recent times, however, artificial intelligence (AI) and machine learning have started making inroads in the asset management domain. As analysis of big data becomes cheaper and more powerful, AI is becoming more widespread with many new applications. The question now arises, what role does AI play in CM, and could it even replace a CM system?

What exactly is machine condition monitoring?

Before we can evaluate AI and its role in a CM strategy, it is important to understand the main objective for CM and the basic CM functions that support that objective. First and foremost, the primary purpose for CM is to identify and localise potential failure modes in a machine at an early enough stage of development, such that focused maintenance can be cost-effectively scheduled ahead of

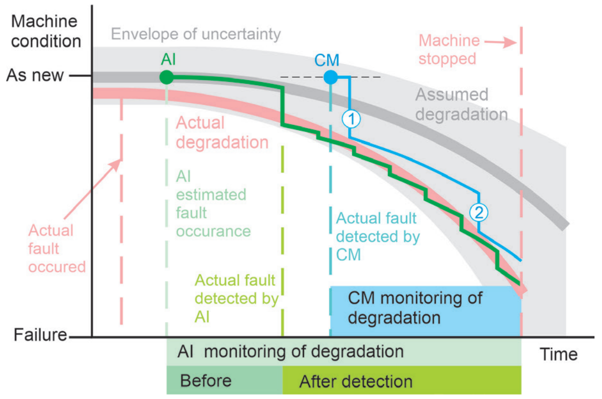

Figure 1. Comparison of artificial intelligence (AI) and condition monitoring (CM) prognosis in a potential-for-failure plot (P-F). AI estimates when degradation starts based on a statistics or physics based model, whereas CM starts only after a fault is detected. Moreover, AI more closely follows degradation because it is automated whereas CM is based on an expert's evaluation at intervals (two shown).

time, without interrupting the production capacity of the machine. To perform CM, a system is needed that consists of sensors, a signal conditioning unit, a CM server and a database. This system, which can be interconnected to other systems for sharing data and processing capability, is accessed by operators, specialists and service providers. Typical CM functions are summarised below:

- Fault detection – Sensors mounted on the machines send signals to a signal conditioning unit that are indicative of developing potential failure modes and of the machine health in general. It is this hardware/firmware unit where the signals are converted into usable information, evaluated and stored in a database on the CM server (which can be an integral part of the CM system, a data historian or other system).
- Diagnostics – Once the fault is detected, its failure mode, location and severity are determined using specialised diagnostic measurements, plots, correlation process data and trending information on a CM server. This analysis is traditionally done manually by CM specialists, but much of it can also be done automatically.
- Prognostics (CM) – By looking at the diagnostic measurements and trending results in the CM server, the lead-time to failure is determined by the specialist's experience, together with an understanding of the fault failure mechanisms. This prognostics CM function is often combined with the diagnostics function as a matter of functional similarity, but here we separate them for clarity.
- Notification – Important machine health information is conveyed to relevant personnel and other systems, so that the appropriate maintenance action can be taken to correct the situation. This is normally done automatically from the CM server.
- Conclusion – If the detected potential failure mode was unexpected or premature, root cause analysis can be done by a specialist to determine the reason for the defect and find a way to ensure it does not happen again under the same circumstances. This involves looking at the CM server data, but also looking at data in the maintenance management system. The performance of the CM system can also be evaluated and fine-tuned during this time, either automatically or by a specialist.

Which CM functions can AI enhance or replace?

AI is defined to be any system that can simulate human intelligence to perform specific 'thinking' tasks. By this definition alone, there are almost an unlimited number of tasks that can be performed by AI in asset management, but in the CM domain, AI is currently performing the following functions:

- Measurement technique optimisation – One of the inherent benefits of AI is its ability to sift through a vast quantity of CM data to identify even more reliable and earlier fault detection and diagnostic measurements. Machine learning algorithms can fine-tune these measurements.
- Automatic decision support for diagnostics – Much of the diagnostics of detected faults can be performed automatically by AI by looking at several measurements associated with a given potential failure mode at the given operating conditions. Again, diagnostic decisions can be fine-tuned through machine learning.
- Prognosis (AI) – Model-based and data-driven AI can predict the remaining useful life (RUL) of machine components with a long lead-time based on algorithms and calculations on the data.

Out of these three AI functions, the first two are dependent on CM data and directly support CM functions for fault detection and diagnostics. The third AI function, i.e. identifying the RUL, is one of the most important functions of both a CM and AI system, and may or may not depend on CM data. It is this third function, prognostics, which is the focus of this article. Both AI and CM prognostics deal with estimating the time to failure of a specific machine component or machine, although it is done in entirely different ways.

Strengths and weaknesses: CM prognosis

CM prognosis is based on using well documented fault progression mechanisms of basic components for a range of potential failure modes that have already been detected. This is accurate for many types of faults, but specialised expertise or experience is usually needed to accurately predict RUL under varying operating conditions.

Because a fault must be present to make a RUL prediction for CM, CM prognosis can be considered to have too little lead-time for long-term maintenance planning. Nevertheless, many faults such as rolling element bearings (REB) of pumps and some gear faults have a long lead-time from the point of detection, which can be a year or more before failure. This lead-time would be somewhat less for the liquid expander REB and sleeve bearings of larger machines, such as the mixed refrigerant and propane compressors and gas turbines. Other faults have very little lead-time to failure and are therefore difficult to predict based on CM prognostics. These include: thrust bearing film breakdown; gas turbine and axial compressor blade cracks; liquid ingestion in a compressor, etc. A protection system is needed to trip the machine in such cases.

The quality and reliability of fault detection depends on the proper type of sensor being used, sensor location, monitoring technique, signal processing, process conditions, alarm limits, etc. A relatively large number of sensors and measurement techniques are needed for certain fault detection applications, which can drive the cost of implementation up.

Strengths and weaknesses: AI prognosis

From an AI prognostic perspective, a fault does not have to be present to determine RUL, so this type of prognosis is more relevant for long-term maintenance planning. In principle, the health of the machine or machine component is always known, as well as its future health and RUL, and this is continuously updated as new data arrives. Moreover, some quick developing faults that may be difficult to detect with sufficient lead-time using a CM system could be predicted with greater lead-time using an AI system.

There are two primary methods for determining the RUL: model-based and data-driven.

Model-based prognostics

The model-based approach uses a physics model based on mathematical computations of degradability and failure. The model, most often finite element analysis based, can use online loading sensor data as input to estimate the current state of degradability and the predicted RUL, which is primarily based on fatigue. This means far fewer sensors are needed compared to a CM system, since fault symptoms are not intended to be detected. In many cases, a single torque meter, a pressure sensor or a strain gauge is sufficient, making such a system much simpler and less expensive compared to a CM system. However, a specialist is needed to implement the system, in order to confirm the accuracy of the results, make model changes and manage the system in general.

The physics model for calculating degradation of many different kinds of components can be very accurate when the loading is known, but it becomes more difficult to predict when the model is complicated or the loading is variable and difficult to predict. Moreover, a wide range of factors can influence the degradation calculations that may not be taken into consideration, such as: casting inclusions; machining faults; assembly error; operator error; unexpected erosion/corrosion/contamination; and unaccounted forces. If the machine component is modified or replaced with another component that has different dimensions, material or heat treating, a new model will have to be made. Lastly, machine manufacturers may not be willing to freely share models of the components they manufacture for monitoring purposes.

Data-driven prognostics

The data-driven prognostic approach uses historical data to create a model that directly correlates the data to degradation and RUL. In its simplest form, no online monitoring hardware is needed for this technique since all the historical data used in the degradation and RUL analysis can be taken from existing databases. This technique therefore runs on top of an existing DCS/SCADA and CM system to access the data, but does not replace any system. A lot of data is needed for this purpose, however, including different kinds of data such as operational parameters, loading parameters, fault symptom data, etc. It is even possible extra sensors may need to be installed. As data is acquired, the amount of degradability of the machine component and the RUL prediction is adjusted. The data-driven approach can be very accurate if there is sufficient data, the right kind of data and the algorithms are set up correctly. A specialist is needed for this.

Conclusion

As previously mentioned, AI is extremely versatile and can potentially be used in several CM related roles, but it is presently used mostly in measurement technique optimisation, diagnostics and prognosis. In time, AI could be used in other CM functions.

Without a doubt, AI is the perfect tool for working with big data and finite element analysis, which fits very well in the prognosis space. The question to answer, however, is what is needed in terms of expertise and resources to get meaningful results from AI for predicting degradation and RUL. The AI algorithms are tools that many have access to, but success in getting results from them depends heavily on expertise. In addition to ensuring the quantity and quality of the data to be used, a major part of the time in building an AI solution is spent on optimising the training set for the correct diagnoses.

AI greatly reduces the workload of CM specialists, but cannot replace them, since AI can only do as much as it is programmed and trained to do. Even as the AI solution is programmed to do more over time, some of the more difficult CM diagnoses will still continue to be done by specialists.

Can an AI solution replace a CM system? A data-driven AI solution requires data from a CM system and therefore does not replace it, but a model-driven prognostic solution, on the other hand, could conceivably replace a CM system. In practice, however, this is not likely, at least not for the time being, because the AI and CM methods have different RUL objectives. The model-driven prognostic solution is a long-term prediction of RUL for long-term spare and maintenance planning. The CM prognostic solution is focused on actual detected potential failure modes, and therefore serves short and medium-term maintenance action purposes better.

Ideally, both the AI and CM systems should be used together to take advantage of the different RUL objectives, while at the same time results of the CM system can be used for fine-tuning the AI system. Moreover, the CM system can detect faults that were not taken in consideration by the AI system. A combined AI and CM RUL solution at an LNG plant would be ideal, especially for the liquefaction process, where there are so many critical machines. Long-term cost-effective planning could be done by the AI system for these machines, which would be supported and optimised by the fault detection capability of the CM system. The CM specialist time in running such a system would be greatly reduced, while AI expertise is needed only for the implementation and fine-tuning of the AI system. **LNG**