Putting Data TO WORK

The pursuit of operational excellence of marine assets

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Advancements in the field of data science are presenting new opportunities for ship owners looking to improve fleet utilization by combining advanced analytics with lessons learned from operations. It is now possible to quantify the reliability of maritime assets, improve decision-making for fleet operations, identify emerging risks and, ultimately, improve vessel availability and scheduling flexibility.

With the use of advanced data analytics, operators can move beyond calendar-based regimes for vessel maintenance into condition-based models, where maintenance and classification schedules are driven by the current condition of equipment.

Central to this new model is the detection of 'anomalies' that help to identify the early onset of the conditions that lead to component and systems failures. Detection of these 'early warnings' can reduce operating costs and maximize the duration of assets and their components.

Today's onboard equipment has hundreds of sensors to detect features such as temperatures, pressures, etc.; combined with high-speed connectivity, these allow large quantities of data to be continuously generated and assessed. All this will have an impact on designs as advanced data analysis provides asset owners unprecedented visibility into the causes of failure.

In this new data-enabled world, where calendar-based maintenance models will be found wanting, demand will grow for Condition-based models (CBM). It is simply the next logical step as fleet strategies evolve.

Detection & Interpretation

The aim of anomaly detection is to pinpoint unusual patterns of behavior. If abnormal conditions are identified, further analyses can confirm findings such as equipment damage, changes in operating conditions and modes, or simply a degraded sensor or other issues related to data quality.

Data from the equipment is fed to an anomaly-detection "engine," which includes the definition of a "normal" pattern. "Normal" conditions are "learned" from the data by simultaneously analyzing the correlations and relations between multiple variables or single parameters, and their various states under multiple operating conditions.

The next step is choosing a technique to detect anomalies. Most methods fall into two categories: Supervised or Unsupervised.

Unsupervised methods find patterns in data by identifying commonalities among sub-groups of the data that are unlabeled; Supervised methods usually require labeled historical data in which past anomalies are identified and categorized into root causes under specific operating conditions.

To identify anomalies in operational data, single- and multi-variable approaches are used. For complex equipment such as engines, using a multivariate method is more robust, as it accounts for different operating modes, and the interaction

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between parameters.

A model for the "normal" state must be constructed, as well as a measure for the "distance" to normal. Therefore, most methods calculate an "outlier" score to estimate a data point from which a "normal" determination is made.

The methods used to detect anomalies can include: **Model-based**: if a data point does not fit a field of known data, it is considered abnormal. Models that summarize data are employed to detect anomalies.

Density-based: methods that find natural 'clusters' of related data also detect data points, which are not part of known clusters. Regions in the data space, with sparse density surrounding them, often point to potential anomalies.

Distance-based: various techniques to determine the distance between two data points or sets have been used to develop methods for detecting anomalies.

There are several important lessons to be learned in developing anomaly-detection processes, broadly related to the availability of data from the sensors; the design of algorithms for anomaly detection; and consumption of the output from the process.

Sensor Variation: the units of measurement and location of installation of sensors on the components usually vary across the fleet. Corrections accounting for this must be deployed.

False Positive /Negative Errors: this bears directly on the assumed risks from missed anomaly alerts (false negatives), or the effort to interpret and respond to all alerts (false alarms). The methods must be optimized based on the acceptable levels of risk.

Selecting the Parameters: in a typical operational marine asset, there could be several thousand parameters being measured. Deciding which parameters to include for anomaly-detection processing for specific equipment poses a challenge. This can be addressed using the historical knowledge of the equipment's design and operations.

Algorithm Deployment: deploying anomaly-detection algorithms at a central location helps to gain insights from across the fleet. However, deploying at the edge can provide earlier threshold-based alerts to onboard personnel.

Anomaly Consumption: a deliberate process to consume the output of the algorithms must be developed. These processes include: characterizing actual alerts vs. sensor issues; the feedback cycle from on-board personnel; and the operating procedures to respond to specific alerts for effective anomaly detection.

Advances in data science are already helping owners and operators to improve their maintenance practices. They hold many of the keys to speeding the transition from calendar-based to more condition-based models for maintenance strategies. Fundamental to this transition is the process and role of using data to help detect the anomalies. To improve on-the-ground benefits of the science, more work needs to be done to discover the inter-connectivity of advanced data-driven methods, data acquisition and the connectivity with business operations.

After that, the next step will be to explore the relationship between data-driven methods and 'soft' factors such as the human element, and their impact on the overall success of the condition-based process.

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