Digital - Benefits for Naval Platforms

Author: D R Chaderton BEng (Hons), MIET

Biography: David Chaderton is an Application Engineer at GE Power Conversion, in the Marine business segment. He leads technical sales for Power and Propulsion Conversions, Modernisations and Upgrades. Previously, David worked as a Principal Officer for the Local Government. Before this he served in the Royal Engineers. He graduated with honours from Derby University with a Degree in Electrical and Electronic Engineering.

Affiliation: GE Energy Power Conversion UK Ltd, Rugby, England.

SYNOPSIS

Royal Navy engineers are faced with the demanding responsibility of maintaining critical equipment to have high levels of reliability, availability, and performance under tight budget constraints. To avoid operating surprises, accurate assessment of equipment operating performance is needed to judge whether mission demands can be satisfied while maintenance costs are controlled.

Large volumes of data about the health of complex system elements are generally available, and the amount of data is growing steadily. However, pulling together large amounts of current data from diverse sources across a system or an enterprise to create actionable intelligence is a challenge to the organization, from the plant engineer to the chief information officer.

The foregoing requirements need to be carefully considered for effective naval asset performance management (APM). This paper considers the use of digital systems on naval platforms for APM to create a purposeful, predictive-analytic solution. It examines both the technology and engineering challenges and demonstrates how data analytics techniques are being used with successful outcomes.

One solution is to use Similarity-Based Modelling (SBM) within an APM system as the technology foundation for development of predictive-analytic solutions to a broad spectrum of real-time modelling needs. Such a development, outlined in this paper, has focused on providing a platform-wide, equipment-agnostic industrial solution that can meet the needs of challenging naval applications and proven commercially in the energy and marine industries.

The paper also considers, from a naval OEM perspective, the Maritime Support and the Exploitation Strategy which enables, equips and empowers the Support Enterprise through Digital Transformation.

1. Introduction

Maintaining critical equipment to ensure high levels of reliability, availability, and performance is a primary focus of Royal Navy engineers on every type of naval platform in service today. Without their attention, equipment failure might be extensive.

Attention includes frequent, accurate assessment of equipment operating performance to judge whether equipment meets operational demands and minimizes operational risks of unacceptable schedule interruptions or maintenance costs. On a typical platform, making this assessment involves the collection and effective analysis of reams of data about the health of complex equipment-system elements, like compressors, turbines, pumps, motors and fans.

The amount of data every engineer needs to analyse effectively is growing steadily. Challenging naval economics frequently command increasing and varied operational demands on ever-aging critical assets. At the same time, government budgets are stretched and changing priority, experienced people are retiring, and new staff needs experience and training to maintain asset health efficiently.

Equipment health and performance data comes from periodic and real-time systems, i.e. automation systems. Methods for taking periodic measurements and analysing equipment elements include handheld vibration-spectra analysers, oil analysis and thermography, and borescope inspection. Such solutions provide a great deal of data about important equipment elements prone to functional failure, but can be time-consuming to translate data to meaningful analytics and are intermittent by nature.

 http://doi.org/10.24868/issn.2515-818X.2018.059

To understand major equipment health, such as all key power and propulsion systems on a naval platform, naval engineers can turn to a near real-time, model-based data solution(s). A near real-time system can create *actionable* intelligence from large amounts and diverse sources of data on key, automated pieces of equipment. Such solutions can detect problems automatically, can provide the basis for diagnosis and prioritise effectively to give alerts and advisory information, and can make periodic inspection methods much more efficient.

The technology already exists to facilitate the prediction of when assets will fail or degrade, thus allowing Royal Navy engineers to target maintenance and control costs more effectively. Health monitoring is frequently referred to as equipment condition monitoring or asset performance management (APM).

2. Selection factors critical to success

The choices made in selection of new software tools and solutions can improve naval platform performance, and therefore mission success. These choices require solid understanding of the problems to be solved and the advantages and trade-offs of potential solutions.

Equipment monitoring tools may be employed in complex and hectic environments; others are deployed from on-shore monitoring centres tasked, concentrating resources to support equipment remotely. Wherever equipment is monitored, selection of the appropriate software tool is important to the success of a naval platform's operations and maintenance.

To design and select the best predictive-analytic *solution*, different *technology, system and performance* factors need to be considered:

- Core algorithm accuracy and robustness
- Core algorithm execution speed
- Simplicity of model design
- Simplicity/ speed of model training
- Simplicity of model results

Condition monitoring and analysis tools need to be aligned and embedded within established *engineering and operating processes* if they are to succeed. Beyond the software, the engineering function should also carefully consider elements that determine whether a solution will fit into naval operational practice and, thus, provide practical results for the navy enterprise, for example:

- Ease of use/ training requirements
- Visualisation to enable decision-making
- Ease of maintenance/ skill-set requirements
- Flexibility across the equipment scope
- Adaptability across the organisational scope
- Ability to grow with organisational vision

Any potential solution for improving power and propulsion performance (or indeed other vessel platform systems) that does not consider both the technology and operational elements together can result in a poor return on investment (ROI) and a lost opportunity to reach the required higher levels of performance at a reasonable cost.

This paper will look at both technology (performance challenge) and engineering (solution fit) challenges in more detail.

3. Technology elements

Here is a brief review of the technology challenges:

- Core algorithm accuracy and robustness is a fundamental requirement for analysing complex equipment and systems. The goal is to provide a highly sensitive ability to detect impending problems at their earliest manifestations in the data. Complex equipment, like compressors, turbines, rotating machines, and fans, presents wide variation in operational condition and in the amount of real-time instrumentation to indicate operating state, performance, and health. The operating environment may strain the instruments' ability to provide high quality data. Any modelling algorithm must, therefore, provide sufficient detection to give early warning of equipment problems despite operational variation, even if some fraction (as much as 25%) of the instruments drift or fail.

- Core algorithm execution speed is required for analysing complex systems at high sample rates or when many assets are monitored, such as in monitoring and diagnostics centres or in decision-support centres.

  In these environments, instrument counts can be in the tens of thousands, with sample rates as frequently as five minutes. Fast execution speeds use models as simplified representations of systems and are characteristic of all the empirical methods at some scale. But the chosen method must be fast enough both to accommodate the existing scale of monitoring requirements, as well as those anticipated in the future. Slower methods are useful for post-mortem analysis.

- Relative simplicity of model design is a critical consideration for engineers integrating monitoring and analytics into their processes. This ensures that interpretation of analytical results does not require knowledge that is limited to industry specialists. Models can be designed around ideas about how particular failure modes can be detected and diagnosed.

- Simplicity and speed of model training comes into importance during initial model build and implementation, during model retraining following major maintenance, and during model rebuilding or re-baselining after equipment overhauls. Identifying the data for an empirical model that best represents full operating range variation must be an intuitive, streamlined process if the methodology is going to fit into an already complex, busy process of operating a power system or even vessel/ combat control system.

  The training process may be automated to a large extent; the resultant quality should be validated easily.

- Simplicity of model output means that a naval engineer can use the model results directly to reduce the complexity of lots of data for the system and quickly diagnose and prioritize problems, without having to consult experts or original equipment manufacturers (OEMs) in statistical (or other methods) to gain the proper level of understanding.

  The solution requires the ability not only to detect problems early, but to provide a platform for rapid, certain convergence to the right diagnosis and prognosis.

4. Engineering elements

Solution development with which the author is familiar has focused on providing and improving the solution requirements for application in marine industries. Application in naval environments requires demonstration of cost-effective value from the single-asset level to a level inclusive of fleets of complex assets originating from different companies. In these industries, benefits to users include improved understanding of asset readiness, improved maintenance costs, and improved resource utilisation – all leading to improved business or operating performance in highly competitive industries.

The potential solution must be able to drop into a Common Support Model within an enterprise without unconstructive or undue amounts of adjustment and transformation. Failure to pay attention to such an important consideration can result in failure of the new ambition.

- Ease of use is a factor that must be considered. Ease of use can include many important considerations, including some of those mentioned above as 'technology elements'. It certainly includes ease of training.

  A solution must enable naval engineers to derive diagnostics and prognostics themselves from the diverse and complex data streams provided from the near real-time evidence of an APM solution. A key step in the detection of a problem is to ensure the return to normal operating service. The logic of analytical results from near real-time monitoring should augment the roles that the naval engineer already knows and should not require specialised statistical or software knowledge or training. This means that the enterprise adjustment doesn't eliminate the ability to utilise the solution.

- Visualization and communication of model results is another critical element of the successful methodology applied to complex systems. Visual representation can carry a lot of information for quick and simplified situational awareness. Visual dashboards should be easily understood and intuitively communicated. They could be accessed through a shared data environment across an enterprise for a 'single version of truth', and a fleet-level view.

A clear representation of all the data being modelled means that analysis and diagnostics can be accomplished more easily than if the representation is buried in analytical details that have to be massaged out of statistics and then represented in an unfamiliar format or even misinterpreted. The key point is that better situational awareness leads to enhanced and more timely decision making.

- Ease of maintenance is critical to the long-term success of any modelling solution. Maintenance will have to be done to every piece of vessel equipment at some time; when it is done, the analytical model for that piece of equipment may also need maintenance. Software maintenance is normally required for one of the following reasons:

    - To adapt models for new behaviour (automatic and manual methods)
    - To account for sensor availability
    - To modify and create new alerts or alarms
    - To make changes to the model design.

  A model that is quick and simple to adapt or retrain has an obvious advantage. The skill-set requirements for maintaining models needs to be in the range possessed by a mid-ranked naval engineer. Model maintenance should not require specialized statistical or software knowledge or training. Yet, powerful modelling capabilities will not be maintained by trivial software capabilities, so model maintenance typically will involve either a central monitoring centre or a subscription service with the software vendor, who will provide expert support. In either case, interaction with industry and OEMs having the proper subject-matter expertise is critical to proper maintenance and rectification.

- Flexibility across the equipment scope ensures both ease of implementation and that the number of monitoring solutions is kept to a minimum. A key problem the APM solution needs to solve is the complexity of many *diverse* operating data streams (e.g. on different pieces of equipment) into a simplified situational awareness and understanding of current system health.

  An effective model is required, for example a mix of temperature, pressure, load, vibration, flow, valve position, and other sensors across the broad range of operating conditions that represent normal operation. Monitored equipment is liable to range from the very old to the very new. To note, at times one or more of the signals providing operating-condition data may fail or be failing. The modelling solution chosen must be able to cope with these scenarios to allow effectiveness. So, this scenario must be easily addressed and be implementable across a single platform or a class.

  A single solution that can do this provides a better ROI than if multiple solutions need to be employed to cover the full scope of important assets.

- Adaptability across the enterprise is an issue for government and naval authorities, especially within typical power and marine industries. As an example, in the power industry, a generating company may have coal-fired, gas-fired, nuclear, hydro, and wind generation capabilities. In the marine industry, the equipment base may include power, propulsion, distribution and operating-process assets.

  In these cases, some centralisation of APM is likely to be used as a method to drive business transformation, business integration, standardization, and collaboration. Business transformation frequently looks to digital technology to enable more efficient use of skilled personnel and to facilitate best practice, given that some monitored platforms may be very remote and leanly staffed.

  So, it is critical that any solution for monitoring can integrate, at different vendor or lifecycle stages, different operating conditions, and different operational cultures. It also should help the enterprise leverage its existing tools used for periodic monitoring.

- Ability to grow with the enterprise vision is one of the last and often-ignored criteria for selecting the right APM solution. It is tempting to limit immediate costs when selecting a solution. But, given the complexity of the performance and engineering requirements discussed here, and given that the lifetime of the asset base is in the tens of years, the real opportunity to drive success from the asset level across the broad scope of the organization is to select a solution that facilitates the continuous need to produce higher performance and efficiency over years.

  Considered from this perspective, the chosen solution needs to be selected based on not only the cost and level of technology, but also based on the people and processes that can be brought to bear by the enterprise to solve the problems. A strong product development vision and a history of past execution are good indicators of an ability to facilitate the vision.

 http://doi.org/10.24868/issn.2515-818X.2018.059

5. APM predictive analytics

5.1. Modelling predictivity

Naval engineers on ship or in a command centre can use models as simplified representations of systems on which to base their understanding and make predictions of equipment health and performance. System engineers have considered a broad range of types of models.

A first principles model is great for understanding the basic physics or thermodynamics of a system and is fast in execution speed, but may quickly be found to be inadequate when the complexity of the system rises or when the quality of the data is poor. Such as in the case of a failed sensor. Even in the case of modelling a simple trajectory, it is found that inability to account for all important variables may lead to prediction errors.

Most useful among modern condition-monitoring methods are empirical regression methods. The empirical methods use historical measurement data for a set of variables known to represent the "inputs" and "outputs" of a system. Parametric methods make some assumptions about the probability distribution from which a data sample is taken – in contrast to non-parametric methods which do not. The non-parametric model structure is not specified by a functional form but is determined only by empirical data. Non-parametric methods make few assumptions about the application in question to allow versatility.

5.2. Data validation

A data collection area on a platform/ ship must be segregated. It is recommended the area data is stored in a demilitarized zone (DMZ). This is defined as a physical or logical subnetwork that contains and exposes the internal and external-facing services. As an example, the internal services would be a platform's automation system. The external would be to allow the access to send data ashore, for example via a satellite communication provider.

Having data sent to, stored and retrieved form a DMZ area has many benefits. A DMZ area is protected with hardware and software, for example physical firewalls and programmed.

The key security features of a DMZ area protecting data through:

System hardening

- Only minimally required services and ports are enabled to reduce the attack surface.
- A limited operating system shell restricts user functionality, however it enables a safe area to rectify fault and to introduce product/ patch enhancements.

Host and ICS security

- Separate multiple firewalls create a secure DMZ (de-militarised zone) between an operator's LAN and control network. Visor is explicitly denied write access to operator control systems.

Network/ app security

- Multiple security evaluations (i.e. SCA, black box testing) performed prior to each release.

5.3. Similarity-based modelling advantages

Empirical methods on which commercial condition-monitoring software applications have been developed include parametric methods such as Neural Networks and nonparametric methods such as Principle Components Analysis, Clustering, and Similarity- Based Modelling (SBM).

OEMs carefully considered the foregoing requirements for a good modelling solution and chose SBM in the marine environment. Other analytical methods have failed to satisfy the key technology and engineering requirements outlined above. Validation of this conclusion may be inherent in the fact that no other analytic method has been applied effectively to APM on such a broad scale as has SBM today.

Similarity-Based Modelling (SBM) is a form of non-parametric regression. SBM was built as a predictive modelling solution for actioning data from diverse automation data sources to capture equipment information, for example on compressors, turbines, motors, and fans brought together in today's complex production systems.

SBM models are quickly built from an asset's historical data, with a structure that mimics a natural engineering design.

This produces a result that is quickly and efficiently implemented, from a single asset to the largest corporate scope. Using a sample of the data collected from a complex system, such as a compressor, a set of "normal" operating conditions can be defined that can be used to reconstruct normal operational behaviour in near real time, and exclude or flag abnormal behaviour.

The SBM model provides the essential fidelity on equipment and within system, and it has the advantage of:

(A) utilizing simple selection guidelines for reference data and
(B) requiring no model parameterization.

Analytic computation can be done very quickly, so predictive analytics can be applied as effectively to an entire enterprise as to a single asset on a platform. Model design can follow familiar engineering principles. This facilitates interpretation of results and post-processing operations, like application of diagnostic logic.

Some of the practical technology benefits of SBM that are not likely to be found in other methods used for equipment monitoring include:

- Fast and easy set-up and execution
  - Few model-design decisions required
  - Models based on engineering logic, not arcane statistical concepts
  - Simple guidelines for reference-data selection
  - Computationally expensive modelling processes done off-line and stored
- A clear estimate of normal behaviour
  - Works for all equipment, all operating modes
  - Easy-to-interpret results
  - Supports automated diagnostics
- Very robust to typical data problems
  - Bad data does not disrupt model
  - Very tolerant of multiple sensor losses

5.4. SBM in predictive analytics

Similarity-Based Modelling (SBM) is a kernel-based, pattern reconstruction technique that uses multi-dimensional interpolation that is designed to exactly fit training data. SBM produces very stable estimates by using a non-linear and non-parametric kernel (similarity operator) to compare new measurements to a set of reference states – without making requirements on the smoothness and statistical distribution of the data.

The SBM approach measures the input vector's closeness (similarity) to the observation vectors (states) in the matrix to generate the estimate for that input vector. This has the effect of deriving a current value estimate from the contents of the training space, normalized to the conditions of the current observation. Weight coefficients are computed by solving a system of equations formed using selected reference data points.

SBM technology outperforms other candidate technologies in detecting faults. While other non-parametric techniques can produce estimates with similar accuracy metric (measure of how closely the estimates follow the actual), SBM outperforms them in robustness, reducing the likelihood that the estimates will over-fit a fault and "spill over" the influence of a fault in one variable within the estimates for the other variables.

SBM is designed specifically for the problems of data analysis and diagnostics encountered in real-life equipment and situations. It has been proven through modelling of tens of thousands of assets in power generation, oil and gas, aviation, and transportation applications.

It can provide accurate estimates for any number of sensors, of any type, over any load range. Even if a quarter of these sensors were to fail during operations, SBM could still generate accurate estimates for the remaining sensors without following the faulted signals, making it a very robust methodology.

Analytical methods such as Principle Component Analysis and Clustering do not have the same level of accuracy and robustness if and when modelled signals fail. Model training is an area in which SBM is strong. Training data can be assembled based on subject-matter expertise from empirical data collected in a data historian. Because the training data can easily be collected over the range of any independent variables of the system, the effect of these variables can easily be normalized. Automated algorithms can be applied to quickly select a set of model conditions that represents the full operating range of the data very well.

SBM training is a non-iterative, single-pass operation that involves a single matrix multiplication and inversion. A model matrix, represents the entire dynamic range of the reference behaviour – selected from historical data, personalized to every piece of equipment. An automated APM proprietary vector-selection method is used to build.

The selection algorithm can rapidly sort through tens of thousands of observation vectors to construct it. SBM, with the training vector-selection algorithm, exhibits consistent modelling behaviour. There is a clear relationship between the model training data and the model structure.

As with the initial model-training processes model, retraining is a quick and simple process, taking a short time to complete. The retraining for a new operating condition involves a simple inclusion of new training vectors into the D matrix from the new operating range via the same vector-selection algorithm used to create the initial model.

Another distinct advantage of SBM is that model designs normally reflect the most sensible structural elements of the asset being modelled. Designing for an SBM model is normally as straightforward as designing a physical model for First Principles methods. The available instruments for an asset can be partitioned into sub-systems that have physical meaning to the engineer.

For example, a steam turbine would have available sensors that can grouped together, such as oil temperatures, metal temperatures, and vibrations sensors. These can be collected to form a mechanical model. These temperatures, pressures, flows, and valve positions can be collected to form an individual model(s) of the high-pressure turbine, intermediate-pressure turbine, and low-pressure turbine.

Because SBM was built from the ground up with the detection and analysis of complex systems in mind – like compressors, turbines, rotating machines, fans, and heat exchangers – it produces results that can be interpreted easily using subject expertise of the equipment expert, rather than requiring the subject expertise of a statistician or vibration expert.

The simplicity of the SBM-model results derives from the simple model structure – this simple structure is not characteristic of statistical methods that have been adapted to real-world modelling problems. Statistical methods such as Clustering-based, Neural-Network-based, or Principle Components Analysis-based model systems all can suffer from the problem of design complexity unless this is well-handled by the application.

Model-design simplicity, the accurate and robust production of estimated normal conditions for each modelled signal and the way this leads to straightforward interpretation of model results, creates another advantage for SBM. The product of the modelling is a set of estimates that mimics the actual data under normal conditions, and it easily shows the trend and magnitude of any differences from normal conditions using a chart format familiar to any plant engineer. This leads to a visualization that complements normal engineering structure, based on familiar failure-mode and failure-analysis representation.

The overall simplicity of SBM models facilitates development and usage of automated expert rules logic to distinguish between normal operating condition and a faulted condition. It can be used to identify a new operating condition, facilitating automated adaptation of models. Expert rules logic also can be extended to provide fault diagnostics in important cases, like the complex plant systems listed above, where “fingerprints” of failure modes are known from development of subject-matter expertise and knowledge capture.

6. Conclusions

Royal Navy ship staff are faced with the demanding responsibilities for maintaining complex power and propulsion equipment. They need to have, and maintain, high levels of reliability, availability, and performance under budget constraints to ensure operational fit-for-mission readiness.

To mitigate and avoid operational issues, an accurate assessment of equipment operating conditions is needed to judge whether demands can be satisfied, with the added advantage that maintenance costs are considered and controlled. Large volumes of siloed data about the health of complex system elements are generally available, and the amount of data is growing steadily. Pulling together large amounts of current data from diverse sources across a plant or an enterprise to create actionable intelligence is a challenge to the organization, from the plant engineer to the CIO.

This paper has been about the use of digital systems for APM to create a predictive-analytic solution. There are both technology challenges and engineering challenges to a successful outcome. The technology challenges involve selecting a solution that has the accuracy and robustness to provide early warning of failure under all operational conditions.

Technology challenges include more than success at automated detection. The technology also must facilitate diagnostics and prognostics of problems by nature of providing simple connection of equipment design, model design, and interpretation of results. One additional requirement is a visual representation of results that fosters communication and understanding.

7. Recommendation

In addition to these technology elements, application choice must carefully consider engineering challenges that determine whether a solution will fit normal, organizational, operational practices and thus provide practical results for the organization. To satisfy engineering requirements, the solution must be easy to use and have reasonable training demands. This lowers the bar to acceptance when introducing something new to an organization that already is busy. Because there is a wide variety of equipment types and ages in any plant in an enterprise, the solution must manage this variation, as well as the variation of operating conditions. A single solution that is flexible in its equipment scope and adaptable to the cultures across an organization improves its ROI. It reduces the cost of implementation, maintenance, and updating application capabilities. And, it is critical that any solution chosen must possess the ability to grow with organizational vision – even to help lead it in the case of advanced technology solutions. This requires attention to not only the technology, but also to the people and processes supporting its implementation and integration into your organization.

Similarity-Based Modelling (SBM) is considered by the author to be the most appropriate foundation for predictive-analytic solutions to a broad spectrum of real-time modelling needs. Product development has focused on providing the solution requirements for application in the power and marine industries.

Successful application in these industries requires demonstration of cost-effective value from the single-asset level to a level inclusive of several divisions of global companies. In these industries, benefits to users have included improved asset availability, improved maintenance costs, and improved resource utilization.

The choice of a technology designed from the ground up to provide predictive analytics provides the basis for continuing innovation of software that makes a bigger vision possible.

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