RESILIENT: Advance a Ship's HM&E resiliency through contextual information models and innovative ML/AI analytics At-The-Edge

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Synopsis

Maritime supply chain disruptions over recent years stemming from causes such as piracy, the COVID-19 pandemic, blockage of the Suez Canal and the ongoing Red Sea crisis, underscore the pressures on navies and commercial ships for higher ship operational availability. Ships are sailing longer distances, at higher speeds and in more challenging environmental conditions. These settings are consequentially increasing demands for more effective ship machinery monitoring. However, although shipboard systems generate more data than ever, using that information to improve operational availability remains elusive; data from a ship's electrical auxiliary and main propulsion systems are often disorganized, undefined, and not timely. Further, data is sometimes undiscoverable and frequently unusable by the ship's information system to prevent or mitigate equipment failures. Moreover, increasing demands for more sophisticated analytics to improve machine reliability, with likely thousands of data points per system without any relationship model to help interpret this data continues to make machinery monitoring efforts more complex and costly. Creating the datasets is just one piece of the puzzle. These data points take on different meanings dependent on grouping. The lack of consistent data requirements definitions and context from one information system to another introduces other challenges to integrating machinery room operational data into the ship's higher-level information system and further up into an organization's fleet maintenance center. To this end, this paper explores two evolving areas of technology: 1) Machine learning schema for common hull, mechanical, and electrical system machinery equipment to improve contextualizing performance anomalies and that equipment's baseline operations and 2) an AI Information model for machinery equipment that could advance the ability of crews to reduce unplanned failures, increase availability, and obtain an accurate representation of the ship's readiness state. These activities will drive improved reliability, maintainability, and supportability of these systems and a higher readiness for a propulsion plant, electrical plant, damage control system, and ship's auxiliaries.

Key Words: Edge Analytics; Reliability Analysis; MCSA; CbM+ Maintenance; AI/ML Diagnostics

1 Introduction

It's often said that the workhorse of manufacturing and industrial control systems is the ubiquitous 3-phase, induction motor. A globally pervasive converter of electrical energy into mechanical energy, electric motors, not just induction, but also synchronous AC, field DC, wound, and more, transform electrical power into a cyclical mechanical activity with a typical robust, long operational life. Moreover, Machine Learning and AI algorithms applied within the technology of variable frequency drives and similar controllers are derived by the foundational principles that operate an electric motor. The current signature, voltage signature, and instantaneous power signature between the motor's stator and rotor are the essential forces that create the initial and continuous torque produced by a motor. Each of these forces can be analyzed to determine motor performance, health and the operational conditions of the equipment driven by the motor with predictive results. This predictive analysis, often termed Condition Based Maintenance Plus (CbM+), is a significantly beneficial result. Accordingly, this paper presents how a spectral analysis of the electric current is a valuable method to separate components of the current sine wave and to associate these components with useful mechanical properties of the motor. For example, a gradual degradation in one of the mechanical features within the motor can be detected by an analysis of the electric field interactions between the rotor and stator. This discovery is determined by comparing healthy, normal operation of the motor (defined as baseline performance characteristics), and deviation from this baseline. Different types of deviation from baseline operations represent different mechanical

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problems developing inside the motor. The mechanical properties of electric motor failure types are revealed in different current signatures within the motor. Research shows that we can use motor current signatures to identify ball bearing wear, rotor rub, outer/inner race bearing faults, motor unbalance, shaft misalignment, and more. Coupling these earlier efforts with today's computer processing advances, we can begin to train an automation system, i.e. machine learning, and define other AI basis tools to describe equipment condition predictively.

Authors' Biographies

Warren Johnson is the Marine Industry Manager for Rockwell Automation. He received a Bachelor of Science degree in Chemical Engineering from the University of Michigan. Mr. Johnson served as a naval officer in the U.S. Navy then transitioned to a career in controls engineering. He has automation systems design, development, and integration experience of over 24 years across various industries including marine and power generation. He has worked in industrial control and automation solutions from Rockwell Automation for a significant portion of that time.

Johnny Walker, CEO/ President of Thor Solutions LLC, is a retired U.S. Navy officer. Afloat, CAPT Walker commanded USS CHAMPION (MCM 4) and USS GUNSTON HALL (LSD 44). Ashore, CAPT Walker served as a Navy Staff, OPNAV N85/95 Requirements Officer / Resource Sponsor, PEO Ships LCAC & SSC (LCAC 100 Class Craft) Acquisition Program Manager—and as the PEO Ships MAAC Ships Program Manager, (PMS 470). He is a University of Oklahoma computer science graduate & completed an MMAS in Middle Eastern Studies at the U.S. Army CGSC.

2 Motor Current Signature Analysis

With the rapid advances in computer processing for capturing high speed minutiae events and their interactions, electric motor performance trends can now be reasoned from the motor's electrical current events (sic. trend analysis). An alternating current (AC) motor's current sine wave is a cyclic event that occurs across a typical frequency range from 1 - 60hz and even higher frequencies depending on application. Whereby the amplitude and waveform vary as the motor poles are passed by each revolution of the motor's rotor. Variable frequency drives are power supply devices to motors which have the electronics to capture a buffer of the motor's 3-phase current waveform. Motor waveform characteristics are critical for today's Motor Current Signature Analysis (MCSA) techniques—establishing a motor's operational baseline and assessing deviations from this baseline. Earlier studies established correlations (or signature analysis), between the motor's current waveforms and known mechanical problems in that motor. For example, each motor type has a general set of correlations established for equivalent mechanical problems like bearing wear, rotor static and dynamic eccentricity, broken bar and shorted windings. To establish these correlations, Fast Fourier Transformations are used to decompose the motor current waveform's components from the time domain into the frequency domain. This analysis reveals the amplitudes (dB) of those different component frequencies (within the output resultant current supplied to the motor stator), whereby those frequencies are derived from effects between the magnetic fields of the rotor and stator. These effects are caused by hardware parts degradation which can cascade into mechanical failure. For a 50Hz motor, the MCSA primary frequency peak is 50Hz and correspondingly 60Hz for a 60Hz motor. Figure 1's MCSA frequency spectrum shows 60Hz motor with a rotor asymmetry condition indicative of a broken bar condition within its rotor cage; the MCSA's two sideband peak frequencies have occurred at those frequencies defined as the motor's "twice slip frequency" as calculated from the motor's 60Hz supplied frequency (Miljkovic, 2015). The magnitude (dB) of the two MCSA sidebands indicates the severity of the rotor's asymmetry which, because those sidebands are more proportionally near the primary frequency dB, indicates a broken bar condition, i.e. a First Principle. The "slip frequency" sidebands for a healthy motor will be at much smaller magnitudes (dB) compared to the primary peak frequency.

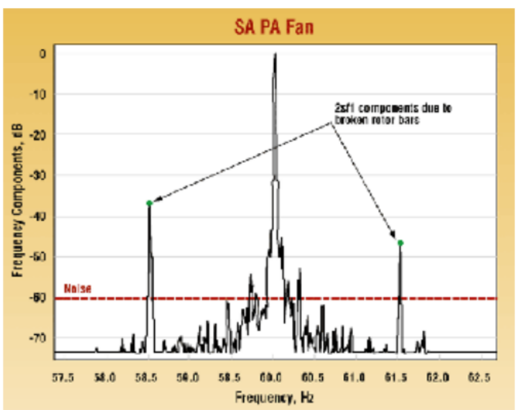

Figure 1: Frequency spectrum from motor with broken rotor bars (Miljković, 2015).

Similar effects of sideband frequencies occur when there are air gap differences between a motor's rotor and stator. This anomaly, which leads to increased vibration, lower output peformance, and even motor failure, is called rotor static eccentricity and rotor dynamic eccentricity. Rotor static eccentricity is when the air gap deviation remains stationary during the rotor's rotation while dynamic eccentricity occurs when the air gap deviation transits around 360 degrees of rotor rotation. This is detected because the rotor's magnetic field will influence the AC current within the stator windings due to the air gap proximity between the rotor and stator at the closest point around the circumference, causing an Unplanned Magnetic Pull force that creates other sideband current peak frequencies (Thompson and Gilmore, 2003). Those sideband frequencies are calculated by equation (1) for the static eccentricity of an induction motor.

$$f_{ec} = f_g\left\{(R \pm n_d)\left(\frac{1-s}{p}\right) \pm n_{ws}\right\} \tag{1}$$

Of which, the f_{ec} is the eccentricity frequency, f_g is the grid or supply frequency, R is the number of rotor bars, n_d is plus/minus 1, s is slip, p is pole pairs, and n_{ws} is 1, 3, 5, 7…. The f_{ec} is seen on a spectral analyzer at multiples of the f_g and is the anticipated motor current frequency signature for this type of motor fault condition (Miljković, 2015).

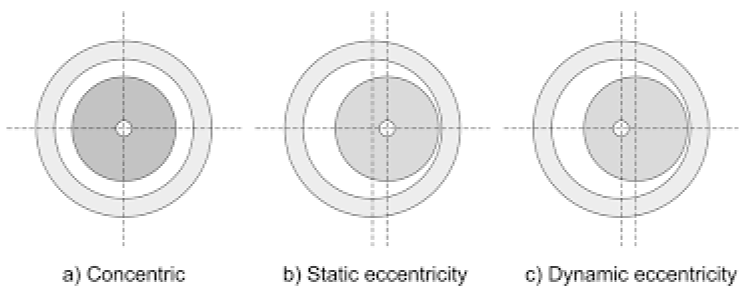

Figure 2: Air Gap Eccentricity (Miljkovic, 2015).

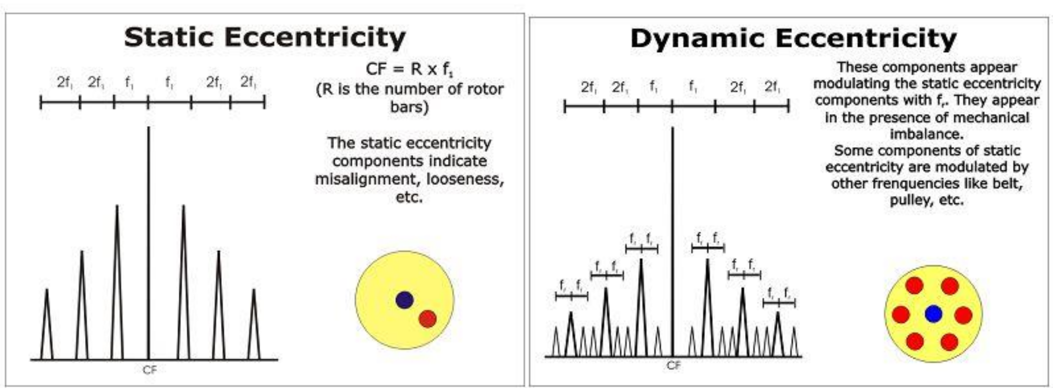

Figure 3: Current Signatures of Static & Dynamic Eccentricity (Lambert-Torres, 2009).

Voltage and Instantaneous Power signatures are used similarly to discern even more motor (and mechanical load) diagnostic conditions. Applying these earlier MCSA principles with today's AI and Machine Learning At-The-Edge technology advances condition-based maintenance plus CbM+ programs to the next level of resilient ship performance: optimal operating levels of the vessel's machinery equipment and determining hardware remaining useful life. Opportunely, new methods can capture these signature data without added spectral analyzers and separate

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current and/or voltage sensing equipment. This no longer needed additional hardware is replaced by intelligent control devices like soft starters and variable frequency drives—which, while operating motors, simultaneously cache the motor current data into their memory and that data is pulled forward to a Machine Learning application.

3 AI & MACHINE LEARNING At-The-Edge

Industry continues to collect voluminous machinery data into Cloud-Based systems to perform data analysis. Using significant computing resources and data scientists, firms pursue process correlations leading to new capacity and optimization. This analytical loop continues refinement with less and less data analysis latency coming near real time to production events on the factory floor. Artificial Intelligence (AI) and Machine Learning have made this possible. Further, the closer AI and Machine Learning get to the data source, the more these processing techniques reach the "Edge." Inasmuch, near/ real-time analytics at sea requires AI and/or Machine Learning to function at the vessel's equipment level. The existing motor soft starters and variable frequency drives in the ship's machinery plant equipment become those data sources, feeding their operational parameters not into a huge data server cluster and up to the Cloud, but rather to immediate local applications within the ship's machinery rooms. For example, integrating a Dockers Container OCI based machine learning app into a ship's PLC-chassis slot processor and connecting it via the ship's network to every soft starter and VFD in the machinery room.

Machine Learning (ML) apps can be straightforward—i.e., don't require significant engineering expertise to determine what data needs to be captured. The operator simply follows a user guide to identify each VFD type for data capture, select its IP address, and then add the particular load device, asset, or motor's nameplate information. Each asset's configured input fields may include bearing information (inner/ outer/ race multiplier, rolling element multiplier, cage multiplier, etc.), for an induction motor as well as the number of blades for a pump or fan. The embedded intelligence within an ML app uses this pump/fan and motor bearing configuration as inputs into its First Principles derived failure modes. When power is applied to the motor and it becomes operational from the vessel's activity, a ML app can begin training itself on motor performance to establish a baseline. If the motor load runs at a single speed/frequency, the app trains on that frequency in minutes. If the motor has operational modes at different frequencies, an ML app can adapt to monitor the change and automatically begin the training process for the new frequency. Or a frequency range can be specified in advance and that guidance sets the range of frequencies which will be trained for that asset within the ML app. This is "no code" machine learning done through the following process steps.

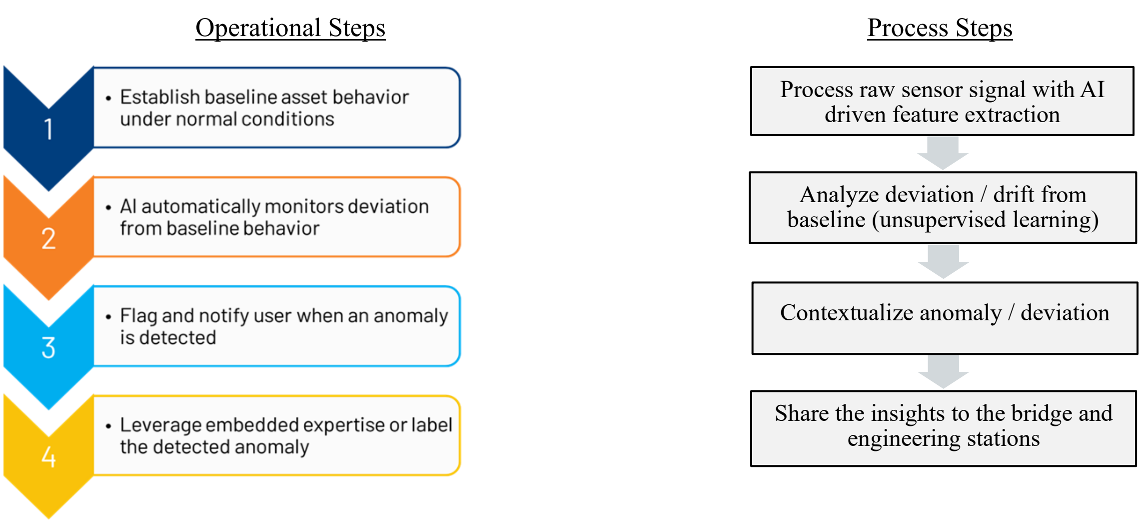

Figure 4: Embedded ML Expertise alignment of the operation to process steps.

The motor's baseline is established by training for each 1/2hz frequencies throughout the user defined operating frequency range. The commanded frequency of the VFD is automatically communicated to the ML app through the ship's network; onwards the ML app accomplishes the training and monitoring simultaneously. Once sufficient data

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is acquired from the asset, the training switches to automatic monitoring. Figure 5 presents an example architecture. Of significance: this design adds no additional equipment that's not already installed in the ship's machinery room other than a single edge analytics processor.

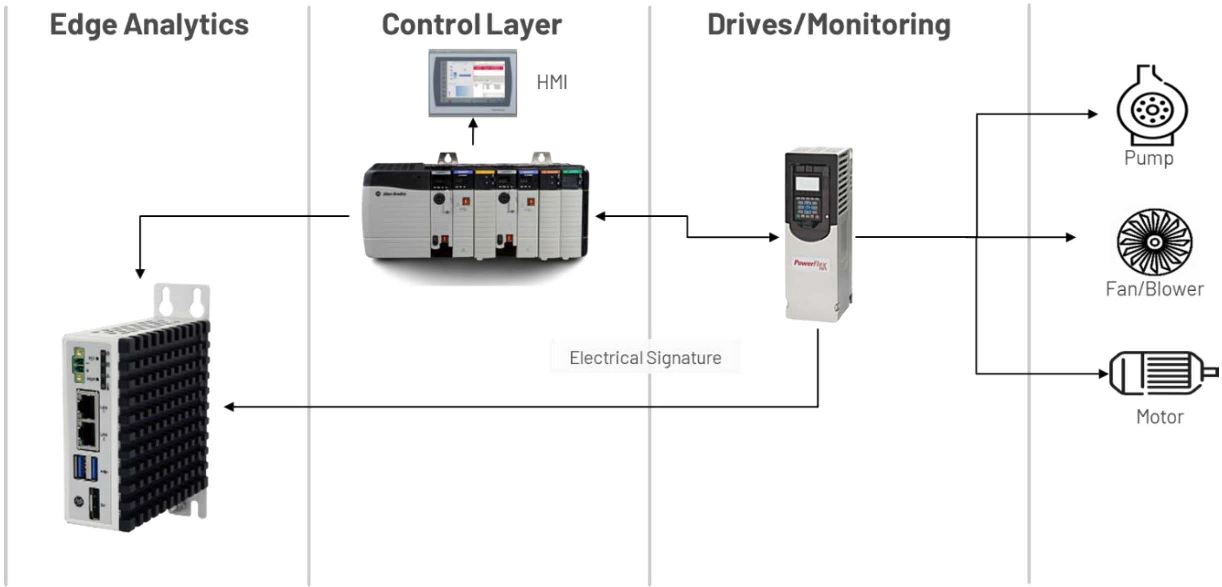

Figure 5: Example ML-At-The-Edge Architecture

Deviations from the asset's established baseline are anomalies which will be evaluated against the embedded expertise of First Principles derived failure modes and effects within the ML app—categorized as a particular failure anomaly. If the deviation is outside of embedded knowledge cases, then the user has the option to flag it as either normal behavior or identify it as a new anomaly issue. This new anomaly becomes a new failure risk for the asset and it is tracked onward.

Rather than being an anecdotal set of concepts, the ML app directly applies those embedded expertise First Principles of MCSA which alleviates the need for those higher-level skills or unique expertise of vibration engineers and data scientists. The ML app addresses the two categories of anomalies: the first anomalies which align to recognized problems like bearing failure, identified through prior industry knowledge and the second category, anomalies unique to the user's application. Beyond the First Principles' recognized anomalies, an ML At-The-Edge app can be applied to those second category of anomalies to reclassify them per the user's definition and accumulate that continuous learning through user training that identifies more unique anomalies at that single asset or from multiple assets. As anomalies are labelled by crewmembers, ML At-The-Edge becomes a critical tool operating around the clock 24 hours, 7 days a week and advancing the crew awareness of machinery plant condition. This is significant because organizations today simply don't have the depth of CbM analysis experts to accomplish round the clock analyses across the breadth of their plant's motors and other assets (Bernet, 2022).

3.1 AI/ML First Order Readiness Improvement

This description of configuration steps annotates an example of an actual, deployable MCSA ML At-The-Edge architecture and shares the extent of how little added capital expenditure is necessary to begin to gain ML predictive analytics of the conditional readiness for a ship's machinery assets. When this ML At-The-Edge is incorporated into an existing Condition Based Maintenance (CbM) system, the result is more than the preventative CbM time-based maintenance and becomes predictive CbM+ maintenance with maintenance activities occurring only when needed. The readiness of the vessel is more predictable and achieved with direct, first order improvements in operational savings, maintenance cost reduction, and failure costs' lead time delays dramatically reduced.

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3.2 AI/ML Second Order Readiness Improvement

We take this another step further to realize there is a second order of improvement to a ship's readiness and resiliency. Couple this onboard MCSA ML At-The-Edge analysis of all electrical assets within a ship's electric and propulsion plants together with the operational parameters already captured by the PLC-controlled system for these same assets' duty cycles and operational modes, leads to an increased knowledge about how certain operational processes effect the asset's optimal performance and captures historical causes of advanced deterioration of that asset. Blade wear, shaft imbalance, bearing failures, etc. are now interconnected with that asset's historical data of its operations and can benefit the ship's engineering officer and engineering department in determining the remaining useful life of components and subsystems thereby gaining a higher understanding about the readiness state of the vessel. For the world's navies and commercial shipowners of large vessel fleets, they could advance their understanding of how different kinds of auxiliary subsystems serving the same purposes, i.e. compressors, pumps, ballast management, blowers, etc., have the longest service life and reliability/robustness factors across their multiple vessel types. These quantifiable results can be inputs into a derivation of the earlier proposed Value Driven Power Management Philosophy (VDPMP) value function to ascertain which assets or subsystems within the electric plant have the greatest improvement to robustness/reliability and therefore return on expense for accomplishing future retrofit upgrades to that ship's electric plant (Ditaranto, Samimi, Walker, Withee, and Woodward, 2014). This further promotes one of the original principles of VDPMP which is achieving those resiliency requirement tenets of a sound, reliable, and robust electrical power generation and distribution system that is composed from a best practice applied standard configuration architecture (Ditaranto, Samimi, Walker, Withee, and Woodward, 2014).

$$F_s(N,O,P,Q,R,S,T,U,V) = A_1N + A_2O + A_3P + A_4Q + A_5R + A_6S + A_7T + A_8U + A_9V \tag{2}$$

The derivation here from the original VDPMP value function F is that the variables N, O, P,… V now represent the value metrics associated of a single asset or subsystem F_s within the electric plant with specific outcome requirements such as remaining useful life, degradation rate, robustness, maintenance cost, and acquisition costs; and the Constants A_n represent their relative weighting factors. By combining MCSA ML At-The-Edge analysis with the existing operational modes/duty cycles of that same asset into a database of metrics, establishes those quantifiable inputs that contribute to a formal method, and an AI information model, to provide the selection of improvements based upon optimal outcomes at the lowest cost. The result of each sub-system's robustness value F_s can then be pulled up into the individual Redundancy/Robustness/Reliability (RRR) variable $F(A_n)$ within the overarching, original VDPMP level analysis of the entire electric plant's VDPMP for resiliency and adaptive capacity. In their paper, Walker et al, state that this is the principal purpose for VDPMP's importance.

4 Information Model toward Remaining Useful Life Metric

A dataset that contains the MCSA analytics, the operational modes, duty cycles, and individual operational parameter values, i.e. pressure, temperature, flow etc. can be applied into a gradient boost decision tree model. Gradient boosting is a machine learning ensemble technique of adding the predictions of weak learners, each a Decision Tree, sequentially. In each iteration, the goal is to optimize the model's predictive weighting of data points based on the previous errors of the last Decision Tree until the predicted output error of the model is minimized. To create this gradient boost model, one begins by establishing a base model from a set of operational parameters that have a relationship to a particular failure mode of the asset and create an initial set of error residuals through the first Decision Tree by using the Gradient boosting regressor function because our target, the predicted remaining useful life, is a continuous function. That base model's error residuals are then plugged into a second Decision Tree and a new data point in the data set is plugged through the first and second Decision Trees to produce another set of error residuals, and this is done iteratively until the model's prediction errors from that collected data point parameter becomes sufficiently close to the observed correlated value (Saini, 2024). If the error of the model becomes greater from one iteration to the next, that particular error residual is weighted higher in the model's next successive decision tree against the other correct predictions giving it precedence in improving the model until these combined weak learners are now a strong model that accurately predicts the future operational correlation. This strong model has the outcome of more reliably predicting the remaining useful life of that asset. The overall iterative process of sequentially adding weak learners is shown in Figure 6 and is the gradient boost principle.

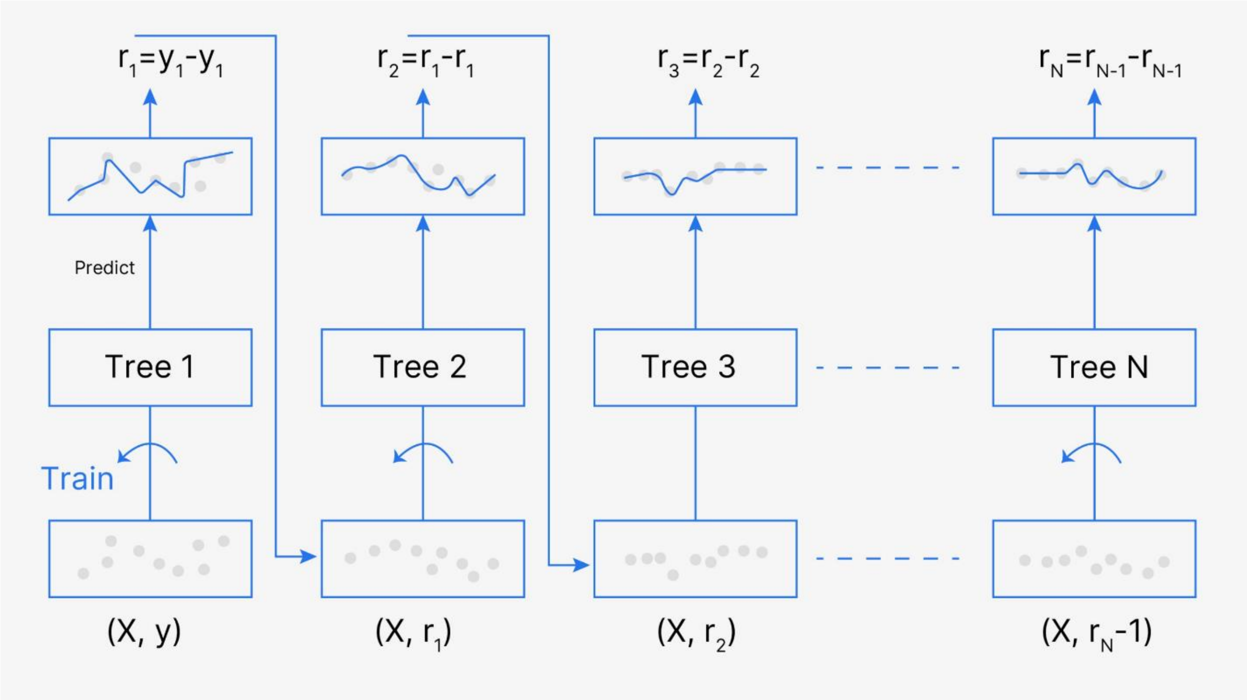

Figure 6: Gradient Boosting Tree regression (Saini, 2024).

In Gradient boosting regression, the loss function used to calculate error residuals from the Base model prediction and then from each Decision Tree iterative prediction is the following equation:

$$L = \frac{1}{n}\sum_{i=0}^{n}\left(y_i - \gamma_i\right)^2 \tag{3}$$

Where n is the number of stumps in the decision tree, y_i is the observed value, γ_i is the predicted value. To find the minimum value of the error, i.e. difference between observed and predicted values, an individual takes the derivative of that loss function and sets it equal to zero. This calculates the minimum error residual for each of the decision tree's leaves. A learning rate, typically a value between 0 and 1, is selected and multiplied to that decision tree prediction to reduce the model's inherent bias. For a learning rate of 0.1, the gradient boosting model can be represented like Figure 7 which in this case the decision trees are for the height data parameter.

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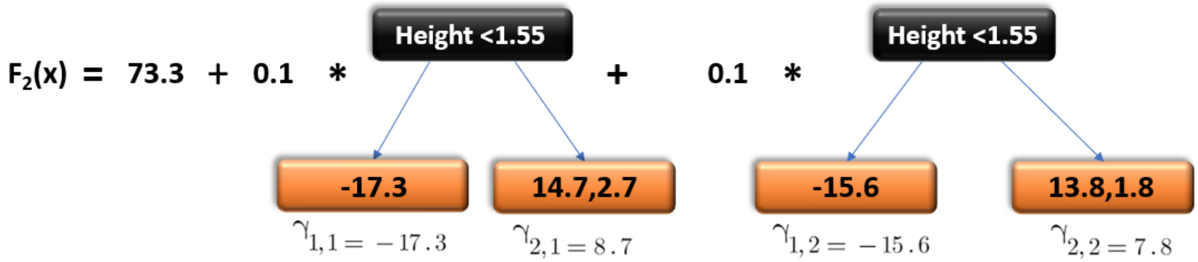

Figure 7: Gradient boost model (Saini, 2024)

This method of creating a gradient boosted tree predictive AI model was applied to a U.S. Air Force facility's compressor system which led to an AI information model result that successfully predicted the remaining useful life of that compressor with a prediction of failure within 40 minutes of that event (Reis and Resseguie, 2023). This result underscores the value of ML At-The-Edge for ships when combined with an AI information model to determine those numerous assets' health and readiness throughout the ship's machinery plant and its auxiliary systems before the vessel deploys and while underway.

5 Conclusions

This paper surveyed the significant benefits of using ML At-The-Edge in shipboard applications to advance crewmembers' efforts to keep the ship's conditional readiness and reliability to meet requirements. Years ago, Motor Current Signature Analysis (MCSA) was performed by contracted CbM/vibration analysts or motor experts on a defined cadence; this and similar traditional CbM monitoring techniques were left to the dedicated few experts to perform. Alternatively, reams of data have been collected into the Cloud for data scientists to comb through to discover possible insights and correlations between operational activities. All at higher costs that came along with delays to transform that data into root causes and preemptive insights needed of real-time operations. These hurdles are even greater to maritime operations of vessels at sea. However, these obstacles can be overcome through embedded expertise ML apps deployed within OCI containers at the deck plates. The embedded knowledge of earlier classified MCSA anomalies of shipboard motor and machinery assets can be trained into the ML app without a CbM analyst's expertise and, even in the unique shipboard environment, can be continuously monitored all the time without pulling voluminous data into the Cloud. Combining this MCSA ML embedded expertise with those assets' operational events and duty cycles into lower density datasets at the ship can lead to greater readiness capabilities from leveraging AI information model algorithms like gradient boosted decision trees. Gaining metrics such as remaining useful life means even greater shipboard readiness is achievable.

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