A Comprehensive Approach to Asset Degradation Modeling via Sensory Data Fusion for Remaining Useful Life Prediction

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Abstract

For effective management of assets, accurate forecasting for system failures is necessary. Sensory data fusion is a viable option to predict Remaining Useful Life (RUL) in assets by combining multiple data sources for improved prediction capabilities. This research paper aims at predicting RUL integrating various sensory data streams. Using Artificial Neural Networks (ANN), this research aims at synthesizing, learning from, and fusing information emanating from different sensors leading to accurate RUL estimations required for proactive maintenance strategies. The methodology in this study involves the use of ANN architectures for processing multivariate time-series data collected from sensors. By iterative training, the ANN captures complex relationships within the data allowing the integration of different information sources thus aiding in RUL predictions. Through the synthesis of sensory data by the ANN model, promising results have been achieved in predicting RUL. The model effectively learns from multiple sources demonstrating enhanced accuracy in estimating remaining operational cycles before asset failure.

Keywords: Sensory Information Fusion; Remaining Useful Life; Predictive Maintenance; Condition Monitoring; Sensor Integration; Prognostics and Health Management (PHM); Multi-Sensor Fusion.

1. Introduction

Asset management stands as a pivotal concern across various industries, where the reliable operation of equipment, machinery, and infrastructure plays a fundamental role in organizational productivity and cost efficiency [1-2]. In this context, understanding and predicting asset degradation become imperative tasks. Asset degradation, defined as the progressive decline in the performance and condition of machinery or infrastructure over time due to various factors like wear, corrosion, and aging, poses a significant challenge to organizations aiming to optimize operational uptime and minimize maintenance costs [3-5]. Traditional maintenance practices based on fixed schedules often lead to inefficiencies and unexpected failures, urging the need for predictive techniques that anticipate degradation and estimate remaining useful life [6].

Advancements in technology have ushered in an era where sensor-based data acquisition and analysis have become integral components in the pursuit of predictive asset management [7]. Sensory data gathered from a plethora of sources including vibration sensors, temperature gauges, oil analysis, and other condition-monitoring instruments, offer a wealth of information regarding the health and performance of assets. Integrating these diverse streams of sensory data into a cohesive framework through data fusion techniques presents a promising avenue for enhancing predictive models [8]. This fusion approach allows for a holistic understanding of asset behavior by amalgamating multi-source data, enabling more accurate and comprehensive degradation modeling [9-11].

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Central to effective asset management strategies is the concept of predicting the remaining useful life (RUL) of critical machinery and infrastructure. RUL estimation involves forecasting the duration for which an asset can operate before reaching a predefined threshold of deterioration or failure. Accurate RUL prediction empowers organizations with proactive decision-making capabilities, facilitating optimized maintenance schedules, part replacements, and resource allocation [12-15]. However, achieving precise RUL estimates remains a challenging endeavor due to the complex and dynamic nature of asset degradation processes.

This paper centers on presenting a comprehensive approach to asset degradation modeling by leveraging sensory data fusion techniques for the prediction of remaining useful life [16-18]. Through a meticulous exploration of various sensor integration methods and predictive modeling algorithms, the research endeavors to offer insights into the development of robust frameworks capable of accurately estimating the RUL of assets. By amalgamating diverse sensory data streams and employing advanced analytics, this study aims to contribute to the enhancement of predictive maintenance strategies, thereby aiding organizations in optimizing asset performance, mitigating downtime, and reducing maintenance costs.

2. Methodology

The methodology employed in this study delineates a systematic approach to harnessing sensory data for the purpose of comprehensive asset degradation modeling and accurate prediction of remaining useful life (RUL).

In this study, the application of Artificial Neural Networks (ANN) is employed to facilitate the learning process for Sensory Data Fusion concerning the prediction of Remaining Useful Life (RUL) in assets. The core problem addressed revolves around leveraging sensory data from diverse sources to predict the remaining operational cycles before the occurrence of system failure. ANN, as a computational model inspired by the human brain's neural structure, serves as the foundational tool in this methodology.

The primary principle underlying ANN involves the utilization of interconnected layers of nodes, also known as neurons or units, organized in a hierarchical fashion [19-20]. Each neuron receives input, processes it through an activation function, and produces an output.

$$\mathbf{z}_n^{(l)} = H\left(\mathbf{a}_n^{(l)}\right) = \left[H\left(a_{1,n}^{(l)}\right)H\left(a_{2,n}^{(l)}\right)\cdots H\left(a_{M,n}^{(l)}\right)\right]^T, \quad (1)$$

$$\mathbf{a}_n^{(l)} = \begin{cases} \mathbf{W}^{(l,n)} \cdot \mathbf{x}_n & \text{for} l = 1 \\ \mathbf{W}^{(l,n)} \cdot \mathbf{z}_n^{(l-1)} & \text{for} l = 2 \cdots L-1, \end{cases} \quad (2)$$

The network's architecture typically encompasses an input layer, hidden layers that perform computations, and an output layer responsible for generating predictions or classifications [21]. The learning process within ANN involves adjusting the weights associated with connections between neurons, enabling the network to adapt and optimize its performance based on the provided data. This adaptation is achieved through iterative training, where the network learns to map inputs to desired outputs by minimizing a defined loss or error function [22-24].

The weight matrices corresponding to the layer l=1, as well as the layers l=2,3,⋯,L−1 connected with $\mathbf{x}n$, are provided as follows:

$$\mathbf{W}^{(1,n)} = \begin{bmatrix} w_{1,1}^{(1,n)} & w_{1,2}^{(1,n)} & \cdots & w_{1,D}^{(1,n)} \\ w_{2,1}^{(1,n)} & w_{2,2}^{(1,n)} & \cdots & w_{2,D}^{(1,n)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{M,1}^{(1,n)} & w_{M,2}^{(1,n)} & \cdots & w_{M,D}^{(1,n)} \end{bmatrix} \text{and} \quad (3)$$

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$$\mathbf{W}^{(l,n)} = \begin{bmatrix} w_{1,1}^{(l,n)} & w_{1,2}^{(l,n)} & \cdots & w_{1,M}^{(l,n)} \\ w_{2,1}^{(l,n)} & w_{2,2}^{(l,n)} & \cdots & w_{2,M}^{(l,n)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{M,1}^{(l,n)} & w_{M,2}^{(l,n)} & \cdots & w_{M,M}^{(l,n)} \end{bmatrix}, \tag{4}$$

This study assesses three prevalent activation functions commonly utilized: the rectifier function, the logistic sigmoid function, and the hyperbolic tangent function. They are expressed as follows:

$$H(a) = max(0, a). \tag{5}$$

$$H(a) = \frac{1}{1+e^{-a}}. \tag{6}$$

$$H(a) = \frac{e^{a}-e^{-a}}{e^{a}+e^{-a}}. \tag{7}$$

The process of ANN learning involves updating the weights within the MLP neural network through successive iterations of feedforward and backpropagation procedures. Employing the equation mentioned earlier, the feedforward computation is executed as illustrated below:

$$\mathrm{z}_n^{(L-1)} = H\left(\mathrm{W}^{(L-1,n)} H\left(\mathrm{W}^{(L-2,n)} H\left(\cdots \mathrm{W}^{(2,n)} H\left(\mathrm{W}^{(1,n)} \mathrm{x}_n\right)\right)\right)\right). \tag{8}$$

The predicted value $\hat{y}_n$, derived from the last output of the feedforward process. This value represents the linear output of at the final layer, where there's no application of an activation function, expressed as follows:

$$\hat{y}_n = a_{1,n}^{(L)} = \mathbf{w}^{(L,n)} \cdot \mathbf{z}_n^{(L-1)}. \tag{9}$$

The training aims to reduce the loss function by modifying the ANN weight, driven by the given loss function, with the objective of minimizing it.

$$J(\mathcal{W}) = \frac{1}{N} \sum_{n=1}^{N} |\, \hat{y}_n - y_n|^2 + \frac{\alpha}{2} \sum_{n=1}^{N} \sum_{l=1}^{L} ||\, \mathrm{W}^{(l,n)} ||_2^2, \tag{10}$$

Following the feedforward phase, adjustments to the weights on each connection are dynamically executed through backpropagation. Originating from initial randomized weights, backpropagation iteratively refines these weights, utilizing gradient descent on the loss function concerning the weights.

$$\frac{\partial J}{\partial w_{j,i}^{(l,n)}} = \frac{\partial J}{\partial a_{j,n}^{(l)}} \left(z_{i,n}^{(l-1)}\right)$$

$$\frac{\partial J}{\partial a_{j,n}^{(l)}} = \begin{cases} H'\left(a_{j,n}^{(l)}\right) \sum_{k=1}^{M} w_{k,j}^{(l+1,n)} \frac{\partial J}{\partial a_{k,n}^{(l+1)}} & \text{for} l = 1 \cdots L-1 \\ \frac{\partial J}{\partial a_{1,n}^{(l)}} & \text{for} l = L, \end{cases} \tag{11}$$

The learning rate, denoted as λ, serves as a crucial hyperparameter regulating the step size during parameter updates. The backward pass initiates from the output layer and propagates towards preceding layers, adjusting weights to minimize the loss, as depicted in the Equation mentioned earlier [25-26]. Once the backpropagation extends to update the first layer's weights, it proceeds iteratively through additional cycles of feedforward and backpropagation. This iterative process continues until the weight values converge to a specific tolerance level, determined by another hyperparameter that defines the model's behavior.

$$w_{j,i}^{(l,n)} \leftarrow w_{j,i}^{(l,n)} - \lambda \frac{\partial J}{\partial w_{j,i}^{(l,n)}} = w_{j,i}^{(l,n)} - \lambda \frac{\partial J}{\partial a_{j,n}^{(l)}} \left(z_{i,n}^{(l-1)}\right), \tag{12}$$

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3. Experimental Design

With the overarching aim of substantiating the proposed methodology, this section delineates the framework devised to conduct controlled experiments and empirical analyses.

In our specific case study, we have utilized the NASA Turbofan Jet Engine Data Set, which comprises multiple multivariate time series. These datasets are segregated into distinct training and test subsets, with each time series stemming from a different engine, collectively representing a fleet of engines of the same type. Each engine initiates operation with varying degrees of initial wear and manufacturing deviations, a feature concealed from the user. Notably, this wear and variation are deemed as normal operational characteristics, devoid of any fault conditions. Within the dataset, three operational settings significantly influence engine performance and are integral components of the provided data. It's essential to note that the data are contaminated with sensor noise, presenting a realistic scenario reflective of operational environments. The data is structured as a compressed text file, comprising 26 columns of numerical values segregated by spaces. Each row denotes a snapshot of data collected during a singular operational cycle, with each column signifying a distinct variable. These columns encompass information such as unit number, time in cycles, operational settings, and sensor measurements, amounting to a comprehensive overview of the engine's operational dynamics. The organization of the data sets involves four distinct subsets labeled FD001 through FD004. Each subset encompasses a varied number of train and test trajectories, differing conditions, and specific fault modes. For instance, FD001 and FD003 comprise conditions classified as "ONE" (Sea Level) with corresponding fault modes, whereas FD002 and FD004 present "SIX" distinct conditions and associated fault modes. These categorizations facilitate a diverse and comprehensive exploration of engine behavior under different operational conditions and fault modes.

4. Results and Discussion

This section encapsulates the outcomes derived from the integration of sensory data for asset degradation prediction and the estimation of remaining useful life.

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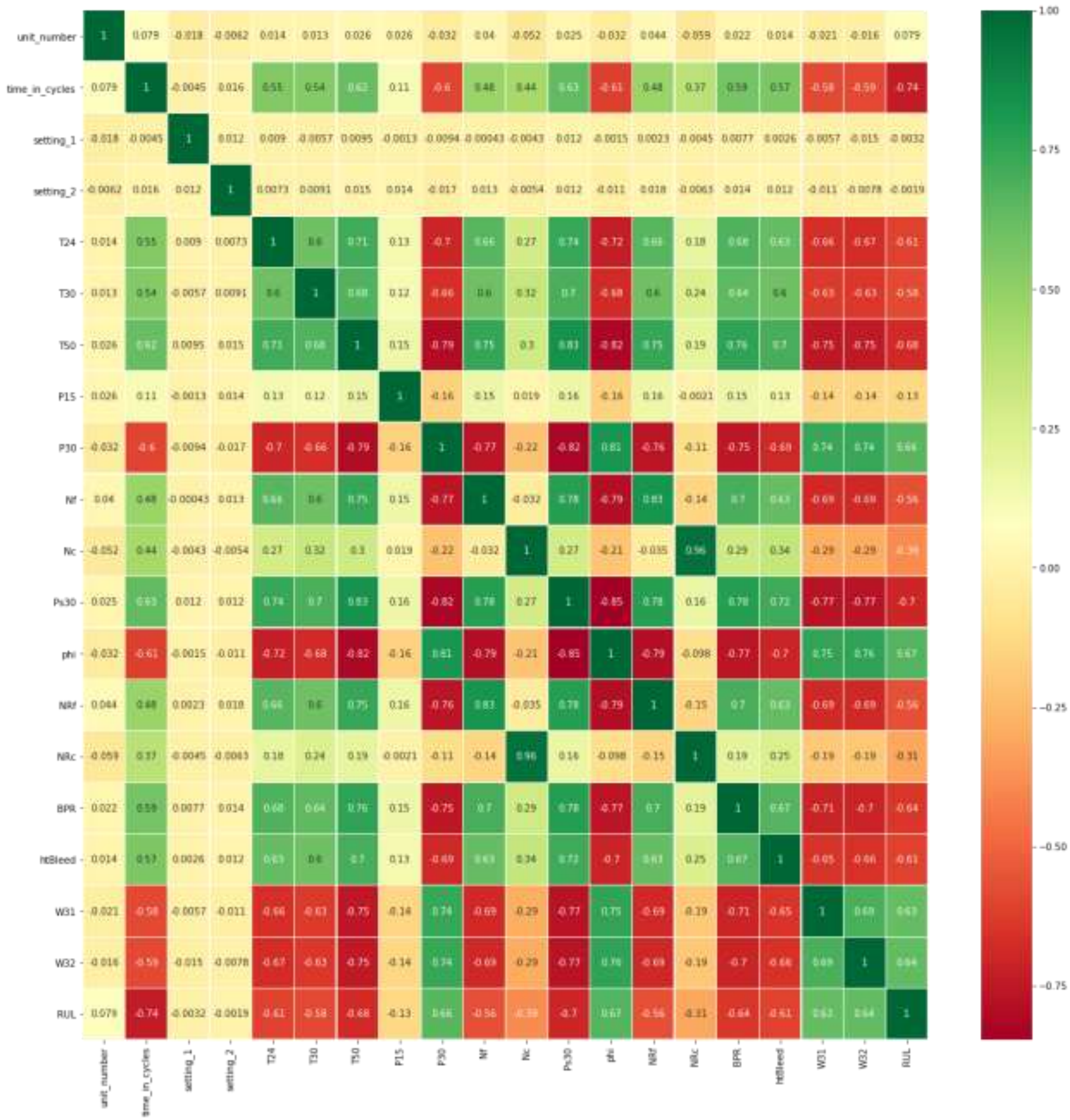

Figure 1: Correlation Map Illustrating Interdependencies Among Engine Features

In Figure 1, we present a correlation map depicting the interrelationships between various features within the dataset. This visualization serves as a comprehensive graphical representation illustrating the degree and direction of associations among different variables. The correlation map enables a quick yet insightful understanding of potential dependencies or patterns existing between operational settings, sensor measurements, and other pertinent parameters. By utilizing color gradients or numerical indicators, this map highlights both positive and negative correlations, providing valuable insights into which features might exhibit a stronger or weaker relationship. This visualization aids

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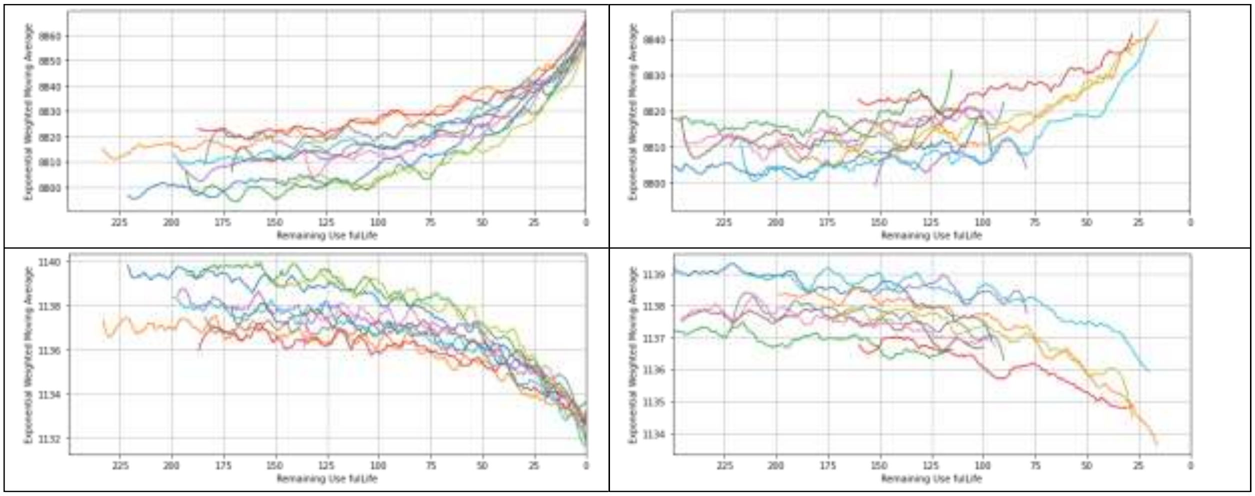

Figure 2: Exponential Weighted Moving Average (EWMA) Application on Ascending and Descending Sensor Time Series

in identifying potential redundancies, multicollinearity, or influential variables, thereby guiding feature selection processes and facilitating a more informed approach to subsequent analysis and modeling techniques.

In Figure 2, we present the exponential weighted moving average (EWMA) applied to both ascending and descending sensor time series. This visualization offers a clear representation of the smoothed trends derived from the original sensor data. By employing the EWMA technique, we achieve a reduced noise representation while preserving the underlying patterns within the time series data. The ascending and descending sensor time series undergo this exponential smoothing process separately, providing distinct insights into how the EWMA handles increasing and decreasing trends within the sensor measurements. This visualization aids in understanding the responsiveness of the EWMA method to different directional trends, highlighting its efficacy in capturing significant changes while minimizing the impact of short-term fluctuations, thereby contributing to a clearer comprehension of the underlying patterns in sensor data.

In Figure 3, we depict the Remaining Useful Life (RUL) analysis conducted on the risky Exponential Weighted Moving Average (EWMA) per week. This visualization serves as a critical assessment of the predicted RUL derived from the risky EWMA model. By aggregating RUL estimations on a weekly basis, this visualization offers insights into the predictive capabilities of the risky EWMA over time, allowing for an assessment of its performance in forecasting the remaining operational cycles before system failure. It enables a comprehensive evaluation of the model's ability to anticipate impending failures and estimate the potential lifespan of the engine components under risk-sensitive conditions. This analysis aids in discerning the model's reliability and accuracy in foreseeing future failures, serving as a crucial tool in decision-making processes regarding maintenance schedules and resource allocation within an operational framework.

In Figure 4, we present the SHAP (Shapley Additive exPlanations) explanations elucidating the model's predictions and their underlying rationale. This visualization offers a comprehensive and interpretable breakdown of feature contributions to individual predictions made by our model. The SHAP framework facilitates a nuanced understanding of the significance and impact of each feature on the model's decision-making process, highlighting their respective influences on the predicted outcomes. By visualizing SHAP values, we uncover the direction and magnitude of the effects of various features, thereby discerning which factors exert substantial influence on the model's predictions.

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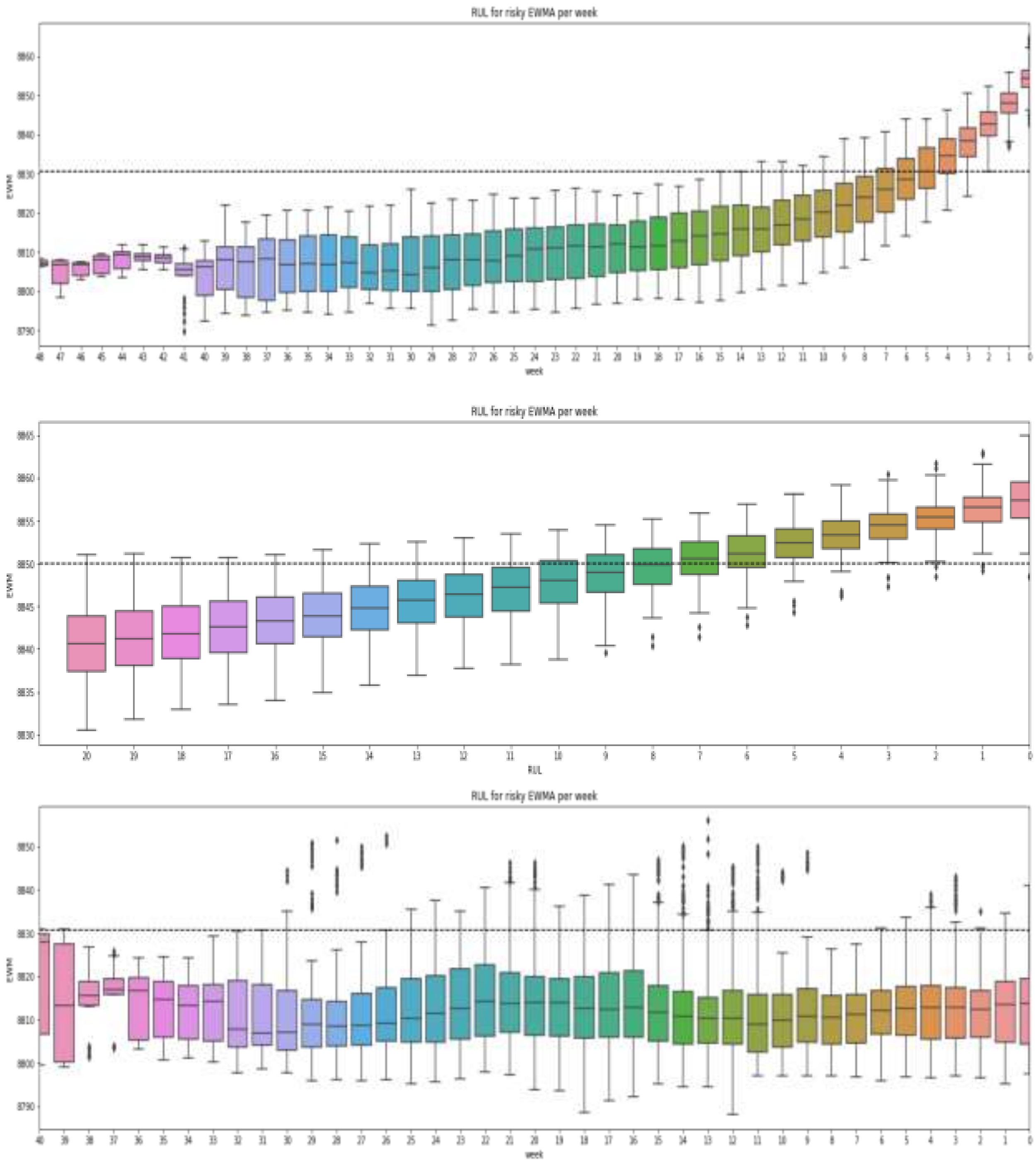

Figure 3: Analysis of Remaining Useful Life (RUL) using Risky Exponential Weighted Moving Average (EWMA) per Week

This interpretability aids in establishing trust in the model's outputs, identifying influential features, and discerning how alterations in specific variables might impact the predicted outcomes. Ultimately, this visualization contributes to enhancing the transparency and comprehensibility of the model's decision-making, empowering stakeholders to make informed decisions based on the insights derived from the model's predictions.

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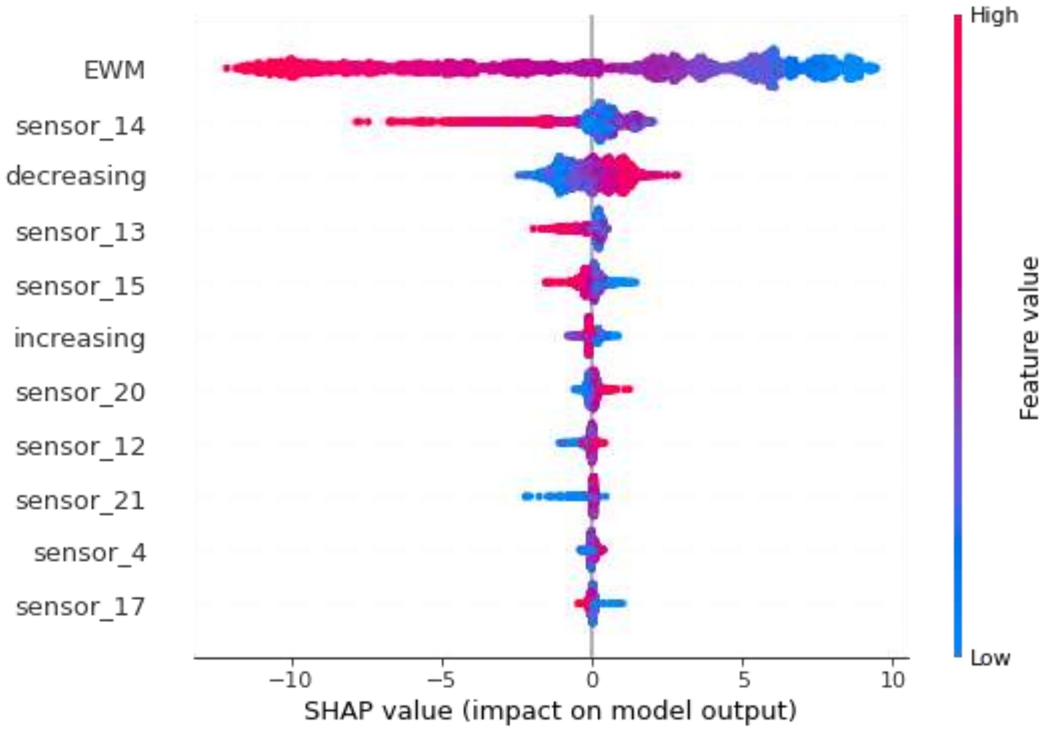

Figure 4: SHAP Explanations Unveiling Feature Contributions to Model Predictions

5. Conclusion and Future Work

This study highlights the efficacy of leveraging Artificial Neural Networks (ANN) for the fusion and analysis of sensory data, significantly contributing to the predictive capabilities essential in asset management. By synthesizing information from diverse sensors, the ANN model showcased notable proficiency in estimating Remaining Useful Life (RUL) for assets, offering valuable insights into potential system failures. The successful application of ANN-based methodologies underscores their potential to revolutionize proactive maintenance strategies, empowering organizations to preemptively address potential faults and optimize resource allocation. The findings underscore the importance of robust predictive models in enhancing operational efficiency and cost-effectiveness within asset management frameworks. Moving forward, the utilization of ANN-driven sensory data fusion stands as a promising avenue for refining prognostic capabilities, paving the way for more resilient and efficient asset management practices in diverse industrial domains.

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