Intelligent Helicopter Turbine Engine Fault Diagnosis Using Multi-Head Attention

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Abstract

A turbine engine provides power to the helicopter, enabling the helicopter to travel and hover in the air. Since the rotorcraft operates at high altitudes, ensuring safety and maintaining a healthy operational status are crucial at all times. Therefore, a prognostics and health management (PHM) system for the turbine engine must be implemented to predict any anomalies or faults to prevent catastrophic accidents. This research proposes a novel fault diagnosis method for helicopter turbine engines based on operational data acquired from actual aircraft. First, the proposed method predicts engine torque using other operational data while accounting for uncertainty. A Bayesian regression approach is employed to predict the engine torque. The torque margin, defined as the difference between the actual torque and the estimated torque, is then used to diagnose engine faults. Specifically, a multi-head attention mechanism is incorporated to capture interactions between various engine parameters. Additionally, domain adaptation techniques are applied to enhance the model's generalization performance, ensuring robustness across diverse operating conditions. The proposed method is validated using seven different datasets, each acquired from a helicopter engine. Four datasets were used for training, while the remaining three were allocated for testing and validation. The results indicated that the proposed method accurately predicted torque. Furthermore, the fault diagnosis showed promising results, leading to a 3rd-place finish in the 2024 PHM Society Data Challenge in terms of validation score.

1. Introduction

A helicopter, as a rotary-wing aircraft, operates by utilizing a turbine engine to drive the rotor blades, enabling vertical takeoff, landing, and flight. The turbine engine is the primary power source that makes these maneuvers possible. However, it is constantly exposed to various environmental factors and harsh operational conditions. Over time, this exposure can lead to a degradation in engine performance, which may result in severe accidents. Therefore, to prevent such accidents, a reliable engine monitoring and fault diagnosis system is essential.

Previous studies have primarily focused on developing monitoring and fault diagnosis methods based on engine performance data. For instance, Fentaye et al. (2021) applied a modular CNN to address the issue of fault detection and classification in helicopter turbine engines. Zhao et al. (2022) utilized transfer learning with an Extreme Learning Machine to improve the prediction of engine torque using operational data. Hu et al. (2024) employed adversarial transfer learning with a Gaussian model to enhance fault diagnosis under varying conditions. However, these AI-based approaches present several challenges. First, AI-based methods often fail to provide information regarding the uncertainty of their predictions. This lack of uncertainty information is particularly problematic in critical systems such as aviation, where operators need not only the prediction but also an understanding of how reliable that prediction is. Without knowledge of prediction uncertainty, operators may over-rely on the AI model's output, even when it is potentially inaccurate. For example, an AI model might predict that an

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engine is functioning normally but fail to convey the uncertainty of this prediction. If the engine is actually in a borderline state, this lack of uncertainty information could result in operators missing early signs of failure, potentially leading to catastrophic outcomes. Therefore, understanding and accounting for uncertainty is essential in making informed decisions in safety-critical environments. Second, the generalized performance across a wide range of operating conditions cannot be achieved. Helicopter turbine engines operate under diverse conditions, but conventional models are trained on specific environments and conditions. Consequently, their performance degrades significantly when applied to data from new or unforeseen conditions.

To accurately predict the state of helicopter turbine engines and diagnose faults, this study proposes a two-step methodology. In the first step, Bayesian regression is employed to predict the torque margin. This approach probabilistically models the uncertainty in the predictions, providing reliable confidence intervals, which are critical in aviation systems where safety is paramount. In the second step, the predicted torque margin from the first step is utilized as a key feature for fault diagnosis. A multi-head attention mechanism is applied to capture complex interactions between various features, and domain adaptation techniques are incorporated to ensure robust performance across diverse and previously unseen operating conditions.

The organization of this paper is as follows. In Section 2, the data challenge task is introduced, including a detailed description of the dataset used for training and evaluation. Section 3 presents the proposed methodology of the feature extraction process, the regression approach for torque margin prediction, and the classification method for fault diagnosis. In Section 4, the results obtained from the experiments are discussed, and Section 5 concludes the paper with key findings and future research directions.

2. DESCRIPTION

2.1. Dataset Description

This dataset contains sensor measurements from seven helicopter turbine engines of the same model, used across different helicopters. For each engine, several key operational parameters were recorded, including torque, external air temperature, mean gas temperature, pressure altitude, indicated airspeed, available power, and compressor speed. The variables included in the dataset are as follows, as shown in Table 1.

The torque margin is calculated using the formula, as shown in Eq. (1).

$$Torque\ Margin = \frac{Measured\ Torque - Target\ Torque}{Target\ Torque} \qquad (1)$$

The dataset is divided into a training set and a test/validation set. The training dataset consists of measurements from four engines, with the asset IDs and observation order anonymized to ensure unbiased modeling. The test and validation datasets comprise the remaining three engines, which are used to evaluate the model's ability to generalize to new data.

Table 1. Data description.

Variable name	Description
Measured Torque (%)	The temperature of the external air, measured in degrees Celsius.
Outside Air Temperature (°C)	The average temperature of gases inside the turbine, measured in degrees Celsius.
Mean Gas Temperature (°C)	The height above the standard atmospheric pressure level, measured in feet.
Pressure Altitude (feet)	The speed of the helicopter relative to the surrounding air, measured in knots.
Indicated Airspeed (knots)	The effective power output of the engine, expressed as a percentage.
Compressor Speed (%)	The speed of the engine's compressor, expressed as a percentage of the maximum speed.
Net Power (%)	The actual torque output of the engine, expressed as a percentage.

2.2. Problem Description

This study focuses on developing models to diagnose faults and predict torque margins in helicopter turbine engines to enhance maintenance and operational safety. A key challenge is ensuring that the models generalize effectively to engines not included in the training set. To address this, data from specific engines are used exclusively for testing and validation, allowing for a rigorous evaluation of model performance on unseen data.

Additionally, the study includes the estimation of confidence levels for each prediction, providing crucial information for maintenance decisions. This approach aims to improve the reliability of fault diagnosis, optimize maintenance scheduling, and enhance the overall operational safety of helicopter engines.

3. PROPOSED METHOD

In this section, the proposed methodology for predicting the torque margin and diagnosing faults of helicopter turbine engines is presented. First, the feature extraction process from the data is described, followed by the identification of distinct and representative clusters that capture key patterns and behaviors of the engine through clustering analysis. Subsequently, a detailed explanation of the regression model used for torque margin prediction and the classification model employed for fault diagnosis is provided.

3.1. Feature Extraction and Modification Based on Air Density

This section describes the process of extracting useful features from the helicopter turbine engine data. The original dataset consists of seven key operational parameters related to engine performance, including measured torque, outside air temperature, mean gas temperature, pressure altitude, indicated airspeed, net power, and compressor speed. In this study, additional features were defined based on these parameters to increase the predictive performance of the model.

Air density is a critical factor that influences the performance of helicopter turbine engines. To account for this, air density was calculated using the International Standard Atmosphere (ISA) model, and key operational variables were adjusted accordingly. The ISA model is valid for altitudes below 11,000 meters, and since the pressure altitude in the dataset is 3097.5 feet (approximately 944.118 meters), the application of the ISA equations was appropriate.

According to the ISA model, the variation in pressure with altitude is calculated using Eq. (2).

$$\frac{p}{p_0} = \left(1 - \frac{ah}{T_0}\right)^{\frac{g}{Ra}} \tag{2}$$

where p is the pressure at altitude h, which corresponds to the pressure altitude from the dataset, p_0 is the sea-level standard atmospheric pressure (constant), a is the temperature lapse rate (0.0065 K/m), T_0 is the sea-level standard temperature (288.15 K), g is gravitational acceleration (9.80665 m/s²), and R is the universal gas constant (8.3144598 J/(mol·K)). Once the pressure p is computed at a given altitude, the air density ρ is calculated using Eq. (3).

$$\rho = \frac{P}{R_S T} \tag{3}$$

where P is the pressure at altitude, R_s is the specific gas constant for air (287.05 J/(kg·K)), and T is the outside air temperature from the dataset.

Based on the calculated air density, air density-adjusted derived variables were generated for each key operational parameter. For example, the net power was adjusted for air density as shown in Eq. (4).

$$Net\ Power\_Air\ Density = \frac{Net\ Power}{\rho} \tag{4}$$

Similarly, other variables such as compressor speed, mean gas temperature, and measured torque were adjusted based on air density. These derived variables reflect the influence of environmental factors, such as air density, on engine performance, thus enhancing the model's predictive accuracy.

3.2. Clustering Analysis using Gaussian Mixture Model

A clustering approach was employed to segment the data based on two key features: compressor speed adjusted by air density and net power adjusted by air density. This was necessary because the helicopter turbine engine operates

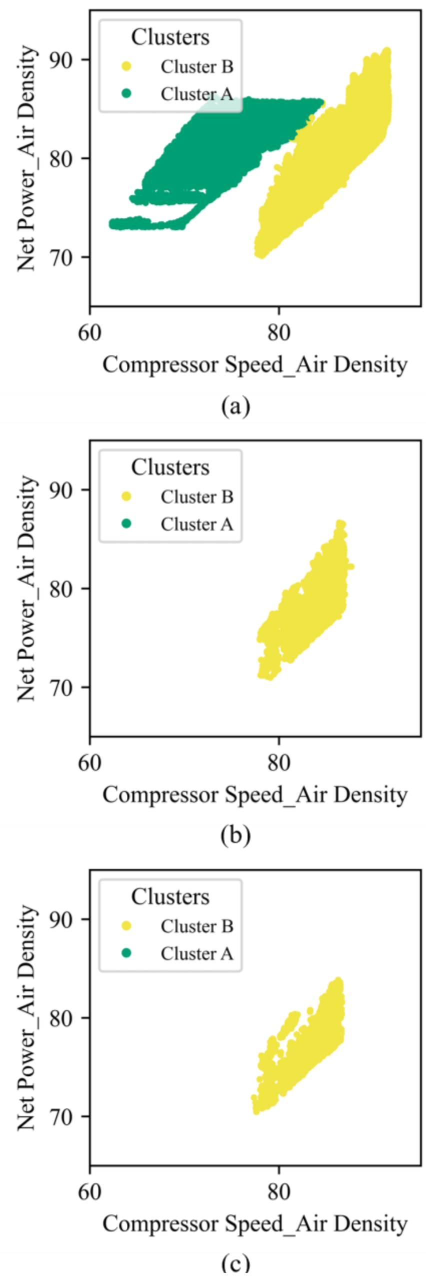

Figure 1. Distribution of GMM clustering: (a) training dataset results, showing two distinct clusters (*Cluster A* and *Cluster B*), (b) test dataset results, where only *Cluster B* is observed, and (c) validation dataset results, where again only *Cluster B* is present.

under varying environmental and operational conditions, which can lead to different performance characteristics. By applying clustering, it becomes possible to identify distinct operational regimes within the data, ensuring that these variations are accounted for in subsequent analysis and modeling, leading to more accurate fault diagnosis.

The distribution analysis of the data showed that the dataset was collected at different conditions, which presented as a multiple number of clusters. Thus, Gaussian mixture model (GMM) was used to identify latent group distributions in the data, as it models the underlying distribution of each cluster.

In this case, the GMM was configured with two components, allowing for the identification of two distinct groups within the dataset. A shared covariance structure was used to capture the relationships between the two selected features, ensuring that the clusters were effectively separated.

Figure 1(a) shows the clustering result for the training dataset, where two distinct and meaningful clusters, *Cluster A* and *Cluster B*, were identified. Conversely, Figure 1(b) and Figure 1(c) display the clustering results for the test and validation datasets, respectively, where only a single cluster, *Cluster B*, was observed. This suggests that when the GMM, trained on the training dataset, was applied to the test and validation datasets, the data points in these sets exhibited characteristics that corresponded only to *Cluster B*, with no data points aligning with *Cluster A*.

Thus, the focus was placed on the data within *Cluster B* when developing the model from the training dataset. This insight helped refine and focus the modeling process by emphasizing the most relevant operational regime, which was present in both the test and validation sets.

3.3. Bayesian Regression for Torque Margin Estimation

To estimate the torque margin and the confidence level of the prediction, the Gaussian Negative Log-Likelihood Loss (GNLLLoss) based Bayesian regression method was used. As the operational condition of helicopters encounter considerable amount of uncertainties, Bayesian regression that treats model parameters as probabilistic variables was used to capture both the mean and the associated uncertainty (variance) in the predictions. In addition, GNLLLoss function allowed the model to express the confidence of the predictions, providing more information than just the predicted value. The GNLLLoss is defined as shown in Eq. (5):

$$GNLLLoss = \frac{1}{2}\left(\frac{(y-\hat{\mu})^2}{\hat{\sigma}^2} + \log(\hat{\sigma}^2)\right) \tag{5}$$

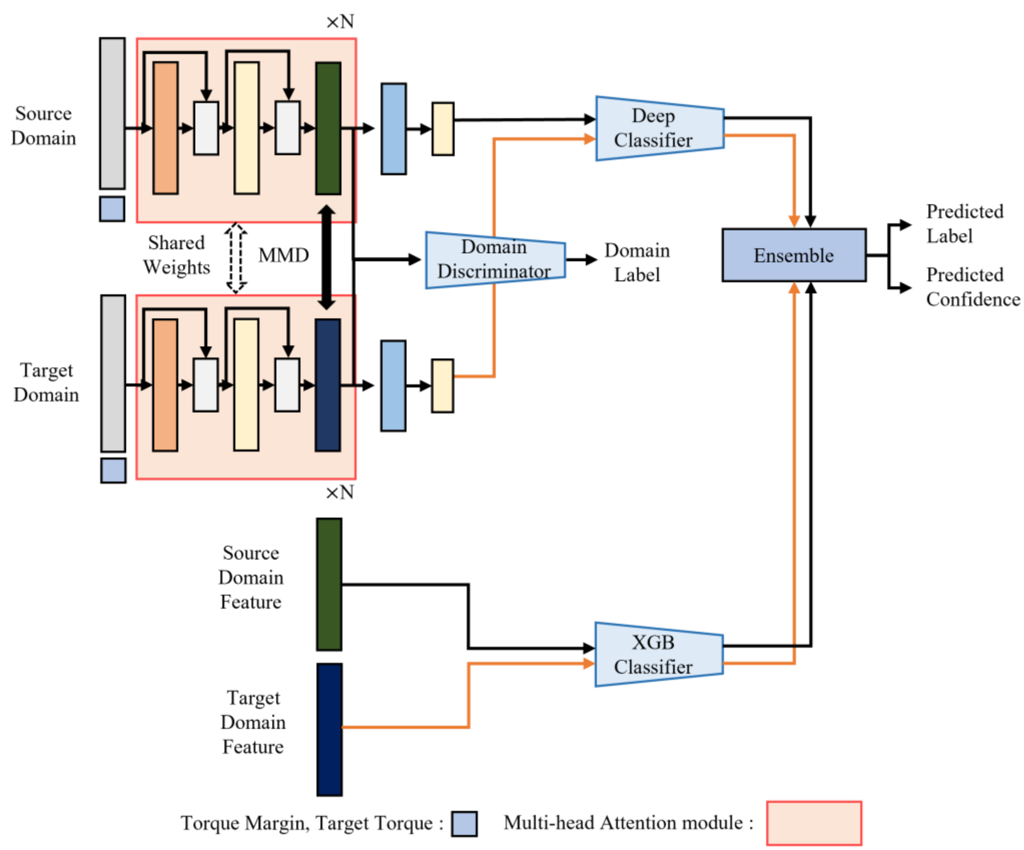

Figure 1. Framework of the proposed fault diagnosis method.

where y is the true value, $\hat{\mu}$ is the predicted mean, and $\hat{\sigma}^2$ is the predicted variance. This loss function optimizes both the mean and the uncertainty of the predictions, allowing the model to obtain results in terms of probabilistic distributions. The optimized mean and the variance are used to present the mean and the variance of a normal distribution, which gives a probability of the predicted sample. This enables more informative predictions that not only give a predicted value but also a measure of confidence, which is crucial for evaluating the performance of helicopter engines, reliably.

3.4. Multi-head Attention Based Domain-Adaptive Fault Diagnosis

The ensemble approach of two different methods were proposed to acquire a robust and reliable fault diagnosis result. Specifically, the extreme gradient boosting (XGBoost) decision tree classifier and the multi-head attention classifier were used. XGBoost showed a robust classification result on the training dataset, however the tree-based model presented an inferior result when used to predict data from different operational environments. Thus, to overcome the domain differences, the proposed methodology leverages the multi-head attention mechanism based deep learning model. Particularly, the multi-head attention mechanism was used in the deep learning model to increase the extraction performance of interactions between features. When compared to the conventional deep learning models, the multi-head attention mechanism allows the model to learn the importance of each feature and the relationships between them, yielding improved performance.

The proposed framework, as shown in Figure 2, incorporates additional variables, including the predicted torque margin from Bayesian regression and the target torque, which is calculated using the measured torque. The framework utilizes the training set as the source domain and the test and validation sets as the target domains. Features are extracted from both the source and target domains through a shared-weight multi-head attention module. To minimize the discrepancy between domains, Maximum Mean Discrepancy (MMD) is employed. Furthermore, the domain discriminator uses a Gradient Reversal Layer (GRL) to ensure that the model cannot differentiate between the source and target domains, thus enabling effective domain adaptation. This approach allows the model to perform fault diagnosis reliably, even in different operational environments.

The features extracted from the source domain are passed through two fully connected layers, leading to fault diagnosis. The predictions are then scaled between 0 and 1 using a sigmoid function, yielding probabilistic outputs. The deep learning model is thus capable of generating both predicted labels and their associated probabilities.

Subsequently, the features extracted from the multi-head attention module are used to train an XGBoost classifier, which generates an additional set of predictions (predicted labels and associated probabilities). These predictions are then combined with those from the deep learning classifier using an ensemble approach. Specifically, if both classifiers produce the same predicted label, the final confidence score is computed as the arithmetic mean of the two confidence scores. However, when the predicted labels differ, the prediction with the higher confidence score is selected, and the final confidence score is adjusted by averaging the two confidence scores. For instance, if one classifier yields a confidence score of 0.1 and the other 0.8, the final confidence score is averaged out as 0.45.

During the evaluation, the two classifiers predicted differently for 3,108 out of 426,625 samples in the training set. Figure 3 is a scatter plot showing the confidence scores when the two classifiers made different predictions. According to the plot, when the XGBoost classifier assigned a confidence score between 0 and 0.5, the deep learning classifier often tended to assign a higher confidence score for the same instance.

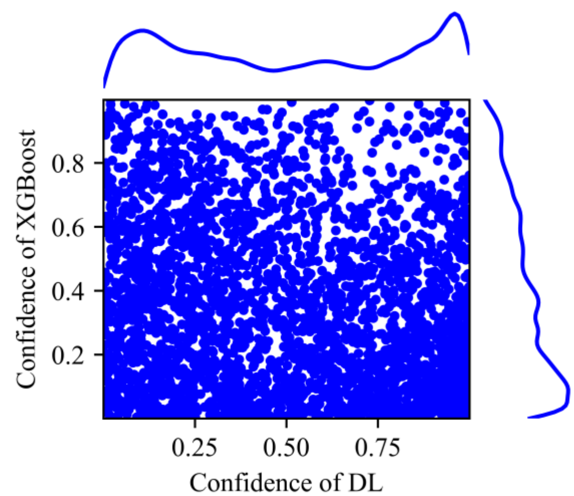

Figure 3. Scatter plot of confidence scores for XGBoost and deep learning (DL) classifiers for discrepant predictions.

Additionally, Figure 4 and Table 2 show the confidence scores and selection ratios between the deep learning classifier and the XGBoost classifier during prediction. When both classifiers made the same prediction, the deep learning classifier's prediction was predominantly chosen. However, when the predictions differed, the XGBoost classifier's prediction was more frequently selected. Furthermore, when the predictions were identical, both classifiers exhibited high confidence scores, but when they diverged, there was a greater variance in the confidence scores. Based on this, the performance of each classifier and the ensemble method on instances where their predictions differed in the training set was compared. As shown in Table 3, the results demonstrate that the ensemble method outperforms the individual classifiers. This indicates that the proposed ensemble approach allows the two classifiers to complement each other, resulting in more robust predictions.

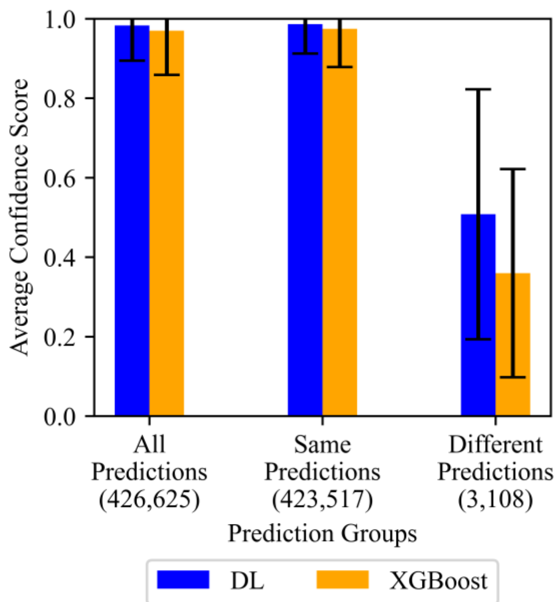

Figure 4. Average confidence scores of deep learning (DL) and XGBoost classifiers for all predictions, same predictions, and different predictions.

Table 2. Prediction selection table.

Prediction Groups	Deep Learning	XGBoost
All Predictions (426,625)	403,397 (94.56%)	23,228 (5.44%)
Same Predictions (423,517)	401,391 (94.78%)	22,126 (5.22%)
Different Predictions (3,108)	1,906 (61.33%)	1,202 (38.67%)

Table 3. Comparison of classifier performance metrics.

Classifier	Accuracy	Precision	Recall	F1 Score
Deep Learning	0.613	0.650	0.666	0.658
XGBoost	0.387	0.437	0.334	0.378
Ensemble	0.679	0.737	0.663	0.698

4. RESULT

In this section, the results of the proposed methodology are presented. The model's performance is evaluated based on the feature selection process and its comparison with existing approaches.

4.1. Selected Features for Torque Estimation and Fault Diagnosis

In this study, the wrapper method for feature selection, which evaluates the performance of different subsets of features based on their predictive power. This method involves training a model on various feature subsets and selecting the subset that produces the highest score on the test set. For the classification model, we selected the feature subset that achieved the highest accuracy on the test set. Similarly, for the regression model that is used for the estimation of the torque, the feature subset with the highest prediction accuracy (based on test set performance) was chosen. The results of the selected features for both the classification and regression tasks are summarized, as shown in Table 4.

Table 4. Selected features for each task.

<table>
<tr><th>Regression</th><th>Classification</th></tr>
<tr><td colspan="2">Measured Torque</td></tr>
<tr><td colspan="2">Mean Gas Temperature</td></tr>
<tr><td colspan="2">Indicated Airspeed</td></tr>
<tr><td colspan="2">Net Power</td></tr>
<tr><td colspan="2">Compressor Speed</td></tr>
<tr><td>Pressure Altitude</td><td>Predicted Torque Margin (%)</td></tr>
<tr><td>Outside Air Temperature</td><td>Predicted Torque Target (%)</td></tr>
<tr><td rowspan="3"></td><td>Mean Gas Temperature adjusted by air density</td></tr>
<tr><td>Net power adjusted by air density</td></tr>
<tr><td>Compressor speed adjusted by air density</td></tr>
</table>

4.2. Results of Torque Estimation and Fault Diagnosis

4.2.1. Evaluation Metrics

The performance evaluation in this study follows the methodology described by the PHM North America 2024 Conference Data Challenge, assessing both regression and

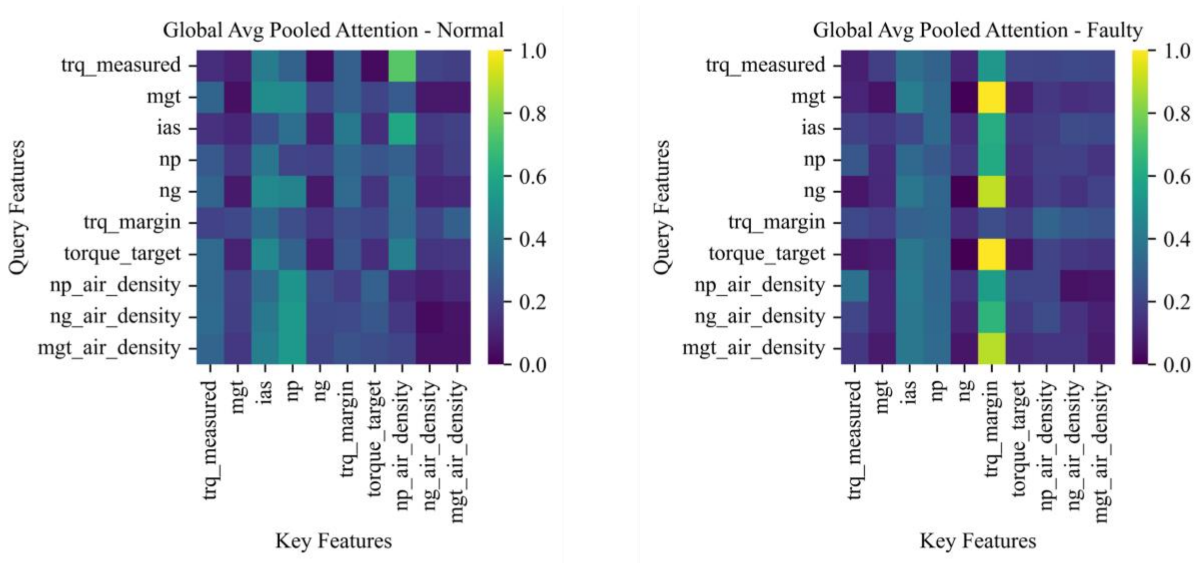

Figure 5. Attention maps of (a) normal engine and (b) faulty engine.

classification tasks based on the accuracy and confidence of the predictions. For the regression task, a probabilistic approach is used to generate a probability density function (PDF) around the predicted values, while the classification task is evaluated based on the predicted labels and associated confidence levels.

The regression score is calculated by determining the intersection between the predicted PDF and the actual value. For each predicted value, a specific distribution (e.g., normal or Cauchy) is selected to generate the PDF, utilizing various distributions from the Scipy library. All PDFs are normalized so that the total area under the curve is equal to 1, ensuring consistency and fairness across different distributions. The score is then determined by the probability density at the actual value, meaning that predictions closer to the true value yield higher scores. In this way, the regression score reflects both the accuracy of the prediction and the model's confidence in that prediction.

For the classification score, both the predicted label (0 = healthy, 1 = faulty) and the confidence level of the prediction are used to calculate the score. If the prediction is correct, the confidence level is directly used as the score, with higher confidence resulting in a higher score. However, if the prediction is incorrect, the score is penalized, particularly in the case of false negatives, where a faulty engine is incorrectly classified as healthy. In such cases, the penalty is more severe, as misclassifying a faulty engine poses a greater risk. Confidence values must fall between 0 and 1, and any value outside this range results in a score of -100.

Finally, the overall performance of the model is computed as the average of all regression and classification scores. This approach ensures that the model is evaluated not only on the accuracy of its predictions but also on the confidence it assigns to those predictions.

4.2.2. Results of Torque Margin Regression and Fault Diagnosis

For the regression task, the performance of the proposed Bayesian regression method is compared with that of a deep neural network (DNN) model using Monte-Carlo simulation (MCS). In the classification task, the proposed multi-head attention-based classification model is compared with DNN model, XGBoost, and multi-head attention-based deep learning method without domain adaptation. Notably, the torque margin and target torque used in the classification task were derived from the proposed regression method, which provided optimized values for the classification process.

The performance comparison results showed that the proposed methodology outperformed other approaches in each task, as summarized in Table 5. In the regression task,

Table 5. Performance of test datasets.

Task	Method	Performance
Regression (Torque Margin Prediction)	DNN+MCS	0.8166
	Proposed Method	0.9918
Classification (Fault Diagnosis)	DNN	-0.1992
	XGBoost	0.9816
	Multi-Head Attention based Deep Learning (Source)	0.9822
	Proposed Method	0.9858

the Bayesian regression method effectively modeled the uncertainty of the predicted values, achieving accurate torque margin predictions. In the classification task, the multi-head attention-based model captured complex interactions between key operational variables, significantly improving fault diagnosis accuracy. Notably, even when compared to XGBoost, known for its strong generalization performance, the proposed multi-head attention-based method demonstrated superior performance. The proposed methodology achieved a performance score of 0.918 on the validation dataset using pseudo-labels from the test dataset.

4.2.3. Analysis of Attention Maps

To further analyze the model's performance in fault prediction, attention maps were extracted from the final attention layer, which significantly influenced fault diagnosis. Specifically, attention maps were generated for each of the eight heads in the multi-head attention mechanism, and global max pooling was applied to these attention maps to highlight the most critical interactions. As shown in Figure 5, the attention maps allow for a direct comparison between the normal engine and the faulty engine.

The attention maps present the attention of key operational variables depending on the condition of the engine. Under normal state, the attention is evenly distributed across various features. In contrast, in the faulty condition, which is shown in Figure 5(b), attention becomes more concentrated on specific features, such as measured torque (*trq_measured*), mean gas temperature (*mgt*), and net power (*np*). The attention based model focuses on the relationship among three features, which aligns with the domain knowledge.

From a domain perspective, torque margin serves as a key indicator of engine health due to its direct correlation with the engine's ability to produce the required torque under various operational conditions. Its interaction with other variables, such as mean gas temperature and net power, affect the engine's thermodynamic efficiency and power generation capacity. Specifically, changes in mean gas temperature reflect variations in the heat energy conversion process, while net power indicates the engine's ability to deliver the expected output. These variables are directly linked to the engine's overall performance and deviations in these metrics can signal potential inefficiencies or emerging faults in the engine’s operation.

In the faulty state, these relationships become more significant, as the model assigns higher attention values to features that heavily impact the engine’s torque margin. This shows that the model is capable of dynamically adjusting its focus based on the real-time condition of the engine, effectively prioritizing critical variables needed for accurate fault diagnosis.

The results validates that the multi-head attention mechanism effectively captures feature interactions and highlights the key variables that contribute to the performance of fault diagnosis. The increased attention to specific features under faulty conditions, especially in relation to torque margin, shows that the model is able to adapt its focus according to the engine's operational state, thereby enhancing the reliability of fault diagnosis.

5. CONCLUSION

This paper proposed a two-step methodology for accurately predicting the state of helicopter turbine engines and diagnosing faults. In the first step, Bayesian regression was used to predict the torque margin, probabilistically modeling the uncertainty in the predictions, and providing confidence intervals, which are crucial for ensuring reliability in aviation systems. In the second step, the predicted torque margin from the first step was utilized as a key feature for fault diagnosis. A multi-head attention mechanism was employed to capture complex interactions between various features, and domain adaptation techniques were applied to ensure robust performance in new operating environments.

Additionally, attention maps were analyzed to provide further insights into the model’s decision-making process. The Attention maps demonstrated that, under faulty conditions, the model focused more heavily on critical features such as measured torque, mean gas temperature, and net power. These attention maps validated the model’s ability to effectively prioritize the most relevant variables for fault diagnosis, further confirming the importance of torque margin and its associated features in distinguishing between normal and faulty engine states. This attention-based analysis provided a deeper understanding of the relationships between key operational variables, reinforcing the robustness of the proposed approach.

However, there were limitations in the feature extraction process due to the absence of specific information about the environmental conditions in which the experiments were conducted (e.g., humidity, atmospheric pressure variations, temperature fluctuations). As a result, constant values for parameters such as sea-level pressure and standard temperature were used. Therefore, the calculated air density should be considered an approximation and may differ from the actual air density in the operating environment.

Despite these limitations, the proposed two-step methodology, along with the insights gained from the attention map analysis, has proven to be highly effective in improving the monitoring of helicopter engine health, providing a reliable framework for aviation safety and maintenance. Future research will focus on further enhancing the proposed methodology by more accurately modeling the complex interactions and causal relationships between variables in both regression and fault diagnosis tasks, while continuing to explore the use of attention mechanisms for deeper interpretability.

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BIOGRAPHIES

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