

POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Remaining useful life estimation in aero-engines via regime-aware transformer architecture

Rejim duyarlı transformer mimarisi ile havacılık motorlarında kalan yararlı ömür kestirimi

***Yazar(lar) (Author(s))**: Gürkan KAYA[1], Hacer KARACAN[2]*

ORCID[1]: 0009-0000-6494-1174

ORCID[2]: 0000-0001-6788-008X

To cite to this article: Kaya G., and Karacan H., "Remaining Useful Life Estimation In Aero-Engines Via Regime-Aware Transformer Architecture", ***Journal of Polytechnic***, 29(4):290448:1-15 (2026).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Kaya G. ve Karacan H., "Remaining Useful Life Estimation In Aero-Engines Via Regime-Aware Transformer Architecture", ***Politeknik Dergisi***, 29(4):290448:1-15 (2026).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1880444

Remaining Useful Life Estimation in Aero-Engines via Regime-Aware Transformer Architecture

Highlights

- *A novel framework named ReACT is proposed by integrating regime-based normalization into a Transformer-based architecture for aero-engines operating under multiple operational conditions.*
- *In the context of Remaining Useful Life (RUL) estimation, a two-stage attentional construct is used together by modelling both temporal dependencies and inter-sensor relationships.*
- *The Efficient Channel Attention (ECA) module is incorporated into the ReACT architecture to learn the relative importance of sensor channels, and its contribution to representation quality is quantitatively demonstrated.*

Graphical Abstract

This study proposes a Transformer-based architecture that integrates regime-aware normalization to achieve robust and generalizable RUL prediction for engines operating across multiple and dynamically changing conditions.

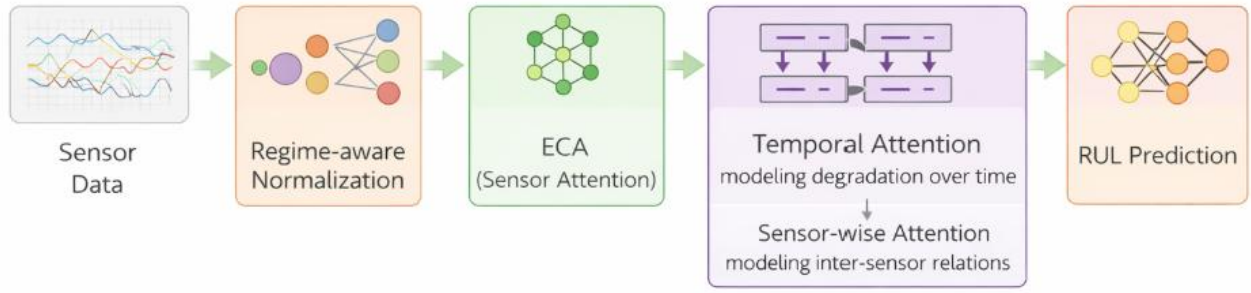


Figure. Proposed React method diagram

Aim

This study aims to enhance Remaining Useful Life (RUL) prediction performance for aero-engines operating under varying operational conditions by proposing a regime-aware Transformer architecture.

Design & Methodology

NASA CMAPSS data were used. In this paper, the used methodology includes regime-aware normalization, piecewise linear labelling, and Efficient Channel Attention (ECA) module. In addition, model decisions are explained through XAI analysis.

Originality

This work presents an interpretable Transformer-based framework for RUL prediction that combines regime-based normalization with a two-stage attention mechanism

Findings

Experimental results obtained with NASA C-MAPSS datasets show that the ReACT consistently outperforms existing approaches in terms of RMSE and NASA Score, especially in datasets with multiple operating conditions.

Conclusion

This study demonstrates that the regime-aware Transformer architecture offers high accuracy and explainability, making it a reliable and viable solution for predictive maintenance in the aviation industry.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Remaining Useful Life Estimation in Aero-Engines via Regime-Aware Transformer Architecture

Araştırma Makalesi / Research Article

Gürkan KAYA[1*], Hacer KARACAN[2]

[1]Graduate School of Natural and Applied Sciences, Computer Engineering Department, Gazi University, Türkiye
[2]Faculty of Engineering, Computer Engineering Department, Gazi University, Türkiye

(Geliş/Received : 02.02.2026 ; Kabul/Accepted : 28.04.2026 ; Yayımlanma/Publication : 09.06.2026)

ABSTRACT

Remaining Useful Life (RUL) estimation has gained significant importance in recent years to improve the reliability of industrial systems. Within the scope of Predictive Maintenance (PdM), RUL estimation plays a critical role in supporting maintenance decision-making processes and planning maintenance activities more effectively. The integration of PdM methods is also needed in the aviation sector. However, the fact that aircraft engines operate under variable conditions, such as different altitudes and speeds, rather than constant conditions, makes the interpretation of sensor measurements difficult. This negatively affects RUL estimation performance. In this study, a regime-aware architecture called ReACT is proposed for aircraft engines operating under different conditions. The proposed architecture consists of two main stages. In the first stage, operating regimes are determined using the K-means clustering method, and regime-aware normalization is applied to the data. In the second stage, a Transformer architecture combining a two-stage attention mechanism with the Efficient Channel Attention mechanism is used. This structure effectively models temporal degradation patterns and relationships between sensors. Experimental results on the NASA C-MAPSS dataset show that the ReACT architecture significantly reduces remaining useful life estimation errors and provides significant improvements in RMSE and NASA Score metrics compared to existing methods.

Keywords: Remaining Useful Life, Transformer, Regime Awareness, Deep Learning, C-MAPSS, Predictive Maintenance.

Rejim Duyarlı Transformer Mimarisi ile Havacılık Motorlarında Kalan Yararlı Ömür Kestirimi

ÖZ

Kalan Yararlı Ömür (Remaining Useful Life - RUL) tahmini endüstriyel sistemlerin güvenilirliğini artırmak amacıyla son yıllarda büyük önem kazanmıştır. Kestirimci bakım (Predictive Maintenance - PdM) kapsamında RUL tahmini, bakım karar verme süreçlerinin desteklenmesi ve bakım faaliyetlerinin daha etkin planlanması açısından kritik bir rol oynamaktadır. Havacılık alanında da PdM yöntemlerinin entegrasyonuna ihtiyaç duyulmaktadır. Ancak havacılık motorlarının sabit koşullar yerine farklı irtifalar ve hızlar gibi değişken çalışma koşulları altında faaliyet göstermesi, sensör ölçümlerinin yorumlanmasını zorlaştırmaktadır. Bu durum RUL tahmin performansını olumsuz etkilemektedir. Bu çalışmada, farklı çalışma koşulları altında çalışan havacılık motorları için ReACT adı verilen rejim farkındalıklı bir mimari önerilmektedir. Önerilen mimari iki ana aşamadan oluşmaktadır. İlk aşamada, K-means kümeleme yöntemi kullanılarak çalışma rejimleri belirlenmekte ve verilere rejime duyarlı normalizasyon uygulanmaktadır. İkinci aşamada ise Etkili Kanal Dikkati (Efficient Channel Attention) mekanizması ile iki aşamalı dikkat yapısını birleştiren bir Transformer mimarisi kullanılmaktadır. Bu yapı sayesinde zamansal bozunma örüntüleri ve sensörler arasındaki ilişkiler etkin biçimde modellenmektedir. NASA C-MAPSS veri seti üzerinde gerçekleştirilen deneysel sonuçlar, ReACT mimarisinin kalan yararlı ömür tahmin hatalarını önemli ölçüde azalttığını ve mevcut yöntemlere kıyasla RMSE ve NASA Skoru metriklerinde anlamlı iyileşmeler sağladığını göstermektedir.

Anahtar Kelimeler: Kalan Yararlı Ömür, Transformer, Rejim Farkındalığı, Derin Öğrenme, C-MAPSS, Kestirimci Bakım.

1. INTRODUCTION

The increasing integration of Industry 4.0 and Internet of Things (IoT) technologies into the contemporary industrial field has increased the complexity of engineering systems [1]. In this context, ensuring operational reliability and long-term sustainability has emerged as a major challenge, especially in capital-intensive and safety-critical applications.

Aviation engine systems are a prime example of situations where unexpected failures can lead to significant cost consequences and serious safety impacts. If failures in these systems are unpredictable, they can cause significant financial losses and safety hazards. In this context, Predictive Maintenance (PdM), designed to predict failures in advance through continuous system health monitoring, has increasingly begun to replace traditional corrective and time-based maintenance methods [2]. Accordingly, the use of data-driven analytics in aviation applications has increased. This has necessitated the development of more effective methods related to data management and system integration [3].

*Sorumlu Yazar (Corresponding Author)
e-posta : gurkan.kaya@gazi.edu.tr

One of the important concepts in the field of Predictive Maintenance (PdM) is Remaining Useful Life (RUL) estimation, which aims to determine how long a component can operate before failing or needing replacement. Accurate assessment of RUL is crucial for minimizing maintenance costs, facilitating spare parts logistics, and improving operational safety [4]. In the last decade, data-driven methodologies have largely replaced traditional physics-based modelling strategies in prognostics and health management. Machine learning and deep learning methodologies can directly derive complex degradation patterns from multivariate sensor data. This has proven superior in reducing reliance on manual feature extraction [5]. One of the key issues for the effectiveness and robustness of these models is also the data preprocessing step, which significantly impacts the capabilities of the models [6], [7].

This article presents a regime-aware Transformer-based approach called ReACT (Regime-Aware Contextual Transformer) to predict RUL under multiple operating conditions. ReACT explicitly incorporates operational regimes into the data preparation phase. This allows the model to adapt to variations in sensor behaviour depending on the operational conditions it is in. The proposed methodology efficiently resolves distribution inconsistencies arising from different operating environments by applying regime-specific normalization instead of global normalization. Experimental results show that this method reduces Root Mean Square Error (RMSE) and NASA Score values, thus improving prediction accuracy and generalization performance in various operational regimes.

2. LITERATURE REVIEW

RUL estimation has attracted continuous interest over the last twenty years. The literature includes many different modelling perspectives for RUL estimation. This section examines the studies most relevant to the present work, and the proposed ReACT framework is positioned within this context. It is also worth noting that recent studies in the Turkish literature indicate increasing local interest in this subject [8], [9], [10].

When examining the first studies on RUL estimation, one largely encounters physics-based degradation models and classical statistical prognostic techniques [11]. These approaches offer interpretability and physical intuition. On the other hand, their success is limited in complex, nonlinear degradation patterns observed in real industrial systems. In the following period, machine learning-based solutions began to emerge. For example, Khelif et al. [12] investigated the Support Vector Regression (SVR) method for RUL estimation. However, such methods are typically developed under the assumption of a single operating condition. Consequently, the performance of such models generally decreases when applied to systems operating in multiple regimes.

With the development of deep learning methods, these approaches have also begun to be used in time-series analysis. Studies such as Wu et al. [5] have suggested that learning degradation patterns directly from raw sensor data can be effective, especially when the amount of data is sufficient. In this context, methods such as Convolutional Neural Networks (CNNs) [13] and Long Short-Term Memory (LSTM) networks [14], [15] have produced successful results and have become widely preferred. Later comparative studies have shown that CNNs tend to efficiently capture local temporal patterns, but LSTM-based models may be more suitable for modelling longer temporal dependencies. Nevertheless, both approaches have some limitations [16], [17], [18].

To address the limitations imposed by single-architecture models, a significant portion of the literature has turned to hybrid modelling strategies. One example in this field is the two-stage degradation assessment framework proposed by Yan et al. [19], which relies on data fusion to separate degradation modelling from health assessment. Arias Chao et al. [20] approached the problem from a different angle, integrating physics-based formulations with deep learning using the Physics-Informed Deep Learning paradigm. Their motivation here is to go beyond prediction accuracy and maintain physical validity in the learned representations. Similarly, the STA-HPINN architecture has been reported to improve prediction performance under certain operating conditions by integrating hidden physical information into neural networks [21]. Some studies moving away from physics-focused designs have combined CNN and LSTM components with attention mechanisms or wave-based noise reduction [22], [23], [24], [25]. These methods have been shown to contribute to reducing the effect of sensor noise on RUL prediction. Other methods include Bi-LSTM architectures enhanced with convolutional layers [26]. In addition, there are Neural Ordinary Differential Equation-based models [27] that attempt to model the degradation as a continuous-time process rather than a completely discrete sequence. In parallel with these developments, Transformer-based architectures, initially introduced for Natural Language Processing, have proven successful in the field of time series modelling and have begun to be used for RUL prediction. This development is largely based on the self-attention mechanism proposed by Vaswani et al. [28]. The self-attention mechanism makes it possible to capture long-range temporal dependencies without relying on recurrent connections. Several studies in the RUL estimation literature have shown that Transformer-based models perform better than many other alternatives, especially when modelling global degradation behaviour in noisy sensor data, including aircraft engine data [29]. For example, Wang et al. proposed a lightweight Transformer architecture adapted to RUL estimation [30]. They later extended this approach through a multi-task learning framework that includes atrous CNNs with self-attention encoding [31]. In this context, related attention-focused architectures, including TTSNet [32] and TCRSCANet [33], have also been investigated. More recent studies have explored a

variety of directions, such as position-aware attention mechanisms [34], hierarchical two-stage Transformer designs [35], graph-based spatio-temporal representations [36], and Temporal Convolutional Networks enhanced with multiscale interaction modules [37].

Despite these methodological advances, an important challenge remains largely unresolved. In practical settings, systems like aircraft engines generally do not operate under constant or homogeneous conditions. The presence of variable conditions often leads to significant distribution shifts in sensor data. This problem is clearly observable in the NASA C-MAPSS dataset [38]. Subsets FD001 and FD003 encompass only one operating condition, whereas FD002 and FD004 encompass multiple operating regimes that make modelling more challenging. Transfer learning [39] and domain adaptation methods [40] have gained interest in addressing such distribution shifts. Beyond aviation applications, RUL estimation has also been investigated in different fields such as lithium-ion batteries [41] and rotating machinery [42], [43], [44], as well as in end-to-end representation learning approaches for estimation [45]. Some recent studies have also focused on estimating RUL along with failure types or health states, which further broadens the problem formulation [46], [47].

Overall, Transformer-based models achieve strong performance in the literature. However, significant gaps remain. In particular, the explicit inclusion of complex operational regimes in model architectures is still limited. Furthermore, the interpretability of model decisions remains a clear concern. Taking all these observations into consideration, this study presents a regime-aware Transformer architecture called ReACT that explicitly considers operational regime information and aims to increase transparency in the model's decision-making process.

3. MATERIALS AND METHODS

In this study, a Regime-Aware Contextual Transformer (ReACT) architecture is proposed for Remaining Useful Life (RUL) estimation of turbofan engines operating under multiple operational conditions. ReACT is a Transformer-based framework that explicitly integrates regime awareness into data representations and employs separate yet sequential attentional mechanisms along the temporal and sensor dimensions. Accordingly, the ReACT architecture is formed of four main components:
(i) regime-aware normalization,
(ii) sensor weighting via Efficient Channel Attention (ECA),
(iii) a patch-based Transformer encoder with a Two-Stage Attention mechanism, and
(iv) a regression-based RUL prediction head.

3.1. RUL Label Definition

During training, to manage the uncertainty in the initial stages of the engine's healthy operation, the RUL labels are limited using a piecewise linear formulation. The maximum RUL threshold is set to $R_{\max} = 125$. This strategy prevents high-variance target values in early life stages from adversely affecting model training.
In the run-to-failure NASA C-MAPSS dataset, the failure time of each engine unit $u$is known. T_u is the total number for operating cycles of the engine u. The RUL at cycle t is defined as:

$$y_t^{(u)} = T_u - t. \quad (1)$$

During the test phase, engine trajectories are truncated before failure, and thus T_u cannot be directly observed. Therefore, the RUL values for test engines are obtained from the separate target RUL file provided with the dataset and are used for model evaluation.

3.2. Regime-Based Normalization

In the C-MAPSS dataset, operating conditions are represented by three operational setting (OS) variables, which directly affect the statistical distributions of sensor measurements. To explicitly account for this effect, ReACT applies regime-based normalization instead of global normalization.
Let $r \in \{1, \dots, K\}$ denote the operational regime. For each regime, normalized sensor values are computed as

$$\tilde{x}^{(r)} = \frac{x - \mu^{(r)}}{\sigma^{(r)}} \quad (2)$$

where $\mu^{(r)}$and $\sigma^{(r)}$ represent the mean and standard deviation associated with regime r. This normalization suppresses variations caused by operating conditions and encourages the model to learn regime-invariant degradation dynamics.
For the FD002 and FD004 subsets, that contain more than one operating conditions, regime labels are obtained via clustering. Since FD001 and FD003 involve only one operating condition, $K = 1$ is assumed. Both K-Means and Gaussian Mixture Models (GMM) were evaluated, yielding similar regime partitions and predictive performance. Due to its lower computational cost, fewer parameters, deterministic behavior, and practical applicability to large-scale time-series data, K-Means was selected for the final architecture. For the FD002 and FD004 subsets, the number of clusters K was explicitly set to 6. This selection is primarily based on domain knowledge, as the original NASA C-MAPSS dataset documentation identifies six distinct operating conditions for these specific subsets [5]. To empirically validate this selection, a sensitivity analysis was performed using the Elbow Method and Silhouette Score. As illustrated in Figure 1, the Elbow curve exhibits a clear inflection point at K=6, and the Silhouette score reaches its maximum value at the same point, confirming that K=6 provides the most natural and optimal clustering for these datasets.

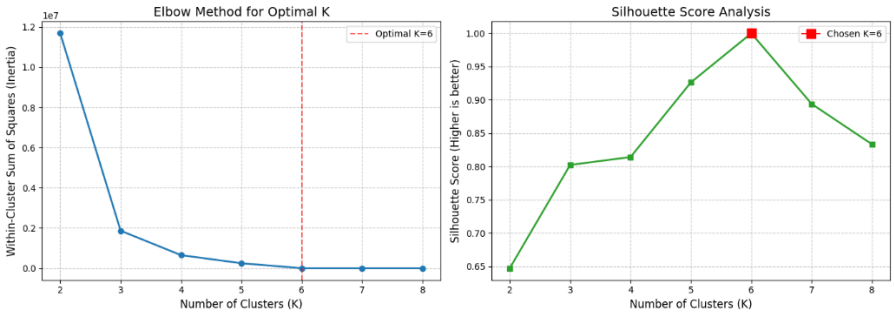


Figure 1. Elbow Method and Silhouette Score Graphics

For each cycle t, the operational condition vector is defined as $\mathbf{o}_t \in \mathbb{R}^3$. In multi-regime subsets, K-Means clustering is applied to these vectors to obtain Koperational regimes. The regime label at time step $t$is assigned as

$$r_t = \arg \min_{k\in\{1,\dots,K\}} \| \mathbf{o}_t - \boldsymbol{\mu}_k \|_2^2 \quad (3)$$

where $\boldsymbol{\mu}_k$ denotes the centroid of the k-th regime.

After regime identification, a separate normalization model is defined for each regime. Different normalization strategies were empirically evaluated, and the most stable methods were selected for each subset:

- **FD001 and FD002**: Since these subsets involve a single fault mode, standard normalization (Z-score) was found to provide stable and consistent performance.
- **FD003 and FD004**: As these subsets contain multiple fault modes, robust normalization based on median–IQR resulted in better generalization performance.

The normalization procedures are defined as

$$\tilde{s}_t = \frac{s_t - \mu^{(r_t)}}{\sigma^{(r_t)}} \text{ (Standard, Z-score)} \quad (4)$$

$$\tilde{s}_t = \frac{s_t - \text{median}^{(r_t)}}{\text{IQR}^{(r_t)}} \text{ (Robust)} \quad (5)$$

where s_t denotes the raw sensor recordings at time step t, and r_t indicates the related operational regime.

3.3. Efficient Channel Attention (ECA)

Another key component of ReACT is the Efficient Channel Attention (ECA) layer [48] which learns the relative importance of sensor channels. Applied after regime-based normalization, ECA provides a lightweight yet effective attention mechanism along the sensor dimension allowing the model to process sensor information according to contextual relevance rather than equal weighting. Following standard literature practices, seven sensors with constant values were discarded. The remaining 14 sensors (2, 3, 4, 7, 8, 9, 11, 12, 13, 14, 15, 17, 20, and 21) were retained across all subsets.

First, a sensor-level summary vector is computed by averaging normalized sensor values over a temporal window of length L:

$$\mathbf{g} = \frac{1}{L}\sum_{t=1}^{L} \tilde{\mathbf{s}}_t \,, \mathbf{g} \in \mathbb{R}^S \quad (6)$$

where $\tilde{\mathbf{s}}_t$ denotes the normalized sensor vector at time step t, and S represents the sensors' number.

In the next step, a 1D convolution with a fixed kernel size $k = 3$ is applied along the sensor axis to capture local inter-sensor dependencies:

$$\mathbf{a} = \sigma\big(\text{Conv1D}_k(\mathbf{g})\big) \quad (7)$$

where $\sigma(\cdot)$denotes the sigmoid activation function. This operation produces a channel-wise weight vector with values in the range [0,1].

Finally, sensor representations are rescaled at each time step using element-wise multiplication:

$$\hat{\mathbf{s}}_t = \mathbf{a} \odot \tilde{\mathbf{s}}_t \quad (8)$$

This process enhances the contribution of sensors that are more informative for degradation modelling while suppressing less relevant channels.

3.4. Patch-Based Representation and Two-Stage Attention Transformer

Following ECA, sensor time series are segmented using a fixed length sliding window with a stride of s=1 across all subsets. To prevent data leakage, windowing was performed strictly per engine (unit ID). Since C-MAPSS inherently provides distinct trajectories for training and testing, zero cross-contamination is guaranteed between the sets. Each window contains L consecutive time steps and S sensor channels:

$$\mathbf{W}_t = [\hat{\mathbf{s}}_{t-L+1}, \dots, \hat{\mathbf{s}}_t] \in \mathbb{R}^{L\times S} \quad (9)$$

To reduce calculation difficulty and enhance the local degradation patterns modelling, each sensor sequence is divided into patches which do not overlap. Patch length is p and patches are resulting in $P = \lfloor L/p \rfloor$ per sensor.

After that, each patch is transferred to a constant size embedding space using a linear embedding layer. To keep sensor identity, a learnable sensor embedding is

added. This enables the model to distinguish patches originating from different sensors. Temporal ordering is captured through learnable positional embeddings, forming the initial representation tensor $\mathbf{H}^{(0)}$, that is subsequently fed into the Transformer encoder.

ReACT is built around a two-stage attentional Transformer encoder which enables the modelling of temporal dependencies and inter-sensor relationships in a sequential but disentangled manner. In the first stage, Multi-Head Self-Attention (MHSA) is applied along the temporal dimension for each sensor independently:

$$\mathbf{H}^{(1)}_{(s,:,:)} = \mathrm{MHSA}_{\mathrm{temporal}}\left(\mathbf{H}^{(0)}_{(s,:,:)}\right) \qquad (10)$$

This stage captures long-term temporal degradation trends within each sensor channel.

In the second stage, MHSA is applied across sensors for each patch position:

$$\mathbf{H}^{(2)}_{(:,i,:)} = \mathrm{MHSA}_{\mathrm{sensor}}\left(\mathbf{H}^{(1)}_{(:,i,:)}\right) \qquad (11)$$

This operation enables the model to learn contextual inter-sensor relationships and to assign higher importance to sensors that are more critical to fault progression [49]. The order of the two-stage attention mechanism is designed based on the temporal nature of degradation processes. Temporal attention is applied first to capture degradation trends within each sensor over time. Subsequently, sensor-wise attention is used to model inter-sensor relationships based on these temporally enriched representations. This design ensures that sensor interactions are learned from context-aware features rather than raw signals. Additionally, the ECA module already provides an initial sensor-level weighting, further supporting this ordering. Together, these two stages constitute the Two-Stage Attention mechanism, allowing explicit and interpretable modelling of temporal and sensor-level dependencies.

3.5. Training and Evaluation

The multi-dimensional representations produced by the Transformer encoder are flattened while preserving learned temporal and sensor information and are then passed to a Multi-Layer Perceptron (MLP)–based regression head to generate the final RUL estimation. The trained model uses the Adam optimizer [50]. The Mean Squared Error (MSE) is utilized as the loss function. Dataset-specific hyperparameters are shown in Table 1. The hyperparameters were selected through a limited empirical search based on validation performance. For each dataset, a small search space was defined around commonly used values in the RUL literature. Specifically, window length was varied within {32, 48, 64}, patch length within {4, 8}, number of Transformer layers within {2, 3}, and the number of attention heads within {1, 2, 4}. Learning rates were selected from {2×10^{-4}, 3×10^{-4}, 4×10^{-4}}, and batch sizes were chosen from {32, 64}. The final configuration for each subset was determined based on the lowest validation RMSE obtained during K-Fold cross-validation. This procedure ensures that the selected hyperparameters are not overfitted to a specific train-test split and provides a fair basis for comparison across different datasets.

Table 1. Dataset-Specific Optimized Hyperparameters

Parameter	FD001	FD002	FD003	FD004
Window length (L)	32	64	64	64
Patch length (p)	4	4	4	4
Model dimension (d)	128	128	128	128
Number of attention heads (h)	1	4	1	1
Number of Transformer layers (l)	3	3	2	3
Batch size	32	64	32	64
Learning rate (lr)	3×10^{-4}	4×10^{-4}	2×10^{-4}	4×10^{-4}
Number of epochs	80	80	80	100
Warm-up epochs	10	10	10	10
Dropout rate	0.1	0.1	0.1	0.1
Conv1D Kernel Size (k)	3	3	3	3

3.6 Evaluation Metrics

Model performance is evaluated using two commonly preferred metrics: RMSE and the NASA Score.

The RMSE metric is calculated as,

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}, \qquad (12)$$

which measures the overall value for prediction errors.

In addition, the NASA Score function is reported, which asymmetrically penalizes early and late prediction errors and is therefore more suitable for practical maintenance scenarios:

$$S(e_i) = \begin{cases} \exp\left(\frac{e_i}{13}\right) - 1, & e_i < 0, \\ \exp\left(\frac{e_i}{10}\right) - 1, & e_i \geq 0, \end{cases} \qquad (13)$$

$$\mathrm{NASA\ Score} = \sum_{i=1}^{N} S(e_i) \qquad (14)$$

4. RESULTS AND DISCUSSION

Experimental evaluations were conducted using C-MAPSS dataset provided by NASA which includes simulated run-to-failure turbofan engine data and is commonly used in RUL prediction studies [38]. Four subsets of the dataset were considered: FD001, FD002, FD003, and FD004. These subsets differ in terms of operational condition and fault mode types, as summarized below:

• FD001: One operating condition and one fault mode
• FD002: Three operating conditions and one fault mode
• FD003: One operating condition and two fault modes
• FD004: Three operating conditions and two fault modes

Three normalization strategies were tested in experiments: Min-Max, Z-score, and Robust. K-means clustering and Gaussian Mixture Models (GMM) were compared for regime identification. To quantitatively assess the similarity between the clustering results, the Adjusted Rand Index (ARI), which measures the agreement between two clustering assignments while correcting for chance, was computed, yielding a score of 1.000, indicating statistically identical clustering assignments. Since both methods produced similar clustering structures and comparable model performance, K-means was chosen due to its lower computational complexity. K-Fold cross-validation is used to evaluate model stability. In Figures 2 and 3, the RMSE and NASA Score results corresponding to different normalization strategies are reported.

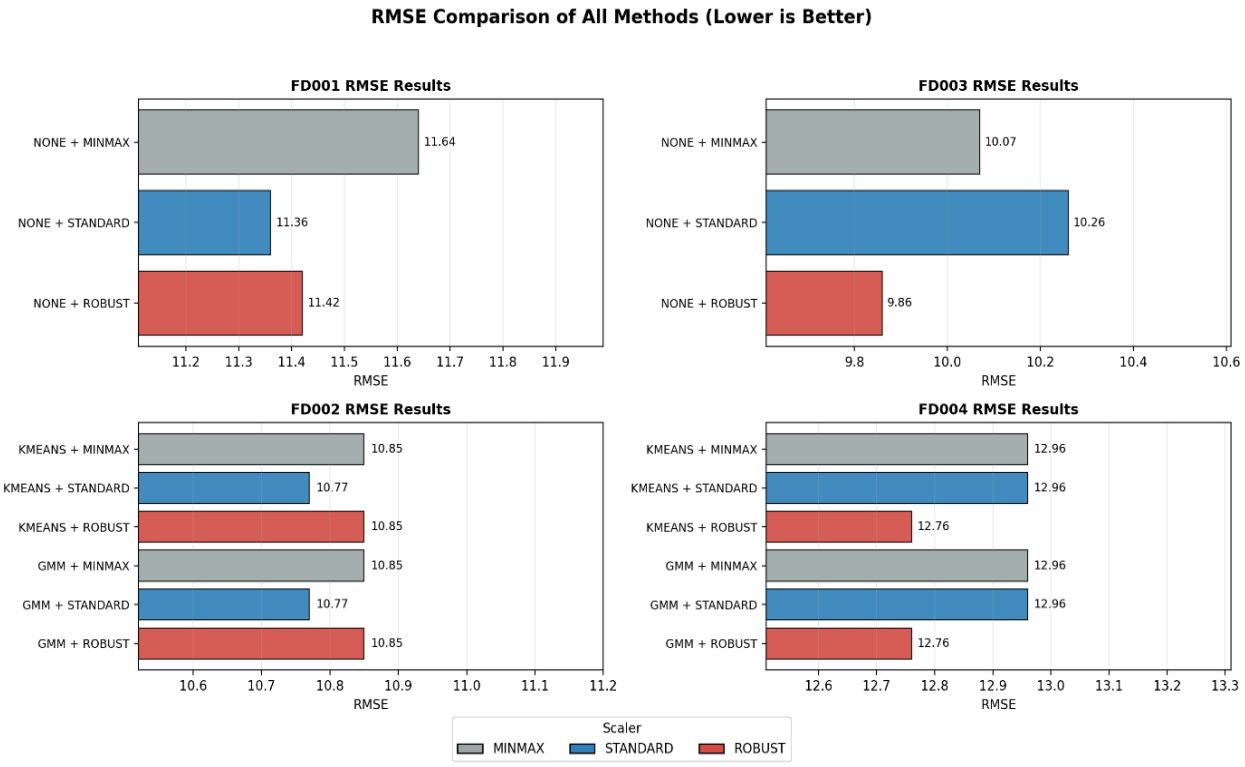


Figure 2. RMSE Results of Experiments

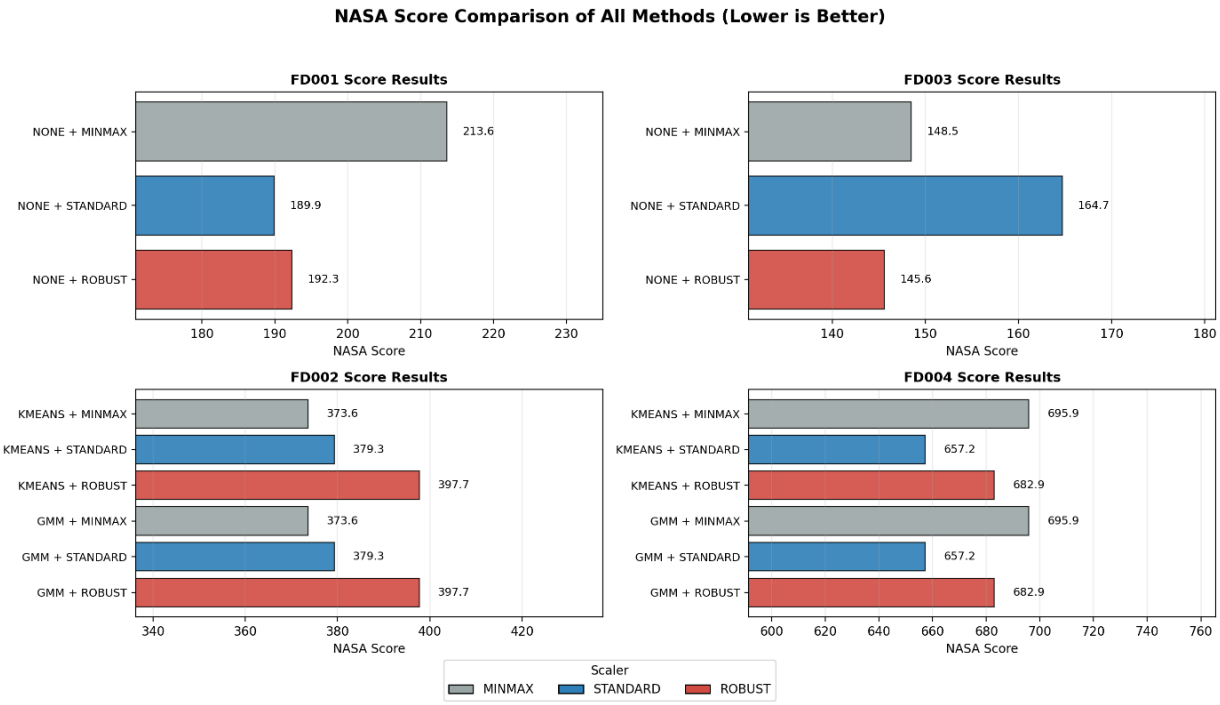


Figure 3. NASA Score Results of Experiments

For FD001, standard Z-score normalization results in the lowest RMSE and NASA Score values (RMSE = 11.36, Score = 189.99). When the system operates under one operating condition and one failure mode, balanced scaling of sensor signals appears sufficient to emphasize degradation-related trends.

In FD002, the two-evaluation metrics favor different normalization strategies. Standard Z Score normalization minimizes RMSE (RMSE = 10.77) and Min–Max normalization leads to the lowest NASA Score (Score = 373.68). Since RMSE is treated as the primary evaluation criterion in this study, Standard normalization is selected for FD002.

Increased variability and the presence of pronounced outliers characterize the FD003 subset. This subset involves two different failure modes. Under such conditions, Robust normalization produces the lowest RMSE and NASA Score values (RMSE = 9.86, Score = 145.61). The use of median–IQR-based scaling limits the influence of extreme sensor readings and supports improved generalization behaviour.

Among all subsets, FD004 poses the greatest challenge due to the coexistence of three operating conditions and two failure modes. For this case, Robust normalization achieves the lowest RMSE (RMSE = 12.77). A summary for best RMSE and NASA Score values across all datasets is provided in Figure 4.

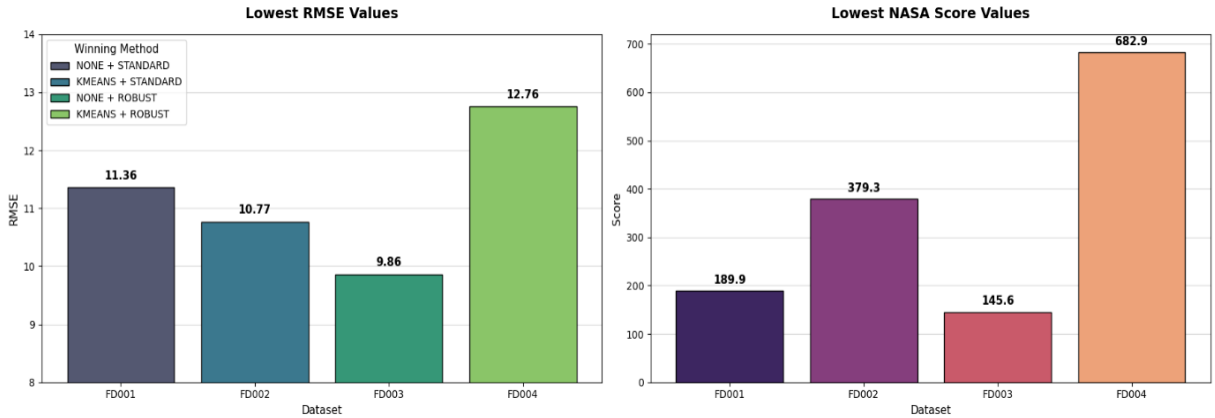


Figure 4. The best RMSE and NASA Score values obtained for each dataset

In addition to these quantitative results, the temporal behaviour of the ReACT architecture on test data was further analysed. Figure 5 displays how the estimated RUL values align with the ground truth for the test engines in datasets FD001 through FD004. The model successfully tracks the overall decreasing RUL trend in all subsets, with predicted trajectories closely matching the ground truth and prediction errors diminishing as failure approaches. This behaviour indicates that ReACT can capture the global dynamics of the engine degradation process in a stable manner.

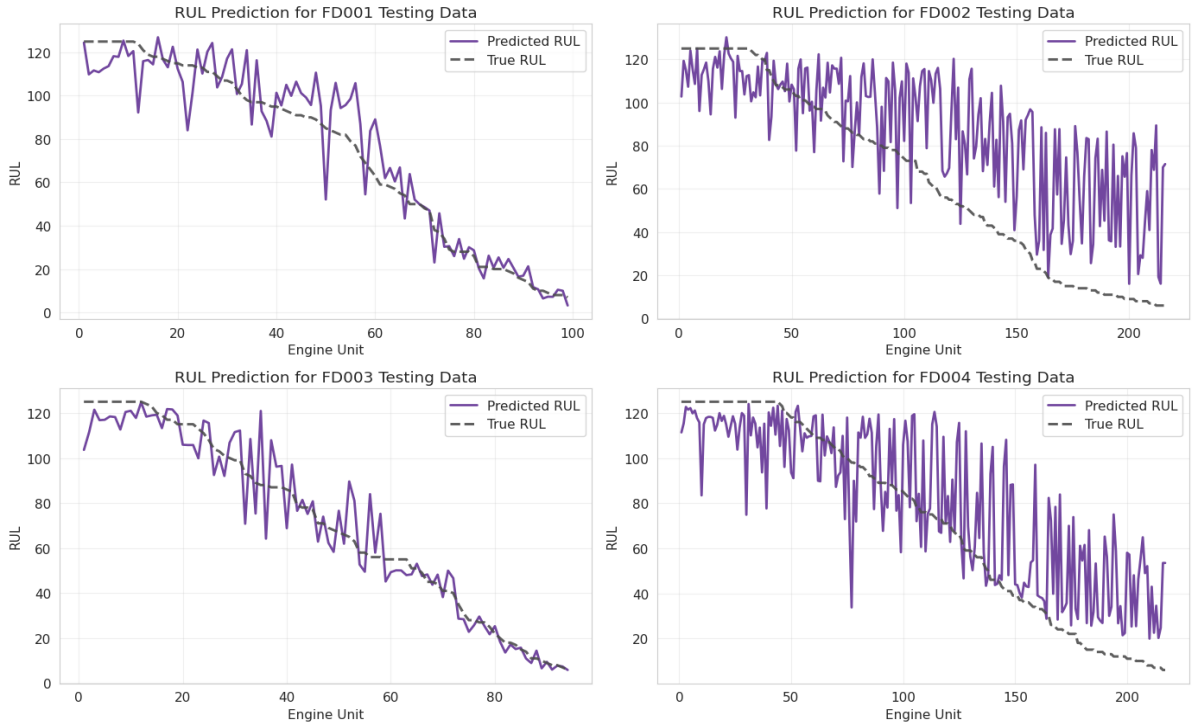


Figure 5. Comparison of True vs. ReACT-Predicted RUL Values on C-MAPSS Test Data (FD001–FD004)

Additionally, a comparative performance analysis between ReACT and existing methods reported in the literature is presented in Table 2. As shown in the Table 2, ReACT against selected methods documented in previous studies based on RMSE metric. While ReACT demonstrates competitive performance on FD001, which involves one operating condition and one fault mode, it achieves notably lower error values on FD002 and FD004, which contain three operating conditions. Additionally, ReACT demonstrates its effectiveness under multiple failure modes by achieving the lowest RMSE value in the FD003. These results highlight the advantage of incorporating regime awareness, especially in complex operating scenarios. To verify the stability of the proposed ReACT model and ensure that no data leakage occurred, the K-fold cross-validation was strictly confined to the official training sets. The analysis of these folds demonstrated high model stability during training, yielding cross-validation RMSE standard deviations of ±1.24, ±0.26, ±1.38, and ±1.34 for the FD001, FD002, FD003, and FD004 subsets, respectively. The final evaluation on the entirely isolated, held-out test engines yielded the highly competitive ensemble results presented in Table 2

Table 2. RMSE Comparison with the Literature on the C-MAPSS Dataset

	RMSE			
Method	**FD001**	**FD002**	**FD003**	**FD004**
Li et al., 2018 [13]	12.61	22.36	12.64	23.31
Ellefsen et al., 2019 [15]	12.56	22.73	12.10	22.66
Zheng et al., 2017 [17]	16.14	24.49	16.18	28.17
Wang et al., 2025 [30]	12.53	13.67	13.59	17.40
Fan et al., 2024 [35]	**10.98**	16.12	11.14	18.15
Wang et al., 2024 [36]	11.62	13.04	11.52	13.62
Lu et al., 2025 [37]	11.39	13.41	10.17	15.28
ReACT (Proposed method)	11.36	**10.77**	**9.86**	**12.76**

The role of the main components forming the ReACT architecture is investigated using an ablation analysis. Throughout these experiments, the network topology, hyperparameter configuration, training strategy, and evaluation protocol were not changed. On the other hand, individual components are selectively omitted. Through this experimental design the isolated impact of each component is examined. Five model variants are examined as part of the ablation study:

• ReACT: The complete architecture that includes both regime-based normalization and the ECA mechanism.

• Without ECA: The variant ECA is removed while all other components are retained.

• Without regime based normalization: The configuration where regime information is excluded from the preprocessing stage.

• Without ECA and regime-based normalization: A reduced version of the model where both components are omitted.

• Without Two Stage Attention: Standard Transformer Model

The performance comparison across these variants is presented in Figures 6 and 7.

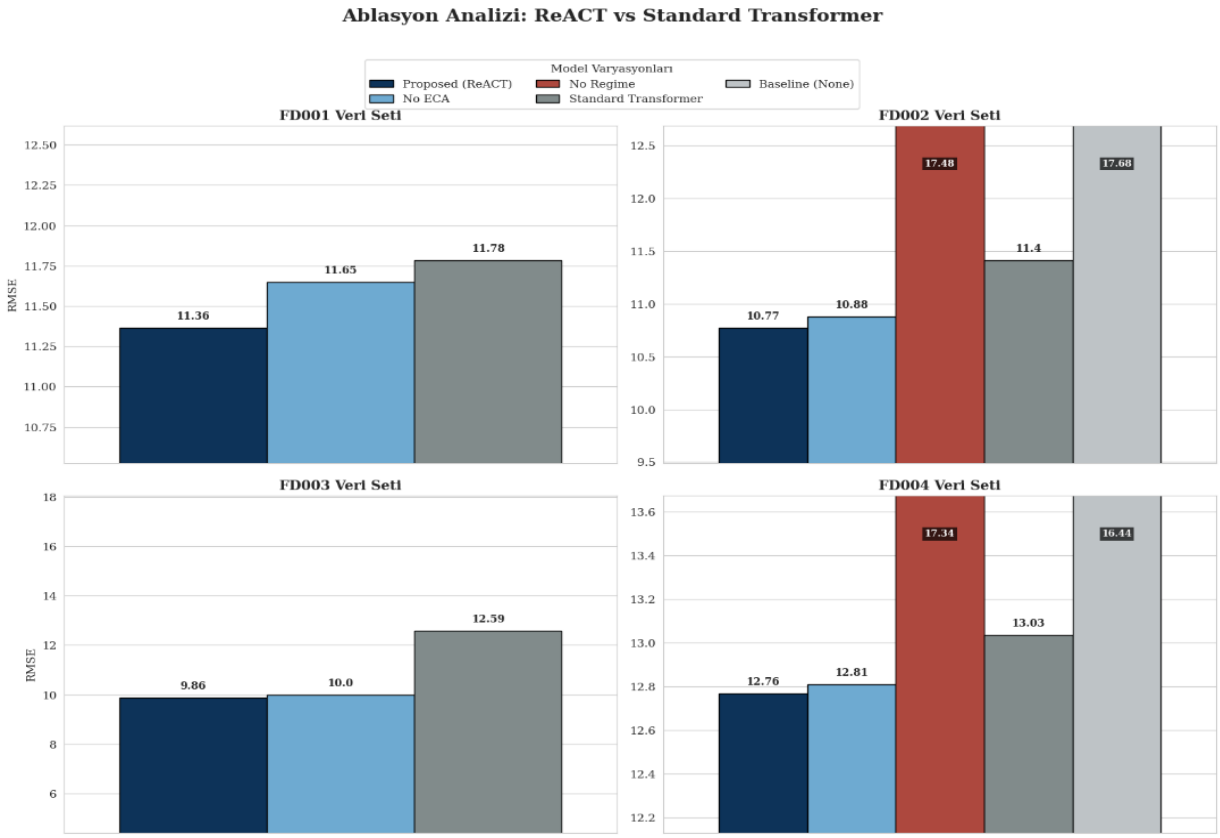


Figure 6. Ablation RMSE Results

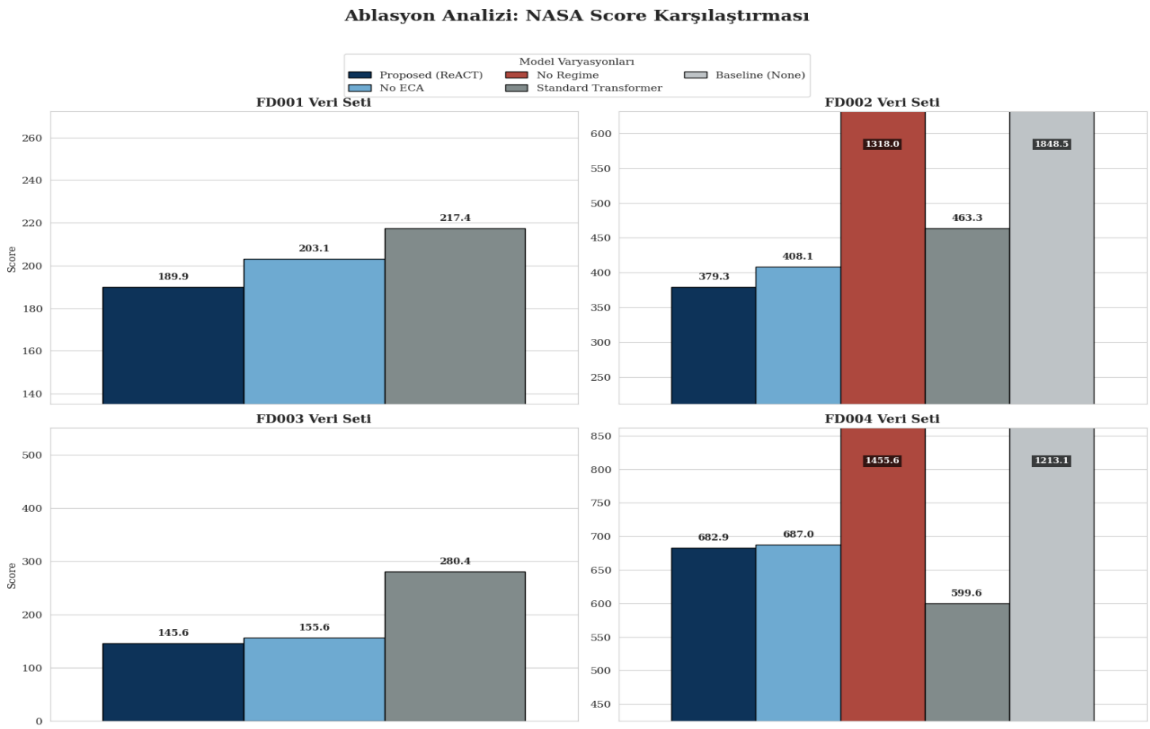


Figure 7. Ablation NASA Score Results

When the ablation results are examined, regime awareness is seen as the more dominant contributing component for the FD002 and FD004 subsets. When regime-based normalization is removed, both subsets experience significant performance degradation in terms of both RMSE and NASA Score. These results show that performance degradation occurs in Transformer-based architectures when deployment shifts resulting from different operating conditions are not explicitly modelled.

To further validate the necessity of the proposed architecture, a baseline comparison was conducted against a Standard Spatial Transformer (SST) which lacks both the regime-aware attention and ECA modules. As illustrated in the updated ablation figures, the SST baseline consistently yields higher error rates across all subsets (e.g., achieving an RMSE of 12.59 on FD003 compared to ReACT's 9.86). The significant performance gap, particularly in complex subsets like FD003 where ReACT provides a 21.68% improvement, confirms that standard attention mechanisms are insufficient for capturing regime-dependent degradation dynamics.

In the ablation analysis where the ECA module has been disabled, a small but consistent performance decrease was observed in all subsets. To further assess this contribution, results were analysed across K-Fold splits, and it was observed that the inclusion of ECA consistently improved RMSE values with low variance across folds. This indicates that the performance gain is stable and not due to random fluctuations. This shows that the effect of the ECA layer produces balanced and informative sensor representations. In this way, ECA contributes to overall performance. A significant performance decrease was observed in the ablation analysis where both components were removed simultaneously. These results show that the primary structural element of the ReACT architecture is regime awareness. ECA, on the other hand, continuously improves model stability and prediction accuracy. This confirms that ECA plays a complementary role.

ReACT is not limited to achieving accurate predictions but also produces physically consistent decisions that align with jet engine behaviour. To verify this, Explainable Artificial Intelligence (XAI) analysis was performed. Especially in high-risk areas such as aviation, the biggest obstacle to deploying deep learning models in industrial applications is the black box nature of the models. That is, the difficulties in understanding the internal structure of the model.

In this study, the Integrated Gradient (IG) method was adopted [51]. Integrated gradients are widely accepted in the literature. This method provides a consistent framework for describing model outputs. In the Integrated Gradients (IG) analysis, the baseline input was set to a zero tensor, following the default behavior of the Captum library. This baseline represents the absence of sensor signals and is commonly used in time-series attribution tasks. We note that the choice of baseline can influence the absolute magnitude of attributions. However, in this study, the focus is on the relative importance patterns across sensors and time steps. Empirical observations showed that the overall attribution structure remains consistent, indicating that the interpretability conclusions are robust with respect to the baseline choice. Some researchers have highlighted

the importance of XAI techniques to improve the understanding of black box models and Jakubiak has investigated the effectiveness of XAI methods in time series data [52].

FD004, the most complex subset of the C-MAPSS dataset, was selected for XAI analysis. The objective was to examine the model's decision-making behaviour under two different conditions:

• Healthy state: Engine samples with RUL greater than 110, which do not exhibit any degradation symptoms.

• Critical failure state: Engine samples with RUL lower than 15, engine examples requiring urgent maintenance.

The IG method links changes in the model output to the input space. This approach makes it possible to measure how much each sensor and time step affects the prediction. The analysis was performed at two levels:

• Local analysis: It covers attribution maps over the time–sensor plane for one healthy state and one critical failure state sample.

• Global analysis: It covers sensor importance ranking obtained by averaging IG attributions computed over randomly selected test samples.

IG attribution maps for healthy and critical failure conditions are presented in Figure 8(a) and Figure 8(b). The key methodological aspect of this visualization is that both heat maps are plotted using the same color scale of ±0.012. This avoids variations in color intensity resulting from rescaling, thus reflecting true magnitude differences.



Figure 8(a). IG attribution map for the healthy engine

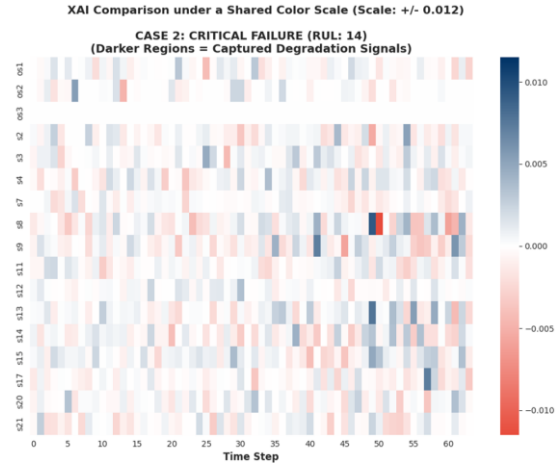


Figure 8(b). IG attribution map for the engine in critical failure condition

For the healthy state with a RUL value of 125, the colours in the IG map are quite faint. This indicates that the model does not show excessive sensitivity to specific sensors or time intervals in the healthy state. This prevents misinterpretation of normal operational fluctuations as fault indicators. On the other hand, for the critical fault state with a RUL value of 14, the IG map contains much darker regions. This can be interpreted as the model showing stronger sensitivity to specific sensors over time intervals. This observation also shows that the model does not process all inputs equally and focuses more carefully on fault-related signals. This selective attention confirms the effectiveness of the attention mechanisms used within the ReACT architecture. This level of attention becomes more pronounced as the fault approaches. However, since these observations are based on individual samples, a global analysis is necessary to characterize the overall decision-making behaviour of the model. For this purpose, 200 random samples were selected from the test set of each subset, and IG attributions were calculated for each sample. The results of this global analysis are shown in Figure 9. The three most dominant sensors for each subset are as follows:

• FD001: s3, s7, s17
• FD002: s7, s3, s21
• FD003: s20, s13, s12
• FD004: s7, s2, s12,

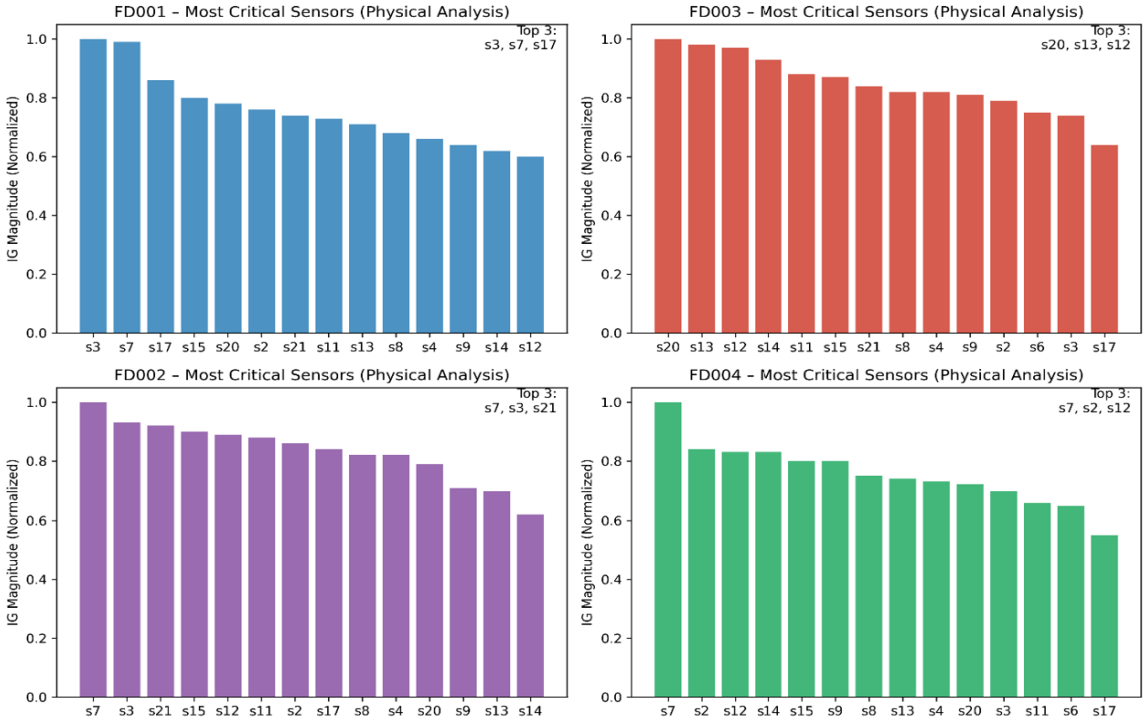


Figure 9. Global Sensor Importance Analysis

Analysis of results indicates that although the same architecture has been applied to every subset of the model, it prioritized different sensors in different subsets. Specifically, the s7 sensor was dominant in the FD002 and FD004 subsets. This suggests that the model relies more heavily on certain sensors under multiple operating conditions. Overall, ReACT's XAI analysis shows that the model's success is unlikely to be incidental. The model consistently focuses on physically meaningful signals while monitoring engine health. This provides an appropriate level of transparency and consistency for industrial and safety-critical applications.

In addition to prediction accuracy, we provide a brief analysis of computational efficiency. The proposed ReACT model contains approximately 10.27 million trainable parameters. The average inference time was measured as 9.69 ms per sample (± 0.62 ms) on an NVIDIA A100 GPU.

Although the two-stage attention mechanism introduces additional computational overhead compared to simpler architectures, the increase remains moderate. The model achieves a favorable balance between predictive performance and computational cost, making it suitable for practical predictive maintenance applications. It is also worth noting that many prior studies in the literature do not report parameter counts or inference latency, which limits direct efficiency comparisons.

5. CONCLUSION

Numerous detailed experiments were conducted on subsets FD001–FD004 of the dataset. These experiments revealed that the proposed ReACT architecture exhibits stable and competitive performance across various scenarios, comparable to studies in the literature. In particular, regime-based normalization was observed to play a decisive role in improving model performance for subsets like FD002 and FD004 which contain multiple operating conditions.

In scenarios that include multiple failure modes like FD003, the use of robust normalization and the two-stage attention mechanism together enables effective modelling of engine remaining useful life estimation even with complex sensor data. Comparisons with existing approaches show that ReACT achieved particularly successful RMSE values in the FD002 and FD004 subsets. Furthermore, XAI and ablation analyses confirmed that the architectural design choices within ReACT were not random; each component fulfilled a specific function corresponding to different problem characteristics.

6. FUTURE WORK

Despite all these successful studies and methods, there are many issues that remain open for future research in this field. Applying advanced interpretable AI techniques to further improve the interpretability of deep learning-based RUL models can reduce the black-box nature of these models and guide future studies in this area [53], [54]. Another important issue is quantifying prediction uncertainty. Reliability in industrial decision support systems can be further improved through conformal prediction approaches that provide statistically valid confidence intervals for model outputs [55], [56]. Additionally, recently proposed hybrid architectures

exhibiting strong performance show additional opportunities for progress in this area [57], [58]. Furthermore, recent studies conducted in different deep learning application domains have highlighted that hybrid architectures, explainable and robust AI systems, as well as computationally efficient edge-oriented deployments, are becoming increasingly important for real-world applications operating under resource-constrained and safety-critical conditions [59], [60], [61]. In this context, uncertainty modelling, multitask learning, lightweight transformer-based architectures, and the development of models that can generalize across different datasets remain promising directions for future research.

ACKNOWLEDGMENT
The author expresses acknowledgments to the Turkish Aerospace (TUSAŞ) for the research environment and technical infrastructure provided.

DECLARATION OF ETHICAL STANDARDS
The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS
Gürkan KAYA: The author designed the study, developed the proposed methodology, implemented the model, conducted the experiments, analysed the results, and wrote the article.
Hacer KARACAN: The author designed the study, developed the proposed methodology, implemented the model, conducted the experiments, analysed the results, wrote the manuscript, supervised the study and provided technical guidance.

CONFLICT OF INTEREST
There is no conflict of interest in this study.

REFERENCES
[1] Lee J., Bagheri B. ve Kao H.-A., "A cyber-physical systems architecture for industry 4.0-based manufacturing systems", ***Manufacturing Letters***, 3: 18-23, (2015).
[2] Jardine A. K., Lin D. ve Banjevic D., "A review on machinery diagnostics and prognostics implementing condition-based maintenance", ***Mechanical Systems and Signal Processing***, 20(7): 1483-1510, (2006).
[3] Stanton I., Munir K., Ikram A. ve El-Bakry M., "Predictive maintenance analytics and implementation for aircraft: Challenges and opportunities", ***Systems Engineering***, 26(2): 216-237, (2023).
[4] Berghout T. ve Benbouzid M., "A Systematic Guide for Predicting Remaining Useful Life with Machine Learning", ***Electronics***, 11(7): 1125, (2022).
[5] Saxena A., Goebel K., Simon D. ve Eholzer N., "Damage propagation modeling for aircraft engine run-to-failure simulation", ***2008 International Conference on Prognostics and Health Management***, 1-9, (2008).
[6] Erdoğan M. ve Mercimek M., "A comparative study on data pre-processing techniques for remaining useful life prediction of turbofan engines", ***International Journal of Materials Engineering Technologies***, 6(2): 50-58, (2023).
[7] Ndao M. L., Youness G., Niang N. ve Saporta G., "Improving predictive maintenance: Evaluating the impact of preprocessing and model complexity on the effectiveness of explainable artificial intelligence methods", ***Engineering Applications of Artificial Intelligence***, 144: 110144, (2025).
[8] Khan S. ve Yairi T., "A review on the application of deep learning in system health management", ***Mechanical Systems and Signal Processing***, 107: 241-265, (2018).
[9] Wu F., Wu Q., Tan Y. ve Xu X., "Remaining useful life prediction based on deep learning: a survey", ***Sensors***, 24(11): 3454, (2024).
[10] Zhu J., Ge Z., Song Z. ve Gao F., "Review and big data perspectives on robust data mining approaches for industrial process modeling with outliers and missing data", ***Annual Reviews in Control***, 46: 107-133, (2018).
[11] Luo J., Pattipati K. R., Qiao L. ve Chigusa S., "Model-based prognostic techniques applied to a suspension system", ***IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans***, 38(5): 1156-1168, (2008).
[12] Khelif R., Chebel-Morello B., Malinowski S., Laajili E., Fnaiech F. ve Zerhouni N., "Direct remaining useful life estimation based on support vector regression", ***IEEE Transactions on Industrial Electronics***, 64(3): 2276-2285, (2016).
[13] Li X., Ding Q. ve Sun J., "Remaining useful life estimation in prognostics using deep convolutional neural networks", ***Reliability Engineering and System Safety***, 172: 1-11, (2018).
[14] Wu Y., Yuan M., Dong S., Lin L. ve Liu Y., "Remaining useful life estimation of engineered systems using vanilla LSTM neural networks", ***Neurocomputing***, 275: 167-179, (2018).
[15] Ellefsen A. L., Bjørlykhaug E., Æsøy V., Ushakov S. ve Zhang H., "Remaining useful life predictions for turbofan engine degradation using semi-supervised deep architecture", ***Reliability Engineering and System Safety***, 183: 240-251, (2019).
[16] Babu G. S., Zhao P. ve Li X. L., "Deep convolutional neural network based regression approach for estimation of remaining useful life", ***International Conference on Database Systems for Advanced Applications***, 214-228, (2016).
[17] Zheng S., Ristovski K., Farahat A. ve Gupta C., "Long short-term memory network for remaining useful life estimation", ***2017 IEEE International Conference on Prognostics and Health Management***, 88-95, (2017).
[18] Guilherme D. N. V. B., "Remaining Useful Life Prediction on the NASA CMAPSS Dataset Comparing LSTM and Transformer Models", ***Master's Thesis***, Instituto Superior de Engenharia do Porto, (2025).
[19] Yan H., Zuo H., Sun J., Zhou D. ve Wang H., "Two-stage degradation assessment and prediction method for aircraft engine based on data fusion", ***International Journal of Aerospace Engineering***, 2021(1): 5876299, (2021).
[20] Chao M. A., Kulkarni C., Goebel K. ve Fink O., "Fusing physics-based and deep learning models for prognostics", ***Reliability Engineering and System Safety***, 217: 107961, (2022).
[21] Jiang F., Hou X. ve Xia M., "Spatio-temporal attention-based hidden physics-informed neural network for

remaining useful life prediction", ***Advanced Engineering Informatics***, 63: 102958, (2025).

[22] Boujamza A. ve Elhaq S. L., "Attention-based LSTM for remaining useful life estimation of aircraft engines", ***IFAC-PapersOnLine***, 55(12): 450-455, (2022).

[23] Akkad K. ve He D., "A hybrid deep learning based approach for remaining useful life estimation", ***2019 IEEE International Conference on Prognostics and Health Management***, 1-6, (2019).

[24] Dida M., Cheriet A. ve Belhadj M., "Remaining useful life prediction using attention-LSTM neural network of aircraft engines", ***International Journal of Prognostics and Health Management***, 16(2), (2025).

[25] Li H. ve Wang J., "Based on wavelet threshold denoising-LDA and BiLSTM aircraft engine life prediction", ***Journal of Physics: Conference Series***, 012019, (2022).

[26] Zhao R., Yan R., Wang J. ve Mao K., "Learning to monitor machine health with convolutional bi-directional LSTM networks", ***Sensors***, 17(2): 273, (2017).

[27] Star M. ve McKee K., "Remaining useful life estimation using neural ordinary differential equations", ***International Journal of Prognostics and Health Management***, 12(2), (2021).

[28] Vaswani A., Shazeer N., Parmar N., Uszkoreit J., Jones L. ve Polosukhin I., "Attention Is All You Need", ***Advances in Neural Information Processing Systems***, 30, (2017).

[29] Mo Y., Wu Q., Li X. ve Huang B., "Remaining useful life estimation via transformer encoder enhanced by a gated convolutional unit", ***Journal of Intelligent Manufacturing***, 32(7): 1997-2006, (2021).

[30] Wang L., Li Y., Liu H. ve Liu T., "A lightweight transformer edge intelligence model for RUL prediction classification", ***Sensors***, 25: 4224, (2025).

[31] Wang H., Lin T., Cui L., Ma B., Dong Z. ve Song L., "Multitask learning-based self-attention encoding atrous convolutional neural network for remaining useful life prediction", ***IEEE Transactions on Instrumentation and Measurement***, 71: 1-8, (2022).

[32] Li Z., Luo S., Liu H., Tang C. ve Miao J., "TTSNet: Transformer–Temporal Convolutional Network–Self-Attention with Feature Fusion for Prediction of Remaining Useful Life of Aircraft Engines", ***Sensors***, 25(2): 432, (2025).

[33] Wahid A., Breslin J. G. ve Intizar M. A., "TCRSCANet: Harnessing temporal convolutions and recurrent skip component for enhanced RUL estimation in mechanical systems", ***Human-Centric Intelligent Systems***, 4(1): 1-24, (2024).

[34] Chen X., "A novel transformer-based DL model enhanced by position-sensitive attention and gated hierarchical LSTM for aero-engine RUL prediction", ***Scientific Reports***, 14(1): 10061, (2024).

[35] Fan Z., Li W. ve Chang K. C., "A two-stage attention-based hierarchical transformer for turbofan engine remaining useful life prediction", ***Sensors***, 24(3): 824, (2024).

[36] Wang Y. vd., "Fully-connected spatial-temporal graph for multivariate time-series data", ***Proceedings of the AAAI Conference on Artificial Intelligence***, 15715-15724, (2024).

[37] Lu Z. vd., "A multi-scale cross-dimension interaction approach with adaptive dilated TCN for RUL prediction", ***Scientific Reports***, 15(1): 19229, (2025).

[38] Ramasso E. ve Saxena A., "Performance benchmarking and analysis of prognostic methods for CMAPSS datasets", ***International Journal of Prognostics and Health Management***, 5(2): 1-15, (2014).

[39] Li X., Li J., Zuo L., Zhu L. ve Shen H. T., "Domain adaptive remaining useful life prediction with transformer", ***IEEE Transactions on Instrumentation and Measurement***, 71: 1-13, (2022).

[40] Liu Q., Zhang Z., Guo P., Wang Y. ve Liang J., "Enhancing aircraft engine remaining useful life prediction via multiscale deep transfer learning with limited data", ***Journal of Computational Design and Engineering***, 11(1): 343-355, (2024).

[41] Hu W. ve Zhao S., "Remaining useful life prediction of lithium-ion batteries based on wavelet denoising and transformer neural network", ***Frontiers in Energy Research***, 10: 969168, (2022).

[42] Chen Z., Wu M., Zhao R., Guretno F., Yan R. ve Li X., "Machine remaining useful life prediction via an attention-based deep learning approach", ***IEEE Transactions on Industrial Electronics***, 68(3): 2521-2531, (2020).

[43] Hou G., Xu S., Zhou N., Yang L. ve Fu Q., "Remaining useful life estimation using deep convolutional generative adversarial networks based on an autoencoder scheme", ***Computational Intelligence and Neuroscience***, 2020(1): 9601389, (2020).

[44] Lei Y., Li N., Guo L., Yan T. ve Lin J., "Machinery health prognostics: A systematic review from data acquisition to RUL prediction", ***Mechanical Systems and Signal Processing***, 104: 799-834, (2018).

[45] Chaoub A., Voisin A., Cerisara C. ve Iung B., "Learning representations with end-to-end models for improved remaining useful life prognostics", (2021).

[46] Hou C. ve Zheng L., "A multi-task joint learning model based on transformer and customized gate control for predicting remaining useful life and health status of tools", ***Sensors***, 24(13): 4117, (2024).

[47] Wang W., He Q., Cui Y. ve Li Z., "Joint prediction of remaining useful life and failure type of train wheelsets: Multitask learning approach", ***Journal of Transportation Engineering Part A: Systems***, 144(6): 04018016, (2018).

[48] Wang Q., Wu B., Zhu P., Li P., Zuo W. ve Hu Q., "ECA-Net: Efficient channel attention for deep convolutional neural networks", ***Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition***, 11534-11542, (2020).

[49] Xiang S., Qin Y., Luo J., Pu H. ve Tang B., "Multicellular LSTM-based deep learning model for aero-engine remaining useful life prediction", ***Reliability Engineering and System Safety***, 216: 107927, (2021).

[50] Kingma D. P., "Adam: A method for stochastic optimization", (2014).

[51] Lundberg S. M. ve Lee S.-I., "A unified approach to interpreting model predictions", ***Advances in Neural Information Processing Systems***, 30, (2017).

[52] Jakubiak N., "Analysis of Explainable Artificial Intelligence on Time Series Data", ***Master's Thesis***, Universitat Politècnica de Catalunya, (2022).

[53] Costa N. ve Sánchez L., "Variational encoding approach for interpretable assessment of remaining useful life estimation", ***Reliability Engineering and System Safety***, 222: 108353, (2022).

[54] Jutte A., Ahmed F., Linssen J. ve van Keulen M., "C-SHAP for time series: An approach to high-level temporal explanations", (2025).

[55] Tibshirani R. J., Barber R. F., Candès E. J. ve Ramdas A., "Conformal prediction under covariate shift", ***Advances in Neural Information Processing Systems***, 32, (2019).

[56] Javanmardi A. ve Hüllermeier E., "Conformal prediction intervals for remaining useful lifetime estimation", (2022).

[57] Deng S. ve Zhou J., "Prediction of remaining useful life of aero-engines based on CNN-LSTM-Attention", ***International Journal of Computational Intelligence Systems***, 17(1): 232, (2024).

[58] Wang H.-K., Cheng Y. ve Song K., "Remaining useful life estimation of aircraft engines using a joint deep learning model based on TCNN and transformer", ***Computational Intelligence and Neuroscience***, 2021(1): 5185938, (2021).

[59] Şener M. C. ve Karacan H., "Deep Learning Technologies in Dental Practice: Current Applications and Research Trends", ***Politeknik Dergisi***, 29(2): 1-17, (2026).

[60] Sözen Z. ve Barışçı N., "Derin Öğrenme ile Hücre Görüntülerinin Tespiti ve Sayımı", ***Journal of Polytechnic***, 28(3): 909-921, (2025).

[61] İşler B., "Deep Learning-Based Speech Emotion Recognition for Iot Edge Devices: A Comparative Study", ***Journal of Polytechnic***, 29(4): 1-13, (2026).