Remaining Useful Life Estimation of Turbofan Engines with Domain-Adaptive Deep Learning

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***Abstract*—Predicting the Remaining Useful Life (RUL) of complex machinery enables condition-based maintenance and reduces unplanned downtime. Although deep learning has achieved state-of-the-art accuracy on benchmark datasets such as NASA CMAPSS, most models assume that training and test data are drawn from the same distribution. In real deployments, the health data distribution often shifts across operating conditions, environments, or asset fleets, leading to performance degradation. This study investigates the use of domain-adversarial training to learn operating-condition-invariant features for RUL prediction. A Batch-Normalized LSTM regressor and a Domain-Adversarial LSTM (DANN) are benchmarked on the four CMAPSS subsets. The DANN reduces cross-domain RMSE by up to 30% compared with a source-only baseline and approaches same-domain performance without accessing labeled target data. In addition to predictive accuracy, model transparency is addressed through SHapley Additive exPlanations (SHAP), providing clear insights into the sensor features that most influence RUL predictions and enhancing the trustworthiness and practical utility of the model.**

***Index Terms*—Remaining useful life, prognostics and health management, domain Adaptation, deep Learning, explainable AI, turbofan engines.**

I. Introduction

Prognostics and Health Management (PHM) is critical for modern industrial assets like turbofan engines, where unscheduled failures incur significant financial and safety risks. By anticipating faults, PHM enables predictive maintenance strategies that reduce costs and downtime while improving fleet safety and availability [1], [2].

Remaining Useful Life (RUL), the time until component failure [3], is a critical prognostic metric. While traditional methods rely on physics-based models, their frequent unavailability for complex systems like jet engines has shifted focus to data-driven approaches [4]. Among these, deep learning models like LSTMs, CNNs, and Transformers have proven superior to shallow learners by effectively extracting nonlinear temporal patterns from multivariate sensor data [5], [6], [7].

While deep learning models can achieve high accuracy for RUL prediction on individual datasets, their performance often degrades significantly under domain shift, where operational conditions differ between training and deployment. This results in unreliable predictions and increased risk in maintenance scheduling. Domain-Adversarial Neural Networks (DANN), a prominent Unsupervised Domain Adaptation (UDA) technique, address this challenge by employing a Gradient Reversal Layer (GRL) to encourage the learning of domain-invariant features, thereby enabling more robust generalization to new, unlabeled target domains [8].

Building on these ideas, this study introduces a domain-adversarial LSTM framework (DANN-LSTM) for RUL prediction of turbofan engines. The architecture combines an LSTM regressor with a gradient reversal layer-based domain classifier, enabling simultaneous minimization of prediction error and maximization of domain confusion. Experiments on the NASA CMAPSS datasets (FD001–FD004) demonstrate cross-domain RMSE reductions of up to 30% compared to a standard LSTM baseline. For practical deployment, the trained model is provided via a lightweight REST API and enhanced with SHAP-based explanations to ensure transparency.

The remainder of this paper covers related work (Section II), CRISP-DM methodology (Section III), results (Section IV), discussion (Section V), limitations (Section VI), and conclusion (Section VII).

II. Related Work

Classical data–driven RUL estimation: Early PHM work relied on exponential or Wiener degradation processes [9], Kalman-filter state estimation [10], and Bayesian particle filters [4]. Deterministic learners such as Support-Vector and Relevance-Vector Regression improved interpretability, but their accuracy degraded under noise and covariate shift [11].

Deep-learning approaches: *Recurrent models*—Zheng *et al.* stacked LSTMs and pushed FD001 RMSE down to 13.5 cycles [5], while bidirectional LSTMs captured degradation context in both temporal directions [13]. *Convolutional models*—Li *et al.* replaced pooling with successive 1-D convolutions for multi-scale pattern extraction, achieving competitive accuracy with lower latency [14]; dilated temporal CNNs further enlarged the receptive field without extra parameters [15]. *Transformer models*—Wu *et al.* introduced a Temporal Transformer and reported state-of-the-art performance, underscoring self-attention's value for long-range dependencies [7]. *Hybrid and attention mechanisms*—CNN–LSTM hybrids fuse spatial and temporal cues [16]; dual-channel networks leverage first-order differencing to emphasise monotonic trends [17]; and sensor-level attention pinpoints salient channels under variable load [18].

Domain Adaptation in Prognostics: DANN's GRL formulation remains the de-facto baseline for UDA [8]. da Costa *et al.*

ported DANN to CMAPSS, achieving 59 % RMSE reduction in FD004 → FD001 transfer [19]. Zhao and Liu embedded GRL into a CNN bearing-health network and demonstrated resilience under variable speed and load [20]. Wasserstein-based alignment (WD-DANN) leverages earth-mover distance for smoother gradient flow and lower mode-collapse risk [22]. Xu *et al.* proposed multi-source adversarial learning to unify heterogeneous machine types [23]. Recent work in aviation exploits flight-phase segmentation and phase-conditioned discriminators to account for multi-modal distributions [24], though at the cost of additional annotation.

Interpretability: Seebold *et al.* demonstrated the feasibility of integrating SHAP into RUL prediction pipelines using the NASA C-MAPSS turbofan dataset [25], highlighting how feature attribution can enhance model transparency in aerospace contexts. However, this work does not incorporate domain-adversarial adaptation, leaving open questions about explainability under domain shift.

III. Methodology (CRISP-DM)

A. Business Understanding

The primary business objective is to develop a predictive maintenance framework for turbofan engines by accurately forecasting Remaining Useful Life (RUL), enabling:

- **Reduced Maintenance Costs:** Transition to condition-based maintenance, servicing engines only as needed.
- **Increased Operational Availability:** Minimized unscheduled downtime through early failure warnings and proactive repairs.
- **Enhanced Safety:** Lower risk of in-flight failures via reliable RUL prediction.

Several key challenges complicate this objective:

- **Multi-Regime Operation:** Engines experience varying operational phases, resulting in multi-modal sensor data and complex degradation patterns.
- **Domain Shift:** Differences between training (source) and deployment (target) environments lead to distributional shifts that degrade model performance.
- **Label Scarcity:** RUL labels are only available at failure, making comprehensive data collection impractical.

The central data mining goal is to build a robust regression model for RUL prediction from time-series sensor data, with a focus on domain adaptation to generalize from labeled source domains to unlabeled or sparsely labeled target domains. Business success is defined by measurable reductions in unscheduled maintenance and costs, while technical success is assessed by RUL prediction accuracy.

B. Data Understanding

This study utilizes the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset, a widely recognized benchmark for prognostics and health management (PHM) developed by NASA. The dataset simulates the degradation of a fleet of turbofan engines over numerous flight cycles, providing a rich environment for developing and evaluating RUL prediction models.

1) Dataset Structure and Features: The C-MAPSS data is partitioned into four subsets, **FD001** through **FD004**, each representing distinct operational conditions and fault modes. Each subset contains multivariate time-series data from a fleet of engines, divided into:

- **Training sets:** Complete run-to-failure trajectories, where engine degradation progresses until failure.
- **Testing sets:** Trajectories are truncated at a point prior to failure. The model's objective is to predict the true RUL for these censored test instances.

Each time-series snapshot consists of 24 features: three operational settings (altitude, Mach number and Sea-level temperature) and 21 sensor measurements that capture the health of various engine components. Details of sensors are given in table I.

TABLE I
C-MAPSS Sensor Descriptions and Degradation Trends. Trend symbols: I (Increasing), D (Decreasing), ∼ (Non-monotonic).

Sensor	Parameter	Description with units	Trend
1	T2	Total Temperature in fan inlet (oR)	∼
2	T24	Total Temperature at LPC outlet (oR)	I
3	T30	Total Temperature at HPC outlet (oR)	I
4	T50	Total Temperature at LPT outlet (oR)	I
5	P2	Pressure at fan inlet (psia)	∼
6	P15	Total pressure in bypass-duct (psia)	∼
7	P30	Total pressure at HPC outlet (psia)	D
8	Nf	Physical fan speed (rpm)	I
9	Nc	Physical core speed (rpm)	I
10	Epr	Engine pressure ratio (–)	∼
11	Ps30	Static pressure at HPC outlet (psia)	I
12	Phi	Ratio of fuel flow to Ps30 (psi)	D
13	NRf	Corrected fan speed (rpm)	I
14	Nrc	Corrected core speed (rpm)	D
15	BPR	Bypass ratio (–)	I
16	farB	Burner fuel air ratio (–)	∼
17	htBleed	Bleed enthalpy (–)	I
18	NF-dmd	Demanded fan speed (rpm)	∼
19	PCNR-dmd	Demanded corrected fan speed (rpm)	∼
20	W31	HPT coolant bleed (lbm/s)	D
21	W32	LPT coolant bleed (lbm/s)	D

2) Exploratory Analysis and Feature Selection: Initial exploratory data analysis revealed that several sensor channels (s1, s5, s10, s16, s18, s19) exhibit near-constant values throughout an engine's lifecycle. As these provide negligible prognostic information, they were excluded from the modeling process, leaving the 14 informative sensors shown in Table I. The analysis also confirmed that engine lifecycles vary significantly, with trajectories ranging from 128 to over 500 cycles, motivating the use of a sliding-window approach to generate fixed-length sequences for the LSTM model.

3) The Domain Shift Challenge: The primary challenge addressed in this work is the domain shift present across the four C-MAPSS subsets. As detailed in Table II, the subsets differ in the number of operating conditions and active fault modes (degradation in the High-Pressure Compressor, Fan, or both). This heterogeneity means a model trained on one domain (e.g., FD001) is likely to perform poorly on another (e.g., FD002) due to the mismatch in data distributions.

TABLE II
CHARACTERISTICS OF THE FOUR C-MAPSS SUB-DATASETS.

Characteristic	FD001	FD002	FD003	FD004
Train Engines	100	260	100	249
Test Engines	100	259	100	248
Op. Conditions	1	6	1	6
Fault Modes	1(HPC)	1(HPC)	2(HPC,Fan)	2(HPC,Fan)
Cycles(min/max)	128/362	128/378	145/525	128/543

4) Operational Regime Diversity: The cross-subset diversity creates four canonical transfer scenarios:

- *Single-to-single regime* (FD001 $\leftrightarrow$ FD003): both domains operate under identical single ambient condition but with varying fault modes, forming the simplest adaptation scenario.
- *Single-to-multi regime* (FD001/FD003 $\rightarrow$ FD002/FD004): source domain with uniform operating condition must adapt to target with six distinct operational regimes, representing a challenging distribution expansion problem.
- *Multi-to-single regime* (FD002/FD004 $\rightarrow$ FD001/FD003): source domain with multiple operating conditions must compress knowledge into a single-regime target, requiring effective feature selection and noise filtering.
- *Multi-to-multi regime* (FD002 $\leftrightarrow$ FD004): both domains exhibit six regimes and two fault patterns, forming the most challenging adaptation pair.

This diversity establishes clear domain adaptation scenarios. For instance, transferring knowledge from a single-regime source (FD001) to a multi-regime target (FD004) is a significant challenge. These characteristics underpin the domain-adaptation strategy developed in coming sections.

C. Data Preparation

The raw time-series data from the CMAPSS dataset requires several preprocessing steps to be suitable for training deep learning models. The data preparation pipeline is designed to structure the data, engineer relevant features, and prevent information leakage between data splits. The process is detailed below.

1) Data Splitting Strategy: To ensure a robust evaluation, the data was partitioned on a per-unit basis, meaning all operational cycles from a single engine were confined to the same data split (training, validation, or test). This strategy is critical to prevent data leakage and to validate the model's ability to generalize to entirely unseen engine life cycles. For each dataset, the provided training file was split into a training set (80% of engine units) and a validation set (20% of engine units). The validation set was used for hyperparameter tuning and to implement early stopping, while the separate, official test files were used exclusively for the final, unbiased performance evaluation.

2) RUL Target Generation and Capping: The ground-truth RUL for the training data was calculated by subtracting the current cycle number from the total operational cycles of each engine unit. This creates a linearly decreasing RUL target. Following established practices in prognostics literature, we applied a piecewise linear RUL model by capping the maximum RUL value at 125 cycles. This technique encourages the model to focus on the more complex, non-linear degradation dynamics that manifest closer to failure, rather than the long, stable period at the beginning of an engine's life.

3) Feature Engineering and Selection: A multi-stage feature engineering process was implemented to enhance the predictive signal.

- **Removal of Static Features:** An initial analysis identified several sensors (e.g., s1, s5, s10) with constant or near-zero variance. As these features offer no predictive information, they were removed from the dataset.
- **Noise Reduction:** To smooth transient fluctuations and highlight underlying degradation trends, a moving median filter with a window size of 5 was applied to the time-series data of each sensor on a per-unit basis.
- **Correlation-Based Selection:** Further feature selection was performed by computing the Pearson correlation between each filtered sensor and the RUL target. Features were retained only if their absolute correlation exceeded a predefined threshold (0.10 for FD001/FD003 and 0.0001 for FD002/FD004, which have more complex operating conditions).

4) Feature Scaling: The selected features were normalized using a MinMaxScaler, which scales each feature to a [0, 1] range. To prevent data leakage, the scaler for each domain was fitted *only* on its corresponding training data. This fitted scaler was then used to transform the validation and test sets for that domain. The scalers were saved for consistent application during inference.

5) Time-Series Windowing: To create input sequences for the LSTM models, we employed a sliding window technique. The time-series data for each engine was segmented into windows of 30 consecutive time steps with a stride of 1. Each window of sensor data constitutes a single input sample $\mathbf{X}$, with the RUL at the final time step of the window serving as the corresponding target label y.

D. Modelling

This section details the deep learning architectures and the experimental framework designed for their evaluation in RUL prediction. First, a baseline LSTM model is introduced to establish performance benchmarks, followed by a DANN aimed at mitigating domain shift. Subsequently, the three experiments conducted to compare their performance are outlined, concluding with the specific hyperparameters used for training.

1) Baseline LSTM Regressor: This model is designed for effectiveness in time-series forecasting while maintaining architectural simplicity. It consists of a single-layer unidirectional LSTM with 100 hidden units that processes the input sequences. To stabilize training and improve convergence, the final hidden state from the LSTM layer is passed through a 1D BatchNorm layer. This normalized feature vector is

then fed into a two-layer feed-forward regression head with a ReLU activation, which maps the learned representation to a final RUL prediction. The model is trained end-to-end by minimizing the Mean Absolute Error (MAE), providing a robust baseline for in-domain performance and a direct point of comparison for the domain adaptation approach.

2) Domain-Adversarial LSTM (DANN-LSTM): To address the challenge of performance degradation across different operating conditions, a DANN-LSTM is implemented based on the principles of unsupervised domain adaptation [8]. This architecture learns domain-invariant features by simultaneously training a feature extractor, a RUL regressor, and a domain classifier in an adversarial manner. The model comprises three key components:

- **Feature Extractor:** A shared two-layer bidirectional LSTM (Bi-LSTM) with 128 hidden units in each direction serves as the feature extractor. By processing sequences in both forward and backward directions, the Bi-LSTM captures a richer temporal context. The final forward and backward hidden states are concatenated to form a comprehensive feature representation.
- **RUL Regressor and Domain Classifier:** Two parallel MLP heads are connected to the feature extractor. The RUL regressor predicts the remaining useful life from the source domain features, while the domain classifier is trained to distinguish between features originating from the source and target domains.
- **Gradient Reversal Layer (GRL):** The GRL is the cornerstone of the adversarial training. Positioned between the feature extractor and the domain classifier, it acts as an identity function during the forward pass. However, during backpropagation, it reverses the gradient by multiplying it with a negative scalar, $-\lambda$. This forces the feature extractor to learn representations that are predictive for the RUL task but indiscriminative for the domain classification task.

The model is optimized using a composite loss function that balances the regression and domain classification objectives:

$$L(\theta_f, \theta_y, \theta_d) = L_{RUL}(\theta_f, \theta_y) - \lambda L_{domain}(\theta_f, \theta_d)$$

where L_{RUL} is the MAE on labeled source data and L_{domain} is the Binary Cross-Entropy (BCE) loss for the domain classifier. The hyperparameter λ controls the influence of the adversarial component.

3) Experimental Design and Training: Three experiments were conducted to systematically evaluate model performance under different domain conditions:

1) **Target-Only Baseline:** The baseline LSTM was trained and evaluated on the same domain (e.g., trained on FD001, tested on FD001). This establishes the upper-bound performance for each dataset in an ideal, domain-matched scenario.
2) **Source-Only Cross-Domain:** The baseline LSTM was trained exclusively on a single source domain (FD004) and evaluated on all other target domains (FD001, FD002, FD003). This experiment quantifies the performance degradation caused by domain shift when no adaptation is performed.
3) **DANN for Domain Adaptation:** The DANN-LSTM was trained using FD004 as the source domain and each of the other datasets as an unlabeled target domain. This evaluates the effectiveness of the adversarial approach in improving cross-domain RUL prediction.

Both models were trained using the Adam optimizer with a learning rate of 1e-3 and a batch size of 256. Training was run for a maximum of 100 epochs with an early stopping mechanism to prevent overfitting. For the DANN-LSTM, the GRL's λ parameter was gradually ramped from 0 to 1 during the initial phase of training to ensure stability. A comprehensive summary of the hyperparameter configurations is provided in Table III.

TABLE III
HYPERPARAMETER CONFIGURATION

Hyperparameter	Baseline LSTM	DANN-LSTM
Optimizer	Adam	Adam
Learning Rate	1e-3	1e-3
Batch Size	256	256
Epochs	100 (with early stopping)	100 (with early stopping)
LSTM Layers	1 (Unidirectional)	2 (Bidirectional)
LSTM Hidden Units	100	128
Dropout	0.5	0.5
Regression Loss	MAE (L1Loss)	MAE (L1Loss)
Domain Loss	N/A	BCELoss
GRL Lambda (λ)	N/A	Ramped $0 \rightarrow 1$

E. Evaluation

The performance of the RUL prediction models is quantitatively assessed using two standard metrics from the prognostics and health management field: the Root Mean Squared Error (RMSE) and the NASA Scoring Function. These metrics were selected to evaluate both the accuracy and the practical utility of the predictions in a maintenance context.

1) Root Mean Squared Error (RMSE): RMSE is a conventional regression metric that quantifies the average magnitude of prediction errors. It is defined as the square root of the average of squared differences between the predicted RUL ($\hat{y}_i$) and the true RUL (y_i) for n test samples. The formula is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

While RMSE provides a general measure of predictive accuracy, it treats all errors symmetrically. This characteristic can be a limitation in applications where the consequences of overestimation and underestimation are not equal.

2) NASA Scoring Function: To address the asymmetric nature of RUL prediction costs, the NASA Scoring Function is employed. This metric is specifically designed for prognostics tasks, where late predictions (overestimating RUL) are significantly less desirable than early predictions (underestimating

RUL). This reflects the higher cost associated with unexpected failures compared to the cost of premature maintenance.

The score S is the sum of individual scores s_i for each test unit. The score s_i is calculated based on the prediction error $d_i = \hat{y}_i - y_i$:

$$s_i = \begin{cases} e^{-\frac{d_i}{13}} - 1 & \text{if } d_i < 0 \quad \text{(Early Prediction)} \\ e^{\frac{d_i}{10}} - 1 & \text{if } d_i \geq 0 \quad \text{(Late Prediction)} \end{cases}$$

The exponential terms ensure that the penalty for late predictions grows much more rapidly than the penalty for early ones.

For both metrics, a lower value indicates superior model performance. RMSE is reported in units of cycles, whereas the NASA Score is a dimensionless quantity.

F. Deployment

Transitioning the RUL pipeline to an operational setting requires a robust architecture that addresses latency, resource, and governance constraints. A prediction service was developed to provide a low-latency endpoint for integration into larger predictive maintenance systems.

1) Inference Service: A stateless RESTful API was developed using FastAPI on a Uvicorn server. The trained model and feature scaler are loaded into memory at startup to ensure minimal latency. The */predict* endpoint accepts a JSON payload of time-series sensor data. The inference workflow validates the input, applies the pre-fitted scaler, extracts the most recent 30-cycle window, and feeds it to the DANN-LSTM model to return a scalar RUL prediction.

2) Fleet-Scale Deployment Topology: A three-tiered topology is proposed for fleet-scale deployment to distribute computation effectively:

- **Edge:** On-engine units perform real-time data buffering, normalization, and inference using a quantized model to generate RUL estimates each cycle.
- **Fog:** On-site servers aggregate engine predictions, flag threshold breaches, and stream data to the cloud.
- **Cloud:** A central MLOps platform manages fleet-wide dashboards, model drift detection, periodic retraining, and new model rollouts.

3) Integration and Maintenance Workflow: The system's output integrates directly into a predictive maintenance workflow. A health dashboard visualizes per-engine RUL predictions and is coupled with a two-tier alarm system that issues warnings and critical alerts based on predefined RUL thresholds. These alerts trigger a maintenance workflow where engineers use the predictions for root-cause analysis and action selection. Feedback from shop visits is logged, providing new labeled data for the continuous improvement of the model through periodic fine-tuning.

IV. Results and Analysis

This section details the performance of the baseline LSTM and DANN models. Model interpretability is subsequently explored using SHAP.

A. Same-Domain Evaluation

The model's performance when trained and evaluated on the same operational domain is summarized in Table IV. The results demonstrate a strong correlation between dataset complexity and prediction error. For datasets with a single operating condition (FD001 and FD003), the model achieves a low RMSE of approximately 15 cycles and a NASA score under 4. However, performance degrades significantly on datasets with multiple operating conditions (FD002) and fault modes (FD004), where the RMSE increases to over 30 cycles and the NASA score rises sharply, indicating a higher penalty for late predictions.

TABLE IV
Target-Only LSTM Performance

Dataset	RMSE	NASA Score
FD001	14.56	3.6
FD002	30.74	131.4
FD003	13.65	3.2
FD004	37.18	1635

The plots in Fig. 1. visualize these results. For FD001 and FD003, predictions tightly follow along the true values, indicating high accuracy. In contrast, FD002 and FD004 show significantly more variance, particularly at higher RUL values. A systematic bias is also evident, with many predictions falling below, signifying an underestimation of RUL that due to the high NASA scores.

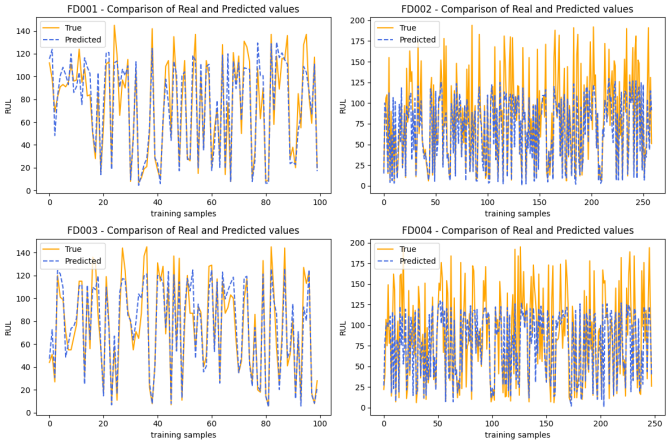

Fig. 1.

B. Cross-Domain Evaluation

As shown in Table V, this naive transfer approach fails to generalize effectively. The performance varies drastically depending on the similarity between the source and target domains. The transfer to FD002, which shares the same six operating conditions as FD004, yields the lowest RMSE. Conversely, the transfer to FD001, which has vastly different operating conditions, results in the highest error. The extremely high NASA scores across all transfers highlight a critical failure mode: the model consistently overestimates RUL for

FD001, FD003 and underestimates for FD002, FD004. A dangerous bias in predictive maintenance. These results confirm that a standard LSTM cannot bridge significant domain gaps without adaptation. The plots in Fig. 2 visualize these results.

TABLE V
CROSS-DOMAIN LSTM PERFORMANCE (SOURCE: FD004)

Source → Target	RMSE	NASA Score
FD004 → FD001	50.98	9.83×10^2
FD004 → FD002	31.909	1.08×10^3
FD004 → FD003	50.77	8.20×10^2

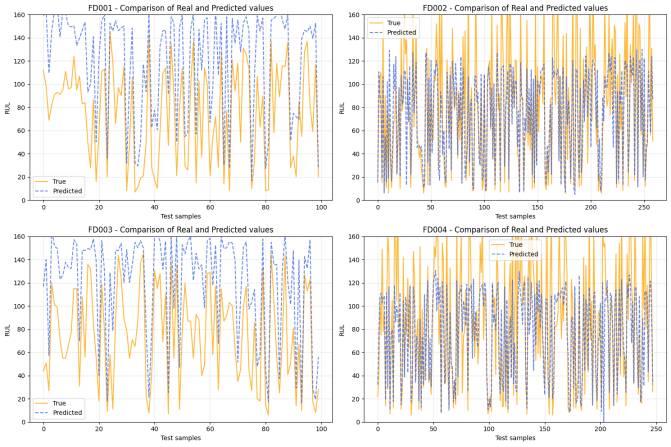

Fig. 2.

C. Domain Adaptation Results

As detailed in Table VI, the DANN architecture yields substantial improvements. For the most dissimilar domains (FD004→FD001 and FD004→FD003), the RMSE was reduced by over 30%. The adversarial training successfully stabilized performance, bringing all transfer RMSE values into a much tighter and more acceptable range (21-30 cycles). The scatter plots of DANN predictions show a marked improvement over the source-only baseline, with predictions clustering much more closely to the ground-truth diagonal, indicating a significant reduction in both error and systematic overestimation bias. The plots in Fig. 3 visualize these results.

TABLE VI
DANN VS. SOURCE-ONLY CROSS-DOMAIN PERFORMANCE

Source → Target	Source-Only RMSE	DANN RMSE	Improvement
FD004 → FD001	50.98	34.55	**32.2%**
FD004 → FD002	31.909	29.67	**7.0%**
FD004 → FD003	50.77	34.62	**31.8%**

D. Interpretability Analysis

To understand the model's decision-making process, a SHapley Additive exPlanations(SHAP) analysis was conducted on the DANN model. The analysis identifies the features that contribute most significantly to the RUL predictions.

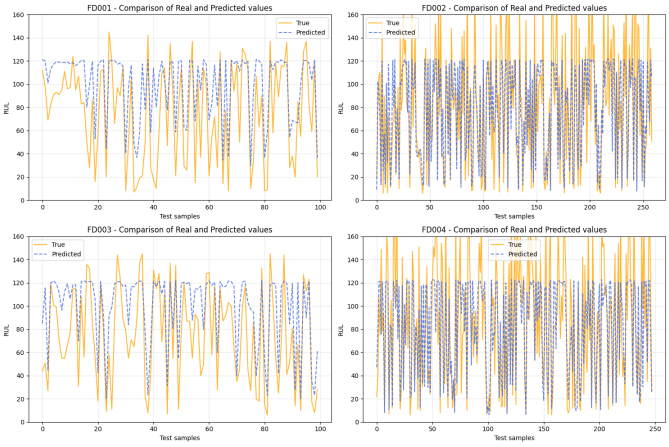

Fig. 3.

The Fig. 4. reveals primary drivers of RUL prediction. The most influential features include:

- s4 (Total Temperature at LPT outle)
- s8 (Physical fan speed)
- s11 (Static pressure at HPC outlet)
- s17 (Bleed enthalpy)
- s21 (LPT coolant bleed)

These features correspond to critical physical parameters that are known indicators of engine health and degradation, aligning with established aerospace engineering principles, confirming that the model has learned physically meaningful relationships from the data. This alignment increases confidence in the model's predictions and provides a basis for trusting its deployment in a real-world maintenance.

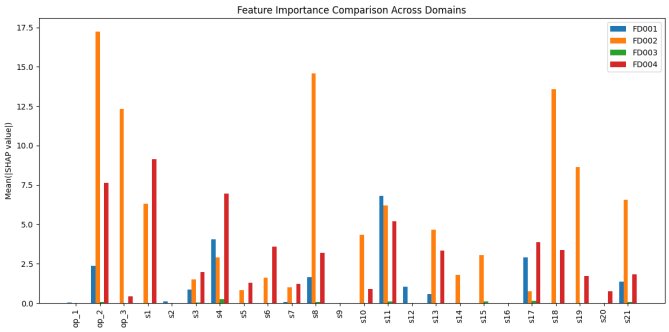

Fig. 4.

V. DISCUSSION

The experimental results confirm that while a standard LSTM excels in same-domain RUL prediction, its performance collapses under domain shift—a critical barrier to real-world deployment. This study demonstrates that a Domain-Adversarial Neural Network (DANN) effectively mitigates this issue by learning domain-invariant features.

Early deep-learning baselines such as the stacked LSTM of Zheng *et al.* [5] achieve RMSE $\approx$ 13 cycles when both

training and testing on the same regime (FD001), while attention-based CNNs push the error below 12 cycles [14]. Under domain shift, accuracy collapses: a source-only LSTM trained on FD004 yields 188 cycles on FD001, whereas the adversarial LSTM-DANN of da Costa *et al.* [19] slashes the error to 31.5 cycles. This study matches closely with cross-domain performance at 34.55 cycles (and $\leq$ 30 cycles on other transfers), delivering a $\sim$30% reduction over a plain LSTM and standing on par with the best published adaptation results—only about 2.5× above the single-domain floor set by recent CNN/LSTM ensembles. These findings reaffirm domain adaptation as a cornerstone for reliable RUL prediction in heterogeneous, real-world fleets.

Furthermore, SHAP-based interpretability analysis enhances the model's credibility. The features identified as most influential align with established physical principles of engine degradation. This confirms the model has learned meaningful relationships from the data, making its predictions not only accurate but also trustworthy for safety-critical applications.

VI. Limitations

Despite the promising results, this study has several limitations. First, the analysis is confined to the simulated CMAPSS dataset. Real-world sensor data may present additional challenges, such as higher noise levels, missing data, and more subtle or unmodeled domain shifts. Second, the current DANN implementation focuses on adapting from a single source to a single target domain. Future work should explore multi-source or multi-target adaptation scenarios, which are more representative of industrial fleets.

VII. Conclusion

This paper applied a domain-adversarial LSTM (DANN) to enhance cross-domain turbofan engine RUL prediction, achieving over 30% RMSE reduction compared to a baseline LSTM. By learning domain-invariant features, the DANN model provides a more reliable solution for real-world predictive maintenance, where equipment frequently operates under varying conditions. SHAP interpretability validated physically meaningful sensor contributions, emphasizing domain adaptation's practical value in predictive maintenance.

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