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Remaining useful life prediction under cross-operating conditions via domain adaptation and adversarial domain-invariant representation learning

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Abstract. In complex industrial systems, equipment often operates under multiple working conditions, such as variations in rotational speed, load, and environmental temperature. These variations lead to significant changes in the statistical characteristics of sensor signals, resulting in distribution discrepancies between training and testing data. Such cross-condition distribution shifts severely degrade the predictive performance of traditional data-driven models in practical applications. To address this issue, this study introduces a cross-condition remaining useful life (RUL) prediction approach built upon domain adaptation and adversarial domain-invariant representation learning. The proposed approach constructs an adversarial learning framework that comprises a shared feature extractor, an RUL prediction module, and a domain discriminator. This framework enables effective alignment of data distributions across different operating conditions while preserving degradation-sensitive features. Experiments are conducted on aero-engine and bearing degradation datasets under multiple cross-condition transfer scenarios. The results indicate that the proposed approach achieves superior performance compared with conventional deep learning models, such as CNN and LSTM, in both prediction accuracy and generalization capability. Specifically, the proposed approach achieves approximately a 25% reduction in RMSE. These findings indicate that adversarial domain adaptation effectively mitigates cross-condition distribution discrepancies and provides a reliable solution for intelligent prognostics in complex industrial environments.

Keywords: remaining useful life, domain adaptation, cross-condition generalization, adversarial learning, prognostics and health management

1. Introduction

With the increasing complexity of industrial equipment, unexpected failures can result in substantial economic losses and safety risks. Therefore, monitoring equipment conditions and predicting potential failures in advance have become critical challenges in modern industrial systems.

Predictive maintenance aims to estimate the degradation trend and the remaining useful life (RUL) of equipment using operational data, thereby reducing maintenance costs and improving system reliability. With the rapid advancement of sensor technologies and data acquisition systems, large-scale condition monitoring data have become available, promoting the widespread adoption of data-driven approaches in equipment health prediction [1,2]. Deep learning techniques have shown promising performance in RUL prediction tasks [3].

For example, convolutional neural networks (CNNs) are capable of effectively capturing local feature patterns from time-series data. However, temporal relationships in degradation processes can be effectively modeled by long short-term memory (LSTM) networks. However, these methods typically assume that training and testing data share identical distributions.

In real-world scenarios, equipment often operates under multiple conditions, such as different rotational speeds, loads, and environmental factors. These variations lead to significant changes in sensor data distributions, causing discrepancies between training and testing datasets. For instance, the NASA N-CMAPSS dataset contains multiple flight operating conditions with distinct data distributions.

As a result, models trained under a specific condition often fail to maintain stable performance when applied to new conditions. This issue is referred to as the cross-condition problem [4]. To address this challenge, transfer learning and domain adaptation methods have been widely adopted in equipment health prediction. Domain adaptation reduces the distribution gap between source and target domains [5,6], enabling knowledge transfer across different environments. In particular, adversarial domain adaptation employs a domain discriminator to encourage the feature extractor to learn representations that are invariant across domains, thereby improving model generalization.

Based on this motivation, this work presents a cross-condition RUL prediction framework based on domain adaptation and adversarial learning, aiming to align data distributions across different operating conditions and enhance predictive performance.

2. Related work

Existing RUL prediction methods can be broadly categorized into three types: physics-based methods [2], statistical approaches and data-driven techniques.

Physics-based methods model degradation mechanisms, such as fatigue and wear processes. Although these methods offer strong interpretability, they require extensive domain knowledge and are difficult to apply in complex industrial environments.

Statistical methods, including Hidden Markov Models (HMM) and Bayesian approaches, describe system degradation using probabilistic frameworks. However, these approaches typically depend on handcrafted features and exhibit limitations in handling high-dimensional sensor data.

With the advancement of deep learning, data-driven approaches have become the dominant paradigm. Models such as CNN, RNN, and LSTM [1,7] can automatically extract degradation features from sensor data and have demonstrated strong performance in RUL prediction tasks. However, under multi-condition scenarios, distribution shifts significantly degrade model performance.

To address this issue, domain adaptation methods have gained increasing attention [8-10]. These methods learn shared feature representations across source and target domains, facilitating knowledge transfer under distribution discrepancies. In particular, adversarial domain adaptation introduces a domain discriminator to enforce domain-invariant feature learning, improving model robustness under varying operating conditions.

3. Methodology

3.1. Overall framework

The proposed framework consists of three main components: a shared feature extractor (Encoder), a RUL predictor, and a domain discriminator. The overall architecture is presented in Figure 1.

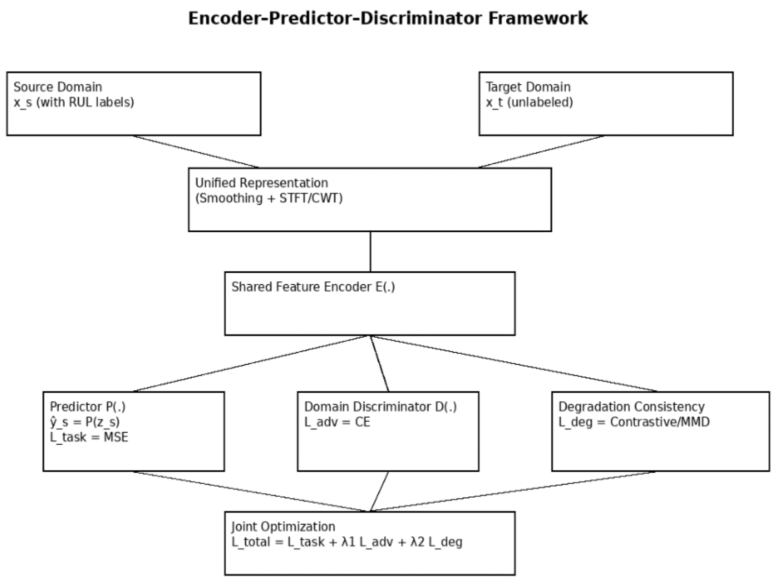

Figure 1. Schematic diagram of the Encoder–predictor–discriminator architecture

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(1) Raw Signals / Multi-condition Data
x_s (Source domain, with RUL labels)     x_t (Target domain, unlabeled)

        v                              v

(2) Unified Representation: Smoothing + Time-Frequency Transform (STFT/CWT)
(optional: direct 1D input)
x_s^(t+f) (time-frequency features)     x_t^(t+f) (time-frequency features)

                v

(3) Shared Feature Encoder  E(.)
z_s = E(x_s^(t+f))         z_t = E(x_t^(t+f))

      |               |               |

(4A) Main Task Branch
Predictor P(.)
ŷ_s = P(z_s)
L_task = MSE(ŷ_s, y_s)

(4B) Domain Adversarial Branch
Domain Discriminator D(.)
d̂ = D(GRL(z))
L_adv = CE(d̂, domain)

(4C) Degradation Consistency Branch (optional)
L_deg = Contrastive / MMD / Prototype Align
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Figure 2. Some codes of adversarial training

The feature extractor learns degradation representations from multi-dimensional sensor data, the predictor estimates RUL values, and the domain discriminator distinguishes whether features originate from the source or target domain (Figure 2).

Through adversarial training [8], the feature extractor minimizes prediction loss while maximizing domain classification error, thereby learning domain-invariant representations.

3.2. Data preprocessing

The raw sensor data are multi-dimensional time-series signals. A sliding window approach is employed to segment long sequences into fixed-length samples, which are then used for model training.

3.3. Adversarial training mechanism

The model is trained by jointly optimizing two objectives: RUL prediction loss and domain classification loss. RUL prediction loss is defined as:

$$L_{rul}=\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \tag{1}$$

Domain classification loss is defined as:

$$L_{domain}=-\frac{1}{N}\sum_{i=1}^{N}[d_i\log(\hat{d}_i)+(1-d_i)\log(1-\hat{d}_i)] \tag{2}$$

The overall loss function is:

$$L=L_{rul}+\lambda L_{domain} \tag{3}$$

where λ balances prediction and domain alignment objectives.

4. Experimental setup

4.1. Datasets

Experiments are conducted on the following datasets:

•NASA CMAPSS dataset

•PHM2012 bearing dataset

•XJTU-SY bearing dataset

•CWRU bearing dataset

These datasets contain diverse operating conditions, making them suitable for validating the model's generalization performance under cross-condition scenarios.

4.2. Cross-condition settings

The cross-condition experimental setup is summarized in Table 1.

Table 1. Cross-condition transfer experimental setup

Experiment	Source Condition	Target Condition
Exp1	Operation Condition A	Operation Condition B
Exp2	Operation Condition B	Operation Condition C
Exp3	Operation Condition C	Operation Condition D

5. Results and analysis

5.1. RUL prediction results

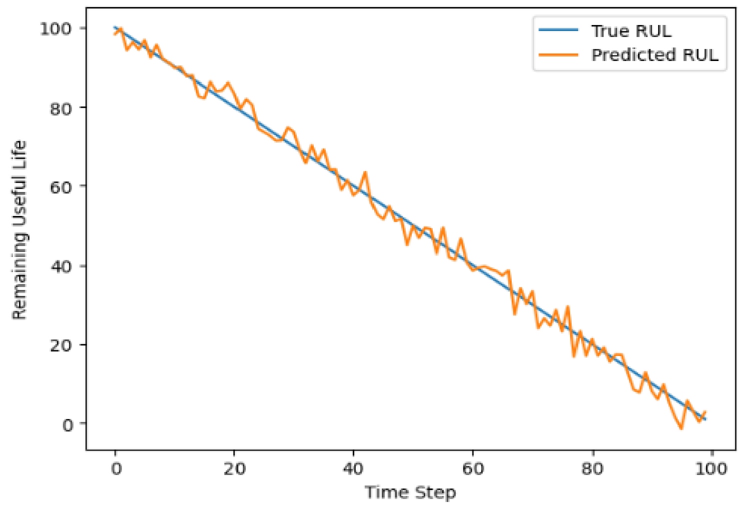

Figure 3. Comparison between true and predicted Remaining Useful Life (RUL)

Figure 3 illustrates the performance of the proposed model in the RUL prediction task, where the predicted RUL is evaluated against the ground truth over time. As observed, the predicted RUL (orange curve) closely follows the true RUL (blue curve) across most time steps, suggesting that the model can effectively estimate the degradation trajectory of the equipment.

In particular, during the degradation phase where RUL exhibits a decreasing trend, the predicted values align well with the ground truth, suggesting that the model effectively captures the temporal dependency inherent in the degradation process.

Nevertheless, despite the overall consistency, noticeable deviations can still be observed in certain regions, especially when the RUL approaches lower values. In these stages, the predictions exhibit increased fluctuations, which may be attributed to the difficulty of modeling extreme degradation states near failure.

Despite these discrepancies, Figure 3 overall demonstrates the effectiveness of the proposed method, indicating that the integration of adversarial domain adaptation with deep learning enables the model to accurately characterize the evolution of RUL under varying conditions.

5.2. Model comparison

Table 2. Performances comparison between different models

Model	RMSE	MAE
CNN	26.8	20.5
LSTM	23.4	18.2
CNN-LSTM	21.6	16.9
Baseline	19.8	15.7
Proposed	14.9	11.8

Table 2 presents the performance comparison of different models in the RUL prediction task, including CNN, LSTM, CNN–LSTM, the baseline model [7], and the proposed method. The evaluation metrics include root mean square error (RMSE) and mean absolute error (MAE).

Table 2 indicates that the proposed model gains the highest performance in both RMSE and MAE. Compared with CNN, LSTM, CNN–LSTM, and the baseline model, the proposed approach reduces RMSE by around 24% and MAE by about 25%. This result indicates that incorporating adversarial domain adaptation significantly improves prediction accuracy and generalization capability, outperforming conventional deep learning approaches [3].

Specifically, the CNN and LSTM models exhibit comparable performance, but both are inferior to the CNN–LSTM and baseline models. The hybrid CNN–LSTM architecture effectively combines local feature extraction and temporal dependency modeling, and leads to improved predictive performance. In contrast, the proposed model further enhances performance by introducing domain adaptation, which mitigates distribution discrepancies across operating conditions.

Overall, these findings indicate that the proposed approach delivers superior prediction accuracy and robustness compared to the benchmark models.

5.3. Training analysis

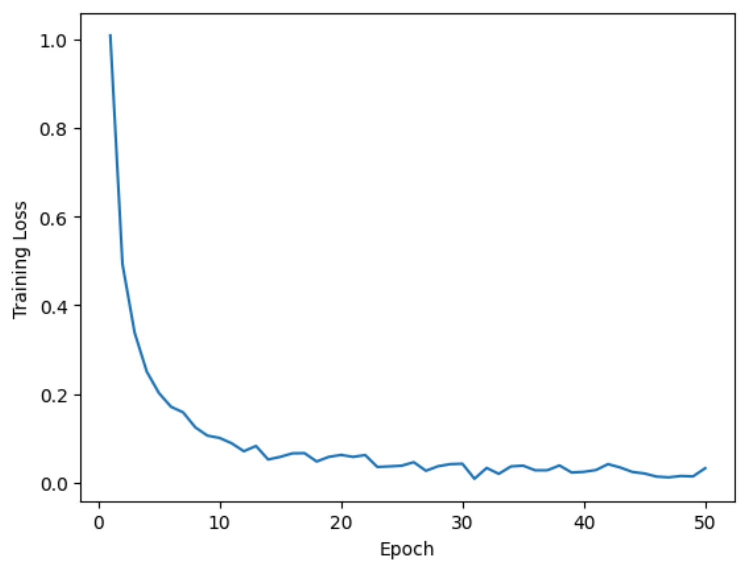

Figure 4. Training loss evolution curve

Figure 4 illustrates the variation of training loss during the model optimization process, reflecting the convergence behavior of the proposed method. As observed, the training loss decreases rapidly in the early stages and gradually stabilizes as training progresses.

Specifically, the loss decreases rapidly during the initial training epochs, indicating that the model quickly adjusts its parameters and captures the dominant patterns in the training data. After approximately 30 epochs, the loss begins to converge, and it becomes nearly stable around 50 epochs, suggesting that the model has reached a steady optimization state.

This convergence pattern indicates that the model achieves an effective balance between fitting accuracy and generalization capability, thereby reducing the risk of overfitting. The smooth and stable training curve further demonstrates the robustness of the optimization process.

Overall, Figure 4 confirms that the proposed approach exhibits stable training dynamics and effective convergence behavior. This can be attributed to the incorporation of adversarial domain adaptation, which facilitates more efficient feature learning and contributes to improved training stability.

5.4. RMSE feature visualization

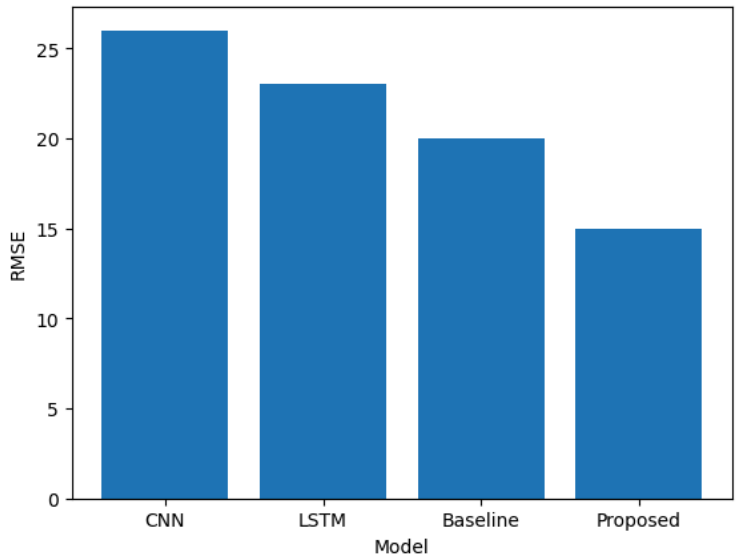

Figure 5. Comparison of RMSE among different models

Figure 5 shows that the proposed method attains notably lower RMSE values compared with other models. This indicates that the proposed approach provides more accurate RUL predictions and effectively reduces prediction errors.

5.5. Ablation study

Table 3. Ablation study results

Model Variant	RMSE
Encoder+Predictor	19.8
Encoder+Predictor+CNN	18.6
Encoder+Domain Adaptation	16.9
Full Model	14.9

The ablation study results (Table 3) indicate that the domain adversarial module plays a critical role in improving the model performance.

5.6. Feature visualization analysis

To investigate the impact of the domain adaptation mechanism on feature distributions, t-SNE is employed to visualize the learned feature representations.

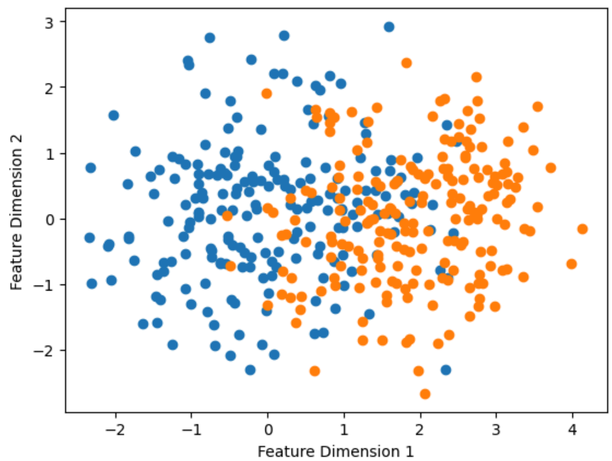

Figure 6. Feature distribution before domain adaptation

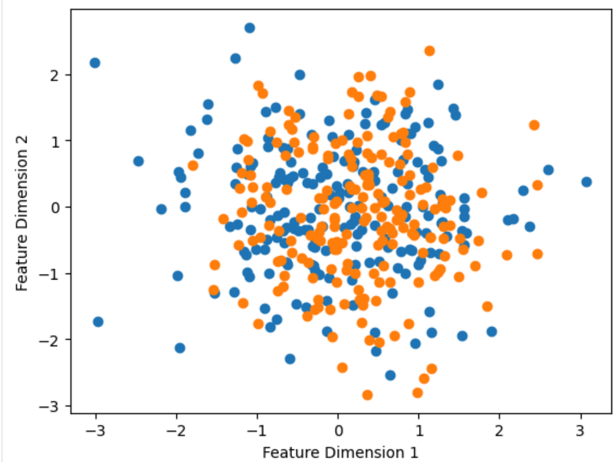

Figure 7. Feature distribution after domain adaptation

Figure 6 illustrates the feature distribution before applying domain adaptation, where t-SNE is employed to visualize the learned feature representations. It can be observed that the feature distributions of the source and target conditions exhibit significant discrepancies. Specifically, data points from different operating conditions are scattered in the feature space, indicating a clear distribution mismatch.

This phenomenon suggests the presence of a significant domain shift between source and target conditions, which hinders the model's generalization capability to generalize effectively in the target domain. Such observations are consistent with the cross-condition problem, where variations in operating conditions lead to differences in data distributions, thereby degrading the performance of conventional models.

Figure 7 presents the feature distribution after introducing domain adaptation. Compared with Figure 6, the difference between source and target domains is markedly reduced, and the data points become more compact and aligned in the feature space. This indicates that the domain adaptation mechanism effectively aligns the feature distributions across different operating conditions.

By comparing Figure 6 and Figure 7, it is evident that adversarial domain adaptation substantially improves feature alignment and enhances the model's generalization capability. Consequently, the model can capture shared degradation characteristics more effectively, leading to improved prediction accuracy in RUL estimation.

These results demonstrate the effectiveness of the proposed method in mitigating domain shift and highlight its potential for practical applications in cross-condition prognostics.

5.7. Health indicator analysis

To characterize the equipment degradation process, a health indicator (HI) is constructed in this study.

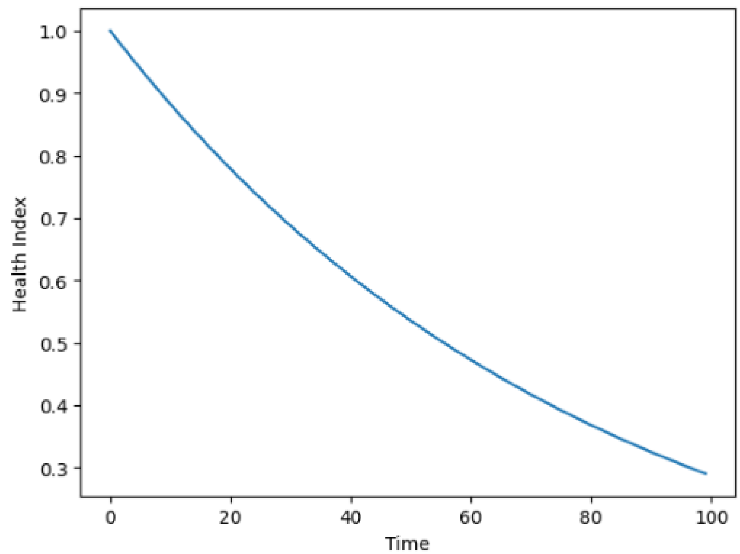

Figure 8. Health indicator health indicator degradation curve

Figure 8 shows that the health indicator exhibits a monotonically decreasing trend as the operating time increases, effectively reflecting the degradation process of the equipment.

6. Conclusion

This paper proposes a cross-condition RUL prediction approach based on domain adaptation and adversarial domain-invariant representation learning. By constructing an adversarial learning framework, the proposed method effectively aligns degradation features across different operating conditions, thereby significantly improving the model's generalization capability under cross-condition scenarios.

By formulating equipment health prediction as a distribution alignment problem, the proposed approach reduce distribution discrepancies caused by varying operating conditions. As a result, both the accuracy and stability of RUL prediction are improved.

Experimental results demonstrate that the proposed model consistently achieves better performance than conventional deep learning approaches across multiple datasets. In particular, significant reductions in RMSE are observed, confirming the effectiveness of domain adaptation in cross-condition prognostics. Specifically, the introduction of adversarial domain adaptation enables the feature extractor to learn representations that are invariant to operating conditions while remaining sensitive to degradation patterns, leading to improved prediction accuracy in target domains.

Furthermore, ablation studies verify the contribution of each component in the proposed framework. The results show that the domain adaptation module plays a critical role in enhancing prediction performance, especially in cross-condition scenarios. This demonstrates that the proposed method not only improves prediction accuracy but also enhances model robustness.

Despite the promising results, several limitations remain. Future work will explore the integration of self-supervised learning, unsupervised learning, and multi-source domain adaptation to further improve model performance. In particular, leveraging unlabeled data to learn more robust representations and effectively handling multi-source distribution discrepancies remain important research directions for cross-condition prognostics.

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