

A Data-Driven Prototype-Constrained Radial Response Network for Robust Aero-Engine Fault Diagnosis

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Abstract : Reliable fault diagnosis of aero-engine bearings is crucial for ensuring flight safety. However, the spectral distributions of different operating states are often distorted by noise and operating-condition variations, making it difficult for existing intelligent diagnosis methods to accurately characterize their intrinsic distribution structures. To address this issue, this paper proposes a Prototype-Constrained Radial Response Network (PCRRN) for aero-engine bearing fault diagnosis based on vibration spectrum analysis. First, representative prototypes are learned to characterize the intrinsic distribution structures of different operating states in a transformed feature space. Subsequently, a similarity-driven radial response modeling is established to quantify the relationships between testing spectra and the learned prototypes, thereby converting the original spectral features into compact prototype-response representations. Finally, a regularized response-space decision model is constructed to accomplish multi-state fault classification through an analytical least-squares optimization. Experimental validation is conducted on the HIT aero-engine bearing benchmark dataset under five signal-to-noise ratio conditions ranging from 0 dB to -8 dB. Comparative results demonstrate that the proposed PCRRN consistently outperforms various intelligent diagnostic methods under different noise conditions. The experimental results verify that the proposed prototype-constrained similarity learning framework effectively improves the robustness, discriminative capability, and computational efficiency of fault diagnosis under noisy operating environments, demonstrating its potential for real-time condition monitoring, intelligent

maintenance decision-making, and safety assurance of aero-engine rotating machinery in practical engineering applications.

Keywords: Aero-engine, Fault diagnosis, Intelligent diagnosis, Multi-state fault classification

1. Introduction

Aero-engines are among the most critical components of modern aircraft, and their operational reliability is directly related to flight safety and maintenance cost [1-3]. Rolling bearings, as key supporting elements in the rotor transmission system, are continuously subjected to complex mechanical loads, high rotational speeds, and harsh environmental conditions during service [4-5]. Localized defects occurring on the inner race, outer race, or rolling elements inevitably alter the dynamic characteristics of the rotor-bearing system and generate distinctive vibration signatures [6-7]. Therefore, accurate fault diagnosis based on vibration analysis plays an essential role in condition monitoring and predictive maintenance of aero-engines.

Among various signal analysis techniques, frequency-domain representations have been extensively employed because they provide an intuitive description of vibration energy distribution and effectively reveal characteristic fault frequencies associated with different failure mechanisms. Based on spectral features, numerous intelligent diagnosis methods have been developed during the past decade. Conventional machine-learning approaches, represented by Support Vector Machine (SVM) [8], construct discriminative decision boundaries using handcrafted features extracted from vibration signals. Owing to their favorable generalization capability under limited

training samples, SVM-based methods have been widely applied to aero-engine-related intelligent diagnosis and decision-making problems. For example, Mei et al. [9] proposed an intelligent assembly method for aero-engine multi-stage rotors by integrating SVM with the artificial fish swarms algorithm and a backpropagation neural network, demonstrating that the combination of machine learning and intelligent optimization can effectively improve nonlinear modeling capability and engineering applicability. To alleviate the influence of imbalanced data distributions, oversampling strategies such as the Synthetic Minority Oversampling Technique (SMOTE) [10] have frequently been combined with SVM, leading to improved classification performance under limited-sample conditions. Along this line, Feng et al. [11] developed an adaptive error detection and optimization enhanced temporal convolutional network, in which an adaptive error detection strategy and an improved optimization algorithm were introduced to optimize synthetic minority samples, thereby alleviating inter-class overlap while preserving class balance and further improving fault recognition performance. However, these conventional methods heavily depend on handcrafted feature design and predefined decision boundaries, making their diagnostic performance highly sensitive to feature quality and domain expertise. Moreover, the spectral distributions of different operating states often exhibit significant overlap under

noisy and time-varying operating conditions, limiting the capability of conventional classifiers to accurately characterize complex inter-class relationships and maintain robust generalization in practical applications.

With the rapid development of deep learning, convolutional neural networks (CNNs) [12-13] and recurrent neural networks, particularly Long Short-Term Memory (LSTM) [14-15] networks, have demonstrated remarkable capability in automatically learning hierarchical feature representations from raw vibration data or spectral inputs, significantly reducing the dependence on manual feature engineering. Benefiting from their powerful nonlinear feature extraction capability, deep learning models have been widely applied to aero-engine health monitoring, fault diagnosis, and remaining useful life prediction. For example, Shen et al. [16] proposed an aero-engine remaining useful life prediction framework by integrating an improved Gray Wolf Optimizer with a one-dimensional convolutional neural network (1D-CNN), in which dynamic perturbation strategies were introduced to optimize network hyperparameters and improve prediction accuracy and stability. Du et al. [17] developed an aero-engine fault detection approach by combining an LSTM auto-encoder with a self-attention mechanism, enabling more effective extraction of long-range temporal dependencies and discriminative latent representations for anomaly detection. These studies demonstrate that deep learning can substantially enhance feature learning capability and diagnostic performance for complex aero-engine systems. However, existing deep learning methods primarily

rely on end-to-end representation learning through iterative parameter optimization, while the intrinsic geometric distribution characteristics of different operating states are rarely modeled explicitly. Consequently, the learned feature representations may become sensitive to limited training samples, measurement noise, and distribution variations, thereby restricting their robustness and generalization capability under practical operating conditions.

To address the above issues, this paper proposes a Prototype-Constrained Radial Response Network (PCRRN) for aero-engine fault diagnosis based on vibration spectra. Instead of directly performing classification in the original spectral space, the proposed framework first learns representative prototypes that characterize the intrinsic distribution structures of different operating states. The similarities between testing samples and the learned prototypes are subsequently quantified through radial response functions, transforming the original spectral features into a compact prototype-response representation. Finally, a regularized least-squares decision layer establishes the mapping between response vectors and operating-state labels through an analytical optimization procedure. By integrating prototype learning, similarity-driven representation, and analytical decision making into a unified framework, the proposed network effectively improves both discriminability and robustness under noisy operating conditions.

The main contributions of this paper are summarized as follows:

- (1) A prototype-constrained distribution modeling framework is proposed for

aero-engine fault diagnosis. Representative prototypes are constructed to characterize the intrinsic geometric distributions of different operating states, providing compact structural descriptions for spectral data and reducing the influence of spectral variability.

- (2) A similarity-driven radial response modeling is developed to establish an interpretable response-space representation. By transforming spectral samples into prototype-response vectors, the proposed method enhances inter-class separability while maintaining robustness against measurement noise and operating-condition fluctuations.
- (3) A regularized response-space decision strategy with analytical parameter estimation is introduced. Unlike conventional neural networks that rely on iterative backpropagation, the output parameters are obtained through a closed-form regularized least-squares solution, leading to improved computational efficiency and stable generalization performance.

The remainder of this paper is organized as follows. Section 2 formulates the fault diagnosis problem and introduces the spectral representation. Section 3 presents the proposed PCRRN, including prototype learning mechanism, radial response modeling, and decision-making strategy. Section 4 reports the experimental results and comparative analyses under different noise conditions. Finally, Section 5 concludes the paper and discusses future research directions.

2. Problem formulation and feature representation

2.1 Problem formulation

Aero-engine systems operate under complex mechanical and aerodynamic conditions, where different fault mechanisms may induce distinct dynamic responses and vibration characteristics. Owing to structural coupling, transmission path effects, and environmental disturbances, vibration signals collected from different operating states often exhibit complicated distribution patterns in the feature space [18]. Consequently, accurately characterizing the underlying distribution structure of each operating state remains a challenging task for intelligent fault diagnosis.

Let

$$X = \{X_1, X_2, \dots, X_K\} \quad (1)$$

denote the training dataset consisting of K operating states, where

$$X_k = \{x_{k1}, x_{k2}, \dots, x_{kN_k}\}, x_{ki} \in \mathbb{R}^d \quad (2)$$

represents the sample set associated with the k -th operating state, N_k denotes the number of samples in that state, and d is the dimensionality of the feature space.

The objective of fault diagnosis is to establish a decision function that assigns an unseen sample to its corresponding operating state.

For a testing sample x , the diagnosis task can be formulated as

$$x \in \Omega_k, k \in \{1, 2, \dots, K\} \quad (3)$$

where Ω_k denotes the distribution region occupied by the k -th operating state in the feature space.

Although samples belonging to the same operating state generally share similar spectral characteristics, their distributions may still exhibit significant variability due to measurement noise, operating fluctuations, and nonlinear system dynamics. Meanwhile, spectral distributions associated with different fault categories may partially overlap in the original feature space, making direct classification increasingly difficult. Therefore, the fundamental challenge is to learn representative representations that accurately characterize the distribution of each operating state while maintaining sufficient separability between different operating states for reliable fault classification.

Consequently, an effective diagnosis framework should establish a representation that simultaneously characterizes the distribution of each operating state and provides reliable discrimination among different states. To achieve this objective, the learned representation should satisfy three fundamental requirements:

(1) Distribution characterization: it should accurately describe the intrinsic distribution structure of spectral samples belonging to the same operating state, providing a representative geometric description of the corresponding data distribution;

(2) Similarity consistency: samples originating from the same operating state should exhibit high representation similarity despite the presence of measurement noise or operating-condition variations, whereas samples from different operating states

should produce significantly different responses;

(3) Decision discriminability: the resulting representation should provide sufficient separability for different operating states, enabling a simple decision model to achieve reliable fault classification.

These requirements motivate the development of a prototype-constrained distribution modeling framework, in which representative prototypes are learned for different operating states and subsequently utilized to construct a similarity-based fault diagnosis model.

2.2 Spectral representation

Rotating machinery faults usually induce changes in the energy distribution of vibration signals [19]. Compared with time-domain observations, spectral representations can more directly reveal fault-related frequency components and their corresponding energy variations [20]. Therefore, the frequency spectrum is adopted as the input representation of the proposed model.

For a vibration sign $s(n)$, its discrete Fourier transform can be expressed as

$$S(m) = \sum_{n=0}^{L-1} s(n) e^{-\frac{j2\pi mn}{L}} \quad (4)$$

where L denotes the signal length, $m = 0, 1, \dots, L-1$.

The corresponding amplitude spectrum is obtained as

$$A(m) = |S(m)| \quad (5)$$

To eliminate the influence of redundant frequency components and improve computational efficiency, only the positive-frequency spectrum within the effective frequency range is retained. Consequently, each vibration sample is represented by a spectral vector

$$x = [A(f_1), A(f_2), \dots, A(f_d)]^T \in \mathbb{R}^d, \quad (6)$$

where d is the dimensionality of the spectral feature vector

The training set can therefore be represented as

$$\mathcal{X} = \{x_1, x_2, \dots, x_N\}, x_i \in \mathbb{R}^d. \quad (7)$$

Each sample corresponds to a complete spectral distribution describing the energy characteristics of the vibration signal in the frequency domain.

Different operating states generally exhibit overlapping frequency components and coupled spectral energy distributions. Consequently, directly comparing spectral vectors in the original feature space is often insufficient to accurately characterize their intrinsic similarity. Therefore, a nonlinear feature representation is required to reveal the geometric relationships among spectral samples more effectively.

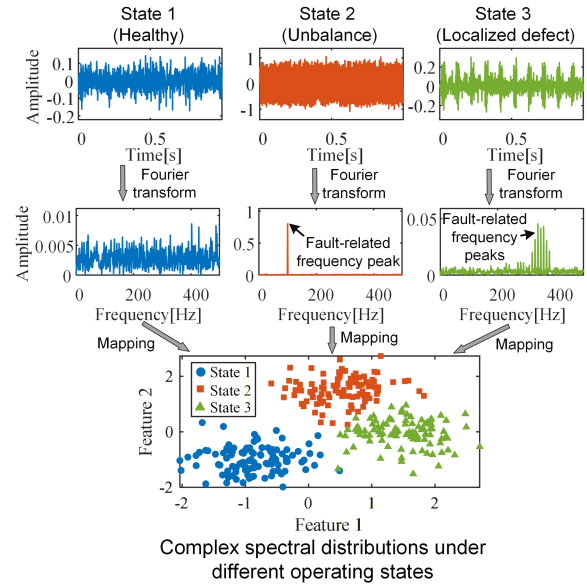


Fig. 1. Problem formulation of spectrum-based fault diagnosis.

To overcome this limitation, a nonlinear mapping

$$\phi: \mathbb{R}^d \rightarrow \mathcal{H} \quad (8)$$

is introduced to project spectral samples into a reproducing kernel Hilbert space $\mathcal{H}$. In the transformed space, the complex distribution of spectra can be represented more compactly, providing a foundation for subsequent prototype learning and radial response modeling. A schematic diagram illustrating the problem is shown in Fig. 1.

The objective of the proposed method is therefore to identify a representative prototype structure in $\mathcal{H}$ and establish a similarity-driven decision mechanism for fault diagnosis.

3. Prototype-Constrained Radial Response Network

3.1 Overview of PCRRN

The spectral representation provides a comprehensive description of the vibration energy distribution across different frequency components. However, for aero-engine systems, spectral characteristics are often influenced by operating-condition variations, structural coupling effects, measurement uncertainty, and environmental disturbances. Consequently, samples originating from the same operating state may exhibit considerable variability, while samples associated with different operating states may partially overlap in the original spectral space. These factors significantly increase the difficulty of fault classification and limit the effectiveness of conventional pattern recognition approaches.

Under such circumstances, the diagnosis problem can be regarded as the characterization and discrimination of multiple operating-state distributions in the spectral feature space. An effective diagnosis model should not only capture the dominant distribution characteristics of individual operating states but also obtain sufficient discriminative information to distinguish different fault categories.

Therefore, a more suitable strategy is to characterize the intrinsic distribution of each operating state by learning representative prototypes and subsequently quantify the similarity between testing samples and the learned prototypes. Such a prototype-based representation provides a compact description of the distribution characteristics of different operating states while maintaining robustness to noise and

measurement uncertainty, thereby facilitating reliable state discrimination.

Motivated by these considerations, a PCRRN is developed, as shown in Fig. 2. The proposed PCRRN learns representative prototypes to characterize the intrinsic distribution of each operating state and subsequently measures the similarity between samples and the learned prototypes through a radial response modeling. The resulting prototype-based similarity representation provides a unified basis for robust and discriminative fault classification under complex operating conditions.

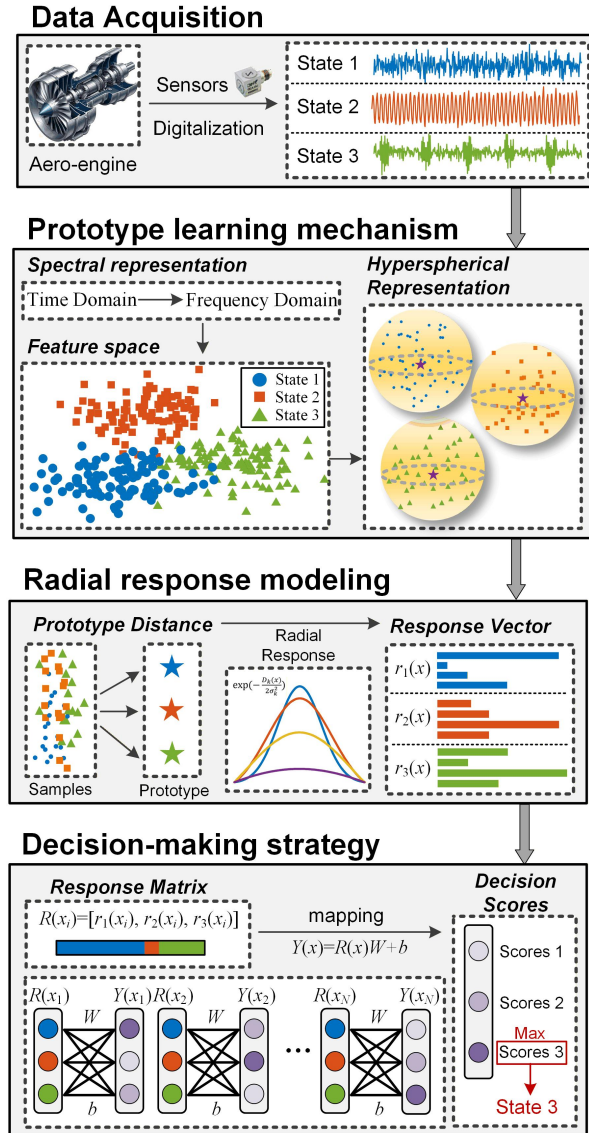


Fig. 2. Overall PCRRN framework.

3.2 Prototype learning mechanism

The objective of the prototype learning stage is to construct a representative distribution descriptor for each operating state. Rather than relying on the arithmetic mean of training samples, the proposed framework seeks a compact hyperspherical representation in a transformed feature space, such that the dominant distribution characteristics of each operating state can be

effectively preserved while reducing the influence of distribution irregularities. A schematic diagram of the prototype learning mechanism is shown in Fig. 3.

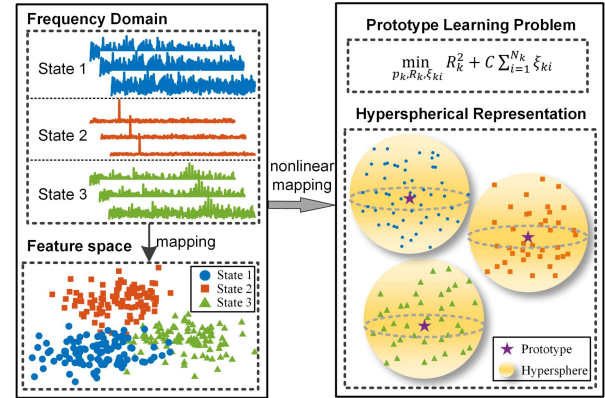


Fig. 3. Prototype learning mechanism.

For the k -th operating state, the corresponding training samples are first mapped into $\mathcal{H}$ through a nonlinear transformation $\phi(\cdot)$. Let $p_k \in \mathcal{H}$ denote the prototype used to characterize the dominant distribution structure of the k -th operating state.

To obtain a representative prototype, a compact hypersphere is then constructed to enclose the mapped samples. Let p_k denote the center of the hypersphere and R_k denote its radius. The prototype learning problem is formulated as

$$\min_{p_k, R_k, \xi_{ki}} R_k^2 + C \sum_{i=1}^{N_k} \xi_{ki} \quad (9)$$

subject to

$$\|\phi(x_{ki}) - p_k\|^2 \leq R_k^2 + \xi_{ki} \quad (10)$$

where $C > 0$ is the regularization parameter controlling the trade-off between hypersphere compactness and tolerance to boundary samples, and ξ_{ki} denotes the slack

variable introduced to improve robustness against noisy observations and distribution variations. $\xi_{ki} \geq 0, i = 1, \dots, N_k$.

The optimization objective simultaneously minimizes the hypersphere volume while allowing a limited number of samples to lie outside the enclosing boundary. Consequently, the obtained prototype captures the dominant geometric structure of the corresponding operating-state distribution instead of being overly influenced by local perturbations.

Introducing the Lagrange multipliers and applying the Karush–Kuhn–Tucker optimality conditions, the prototype can be expressed as a weighted combination of training samples in the transformed feature space:

$$p_k = \sum_{i=1}^{N_k} \beta_{ki} \phi(x_{ki}) \quad (11)$$

subject to

$$\sum_{i=1}^{N_k} \beta_{ki} = 1, \beta_{ki} \geq 0 \quad (12)$$

Unlike conventional centroid-based representations, the weighting coefficients are determined automatically through the hypersphere optimization process. Consequently, the learned prototype is primarily influenced by samples that define the distribution boundary, enabling it to more accurately characterize the intrinsic geometric structure of the corresponding operating state.

By applying the above procedure to all operating states, a prototype set can be obtained as

$$P = \{p_1, p_2, \dots, p_K\} \quad (13)$$

where K denotes the total number of operating states. The prototype set provides a compact representation of the state-wise distribution structures in the transformed feature space and serves as the foundation for the radial response modeling described in the subsequent section.

3.3 Radial response modeling

After obtaining the prototype representations, the relationship between a sample and different operating-state prototypes is characterized through a radial response modeling, as shown in Fig. 4.

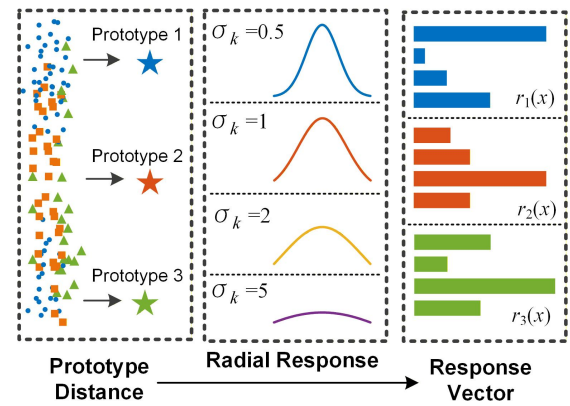


Fig. 4. Radial response modeling.

Given a testing sample x , the distance between the sample and each learned prototype is first computed in the transformed feature space to characterize their similarity. For the k -th prototype p_k , the prototype distance is defined as

$$D_k(x) = \|\phi(x) - p_k\|^2 \quad (14)$$

Substituting Eq.(11) into Eq.(14) gives

$$\begin{aligned} D_k(x) = & \langle \phi(x), \phi(x) \rangle - 2 \sum_{i=1}^{N_k} \beta_{ki} \langle \phi(x), \phi(x_{ki}) \rangle \\ & + \sum_{i=1}^{N_k} \sum_{j=1}^{N_k} \beta_{ki} \beta_{kj} \langle \phi(x_{ki}), \phi(x_{kj}) \rangle \end{aligned} \quad (15)$$

To avoid explicit computation in the high-dimensional feature space, a positive-definite kernel function is introduced as

$$G(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle \quad (16)$$

Accordingly, the prototype distance can be rewritten as

$$D_k(x) = K(x, x) - 2 \sum_{i=1}^{N_k} \beta_{ki} G(x, x_{ki}) + \sum_{i=1}^{N_k} \sum_{j=1}^{N_k} \beta_{ki} \beta_{kj} G(x_{ki}, x_{kj}) \quad (17)$$

For spectral data, the Gaussian kernel is employed:

$$G(x_i, x_j) = \exp \left(-\frac{\|x_i - x_j\|^2}{2\sigma_G^2} \right) \quad (18)$$

where σ_G denotes the kernel width.

A smaller value of $D_k(x)$ implies that the testing sample is located closer to the learned prototype and exhibits stronger consistency with the distribution characteristics of the k -th operating state. Conversely, a larger distance suggests weaker structural similarity.

Based on the deviation measure, a radial response function is introduced to transform the geometric distance into a normalized similarity representation. The response generated by the k -th prototype is expressed as

$$r_k(x) = \exp \left(-\frac{D_k(x)}{2\sigma_k^2} \right) \quad (19)$$

where σ_k denotes the response width associated with the k -th prototype.

The radial response function possesses several desirable properties for fault diagnosis. First, the response reaches its

maximum value when the testing sample coincides with the prototype. Second, the response decreases monotonically as the deviation increases, enabling the network to gradually distinguish samples that deviate from the corresponding operating state. Third, the exponential decay mechanism provides a smooth nonlinear mapping between distance and similarity, thereby improving the robustness of the network against noise and local fluctuations in the spectral distribution.

For a given testing sample, the responses generated by all prototypes collectively describe its relationship with the learned distribution structures. Therefore, the radial response modeling process transforms the original spectral representation into a similarity-based representation, in which each response reflects the degree of consistency between the testing spectrum and a specific operating-state prototype.

3.4 Decision-making strategy

The prototype learning mechanism establishes a set of representative prototypes that characterize the distribution structures of different operating states. Subsequently, the radial response modeling quantifies the similarity between the testing spectrum and each learned prototype. As a result, each testing sample can be represented by a collection of prototype responses.

For a testing x , the radial responses generated by all learned prototypes are organized into a response vector

$$R(x) = [r_1(x), r_2(x), \dots, r_K(x)]^T \quad (20)$$

where K denotes the number of operating states.

The response vector provides a compact representation of the relationship between the testing sample and all learned distribution structures. Each element reflects the consistency between the input spectrum and a specific operating state in the transformed feature space. Consequently, samples belonging to different operating states tend to exhibit distinct response patterns in the prototype-response space, thereby facilitating subsequent classification.

To establish the mapping from the prototype-response space to the target labels, the response vectors of all training samples are first organized into a response matrix

$$\Phi = [R(x_1), R(x_2), \dots, R(x_N)]^T \quad (21)$$

where N denotes the number of training samples. The corresponding target labels are encoded as a one-hot matrix

$$T = [t_1, t_2, \dots, t_N]^T \quad (22)$$

where each row vector $t_i \in \mathbb{R}^K$ represents the class label of the i -th training sample.

Instead of employing iterative parameter optimization, the output mapping is determined by minimizing the following regularized least-squares objective:

$$\min_W \|\Phi W - T\|_F^2 + \lambda \|W\|_F^2 \quad (23)$$

where W denotes the output weight matrix, $\lambda > 0$ is the regularization parameter, and $\|\cdot\|_F$ denotes the Frobenius norm. The first term minimizes the fitting error between the predicted outputs and the target labels, whereas the second term improves the generalization capability by preventing overfitting.

By setting the derivative of Eq. (23) with respect to W to zero, the optimal weight matrix can be obtained analytically as

$$W = (\Phi^T \Phi + \lambda I)^{-1} \Phi^T T \quad (24)$$

where I denotes the identity matrix.

After obtaining the output weights, the bias vector is estimated from the average residual of the training samples,

$$b = \frac{1}{N} \sum_{i=1}^N (t_i - \Phi_i W) \quad (25)$$

where Φ_i denotes the i -th row of the response matrix.

For a testing sample, the decision scores are computed by

$$Y(x) = R(x)W + b \quad (26)$$

where, $W \in \mathbb{R}^{K \times K}$ denotes the output weight matrix, $b \in \mathbb{R}^K$ is the bias vector.

The output vector

$$Y(x) = [y_1(x), y_2(x), \dots, y_K(x)] \quad (27)$$

contains the decision scores corresponding to different operating states. The final diagnosis result is determined according to the maximum-response principle:

$$\hat{y} = \arg \max_k y_k(x), k = 1, 2, \dots, K \quad (28)$$

where $\hat{y}$ denotes the predicted state label of the testing sample.

From a geometric perspective, the proposed decision mechanism transforms the original fault diagnosis problem into a classification task in the prototype response space. Instead of directly comparing spectral samples in the

original high-dimensional frequency domain, the classification is performed based on their relationships with the learned prototypes. Consequently, the influence of spectral variability and measurement uncertainty can be effectively reduced while preserving the discriminative characteristics associated with different operating conditions. The process of decision-making strategy is illustrated in Fig. 5.

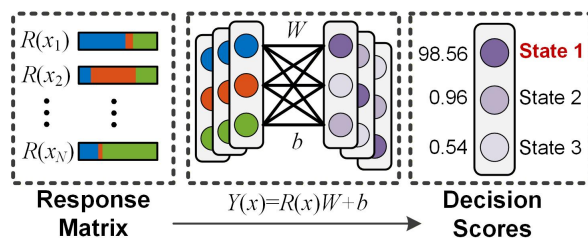


Fig. 5. Decision-making strategy.

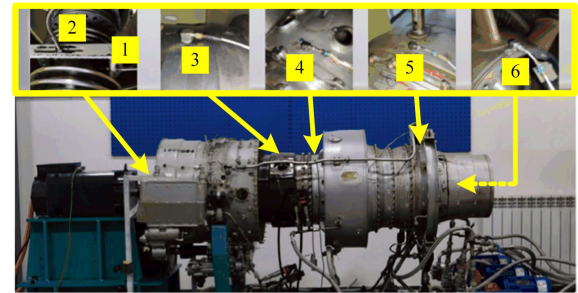
Through the integration of prototype learning mechanism, radial response modeling, and response-space decision making, the proposed PCRRN establishes a unified framework for aero-engine fault diagnosis. The resulting model is capable of capturing representative distribution characteristics of different operating states and provides reliable classification performance under limited-data conditions.

4. Experimental verification

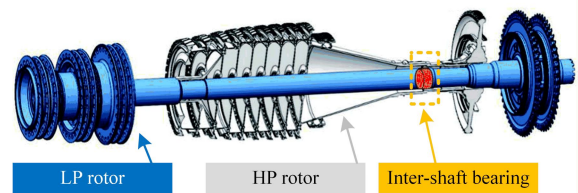
4.1 HIT aero-engine dataset

To evaluate the effectiveness of PCRRN, experiments were conducted using a real-life aero-engine bearing fault dataset developed by Harbin Institute of Technology (HIT) [21]. Compared with conventional laboratory-scale bearing test rigs, this platform reproduces the vibration transmission characteristics and dynamic interactions encountered in practical aero-

engine systems, thereby providing a realistic benchmark for fault diagnosis studies.



(a) Experimental platform and sensor installation locations



(b) The structure of experimental platform



(c) Faulty bearings

Fig. 6. The aero-engine experimental platform.

The experimental platform consists of a lubrication system, a motor drive system, and a dual-rotor structure, as illustrated in Fig. 6(a) and Fig. 6(b). The motor drive system provides the rotational power required for the dual-rotor operation. The lubrication system consists of three oil supply pumps, one oil return pump, and a heat pump equipped with temperature sensors, ensuring continuous lubrication, cooling, and temperature control during testing. The dual-rotor structure includes the low-pressure compressor, high-pressure compressor, low-pressure turbine, and high-

pressure turbine, allowing the platform to realistically reproduce the operating characteristics of an aero-engine rotor system. Four bearing conditions were considered, including one healthy condition and three faulty conditions. The corresponding bearings are shown in Fig. 6(c). Specifically, the fault categories include a normal bearing, an inner-race fault (IF1) with a defect depth of 0.5 mm and a defect length of 0.5 mm, an inner-race (IF2) fault with a defect size of 0.5 mm $\times$ 1.0 mm, and an outer-race fault (OF) with a defect size of 0.5 mm $\times$ 1.0 mm.

Table 1. Rotational speed combinations for vibration signal in the experiment.

Speed index	LP speed (r/min)	HP speed (r/min)
1	1000	1200
2	1500	1800
3	2000	2400
4	2500	3000
5	3000	3600
6	3500	4200
7	3600	4320
8	3700	4440
9	3800	4560
10	3900	4680
11	4000	4800
12	4100	4920
13	4200	5040
14	4300	5160
15	4400	5280
16	4500	5520
17	4600	5640
18	4700	5760
19	4800	5760
20	4900	5880
21	3000	4200
22	3000	4500
23	3000	4800
24	3000	5100

25	3000	5400
Acceleration sensors mounted on the bearing housing were employed to measure the vibration responses generated under different operating conditions. The original vibration signals were acquired at a sampling frequency of 25000Hz. The vibration signals were collected under various rotational speed combinations, as shown in Table 1.		

To construct the diagnosis dataset, the acquired vibration signals were segmented into equal-length samples.

4.2 Experimental settings

Following the segmentation procedure, the original vibration signals were segmented into non-overlapping samples with 1024 sampling points. The dataset was divided into training and testing subsets at the experimental-run level before signal segmentation, ensuring that samples from the same experimental run were not simultaneously included in both subsets.

Since the proposed PCRRN operates in the frequency domain, Fast Fourier Transform was applied to each vibration segment to generate its corresponding spectrum. Compared with time-domain representations, spectral features provide a more intuitive description of fault-related frequency components and energy distribution characteristics. Consequently, the obtained frequency spectra were directly employed as the input features of the proposed network.

Prior to network training, each spectral sample was normalized to eliminate the influence of amplitude variation and improve numerical stability during model optimization. The normalization parameters were calculated only from the training set

and subsequently applied to the testing set to avoid information leakage. The entire dataset was randomly divided into training sets and testing sets at a 7:3 ratio. All comparative methods employed the same data partition adopted to ensure a fair performance evaluation. The proposed PCRRN was implemented in MATLAB R2022b.

The diagnostic performance of the proposed method was evaluated using four widely adopted metrics, namely Accuracy, Macro-F1 score, and Area Under the Receiver Operating Characteristic Curve (AUC). Accuracy reflects the overall classification performance, whereas Macro-F1 provide a more comprehensive assessment of class-wise recognition capability. AUC was employed to evaluate the discriminative ability of different methods from a probabilistic perspective.

The classification accuracy is defined as

$$\text{Accuracy} = \frac{N_c}{N} \quad (29)$$

where N_c denote the numbers of correctly classified samples.

The Macro-F1 score is calculated as

$$\text{Macro-F1} = \frac{1}{K} \sum_{i=1}^K F_i \quad (30)$$

where F_i denotes the F1-score of the i -th class.

The AUC is defined as

$$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR}) d\text{FPR} \quad (31)$$

where TPR and FPR represent the true positive rate and false positive rate, respectively.

To comprehensively evaluate the effectiveness of the proposed PCRRN, four representative fault diagnosis methods were selected as benchmark approaches, including SVM, Synthetic Minority Oversampling Technique combined with SVM (SMOTE+SVM), 1D-CNN, and LSTM. Among these methods, SVM was adopted as a representative conventional machine learning classifier due to its strong generalization capability in fault diagnosis tasks. SMOTE+SVM was introduced as a representative data augmentation strategy for evaluating whether synthetic samples can improve classification performance under limited training samples. The oversampling operation was performed only on the training set, and the testing set was kept unchanged. In addition, 1D-CNN and LSTM were selected as representative deep learning approaches that have been widely employed in machinery condition monitoring and intelligent fault diagnosis. Specifically, 1D-CNN is capable of automatically extracting local discriminative features from vibration signals. The 1D-CNN model contains three convolutional blocks with 32, 64, and 128 filters, respectively. Each convolutional block consists of convolution, batch normalization, and ReLU activation operations. A global average pooling layer and fully connected layers were employed for final classification. LSTM is designed to capture temporal dependencies embedded in sequential data. The LSTM network adopts a bidirectional LSTM layer with 64 hidden units and an LSTM layer with 32 hidden units. The output representation was fed into a fully connected layer for classification.

The network was trained using an initial learning rate of 1×10^{-3} , a batch size of 32, and 60 training epochs.

4.3 Diagnostic performance comparison

To comprehensively evaluate the effectiveness of the proposed PCRRN, comparative experiments were conducted under different noise conditions. Gaussian white noise was added to the original vibration signals to simulate practical measurement disturbances, and the signal-to-noise ratio (SNR) was successively set to 0 dB, -2 dB, -4 dB, -6 dB, and -8 dB. For each SNR condition, the corresponding training and testing datasets were reconstructed, and a separate PCRRN model was trained to evaluate the diagnostic performance under the corresponding noise environment. All comparative methods were evaluated using the same noisy datasets and identical data partitions to ensure a fair comparison. As the SNR decreases, the fault-related spectral components become increasingly submerged by noise, resulting in a progressively more challenging fault diagnosis task. The detailed results for all 25 operating speeds are illustrated in Fig. 7, Fig. 8 and Fig. 9.

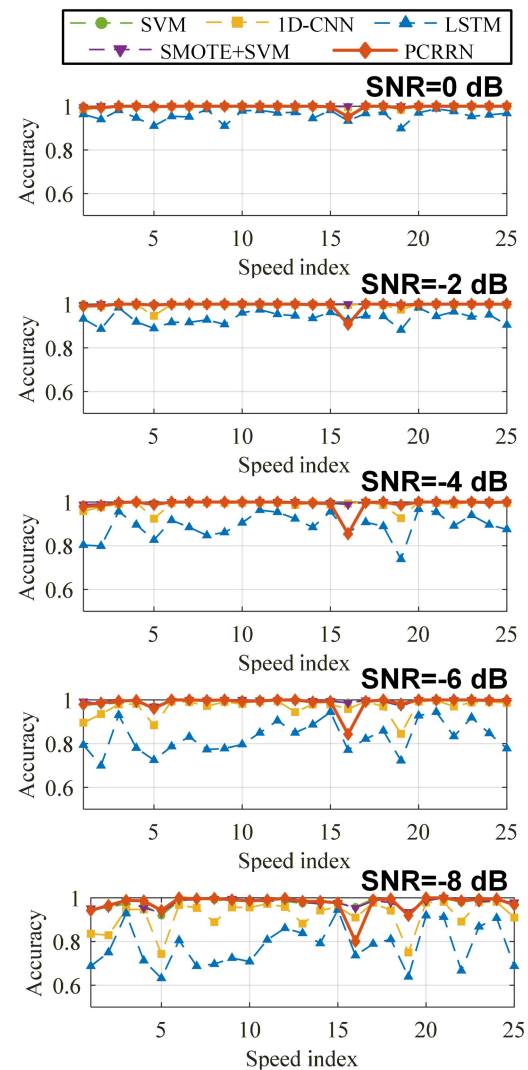


Fig. 7. Accuracy of all comparison methods at different SNRs and different speed combinations.

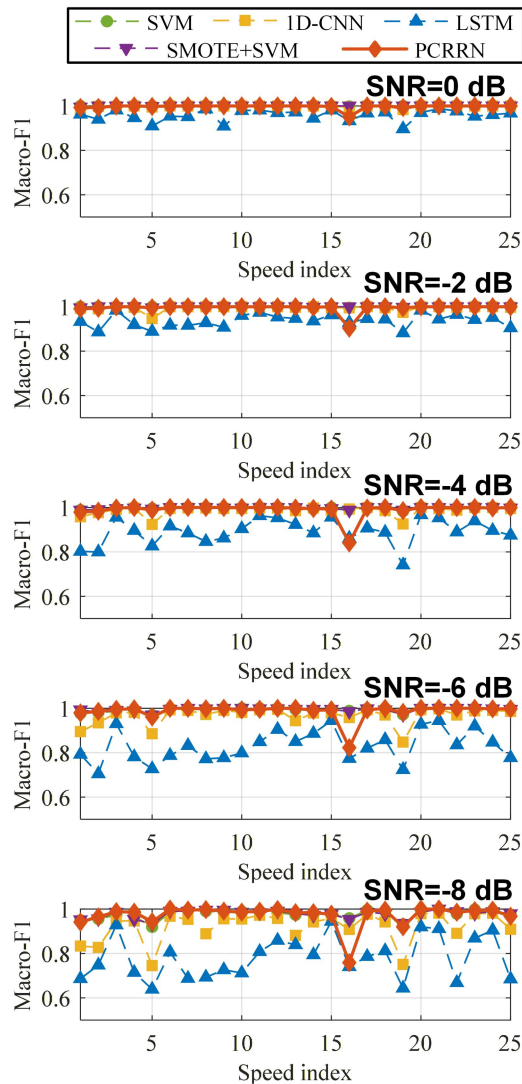


Fig. 8. Macro-F1 of all comparison methods at different SNRs and different speed combinations.

As illustrated in Fig. 7, Fig. 8 and Fig. 9 the proposed PCRRN consistently achieves the highest diagnostic performance under all SNR conditions. Across the entire range of operating speeds, the accuracy and Macro-F1 of PCRRN remain consistently high, exhibiting negligible degradation even when the SNR decreases to -8 dB. Similarly, the AUC remains stable across all operating speeds, indicating that the proposed network

maintains excellent class separability under severe noise interference. These results demonstrate that the learned prototype representation possesses remarkable robustness against spectral distortion and operating-condition variations.

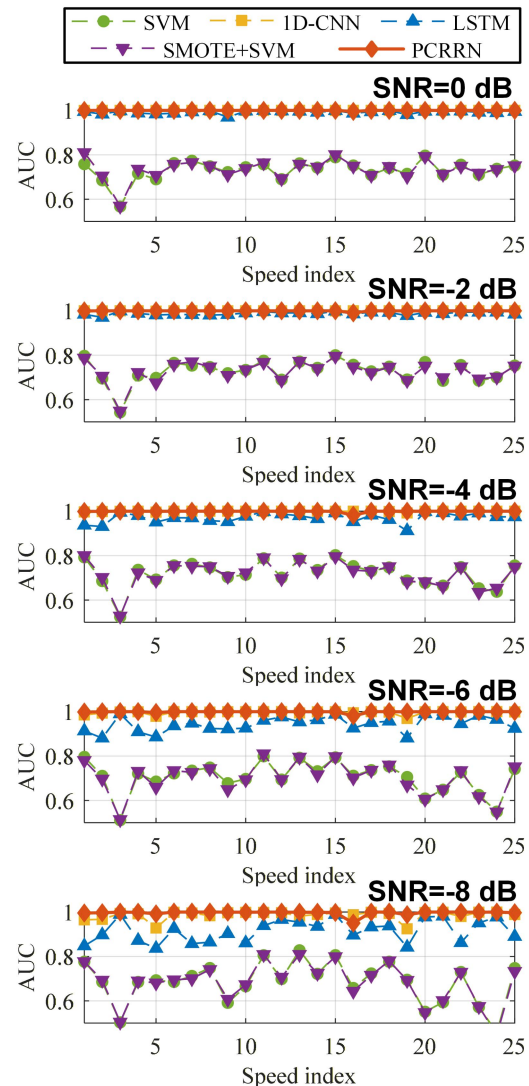


Fig. 9. AUC of all comparison methods at different SNRs and different speed combinations.

In contrast, the competing methods exhibit different degrees of performance degradation as the noise level increases.

Among them, LSTM is the most sensitive to noise contamination. Although satisfactory performance is achieved at 0 dB, both accuracy and Macro-F1 decrease progressively as the SNR decreases, accompanied by increasingly larger fluctuations across different operating speeds. At -8 dB, the classification performance varies considerably among operating conditions, indicating that the feature representations learned by LSTM are more susceptible to noise-induced spectral disturbances when only limited training samples are available.

Compared with LSTM, 1D-CNN demonstrates stronger robustness under moderate noise conditions. Its accuracy and Macro-F1 remain close to unity from 0 dB to -4 dB, suggesting that local convolutional feature extraction effectively suppresses part of the high-frequency noise. Nevertheless, noticeable performance degradation appears at -6 dB and becomes more pronounced at -8 dB, where several operating speeds exhibit reduced classification accuracy. This observation indicates that although convolutional feature learning improves robustness, the extracted features remain influenced by severe spectral distortion.

The conventional machine-learning approaches, namely SVM and SMOTE+SVM, exhibit relatively stable Accuracy and Macro-F1 across different SNR levels. However, as shown in Fig. 9, both methods consistently produce substantially lower AUC values than the proposed PCRRN and the deep learning approaches. Moreover, the AUC fluctuates significantly with operating speed, especially under low-SNR conditions. This phenomenon suggests that although the decision boundaries of SVM-based

classifiers can correctly classify most samples, the confidence and separability of the resulting decision function deteriorate considerably under noise interference. The incorporation of SMOTE alleviates the influence of class imbalance to some extent, but cannot fundamentally compensate for the degradation of the intrinsic spectral distribution caused by severe noise.

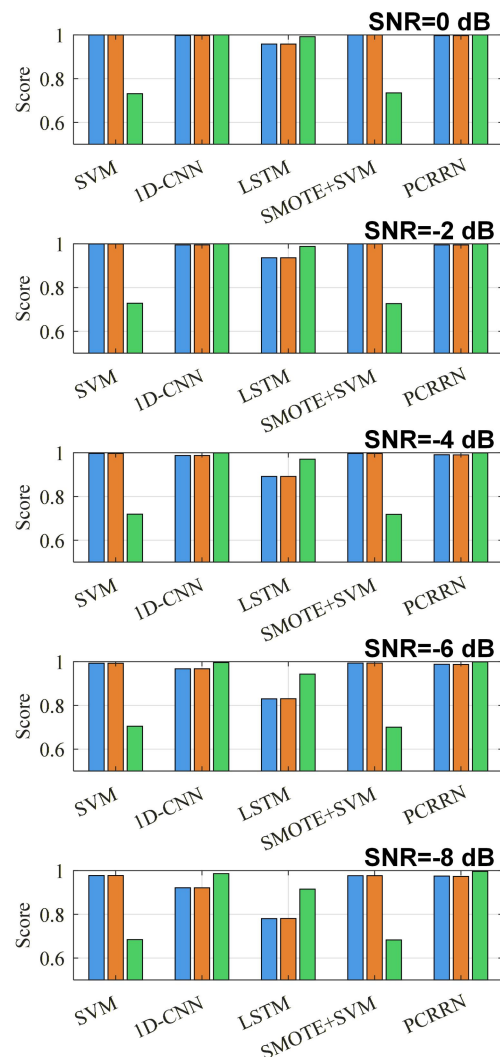


Fig. 10. Average values of accuracy, Macro-F1, and AUC for all comparison methods across different SNRs.

The superiority of PCRRN becomes more evident from the average performance comparisons shown in Fig. 10. For all five SNR levels, PCRRN consistently achieves the highest average accuracy, Macro-F1, and AUC among all competing methods. More importantly, the average performance of PCRRN remains nearly unchanged as the SNR decreases from 0 dB to -8 dB, whereas the competing methods exhibit varying degrees of degradation. This observation confirms that the proposed network maintains both high diagnostic accuracy and excellent robustness under increasingly adverse operating conditions.

To further investigate the class-level accuracy of the proposed PCRRN, the confusion matrices under different noise levels are presented in Fig. 11. Unlike the overall evaluation metrics, the confusion matrix provides detailed information regarding the classification performance and reveals the specific confusion patterns among different fault categories.

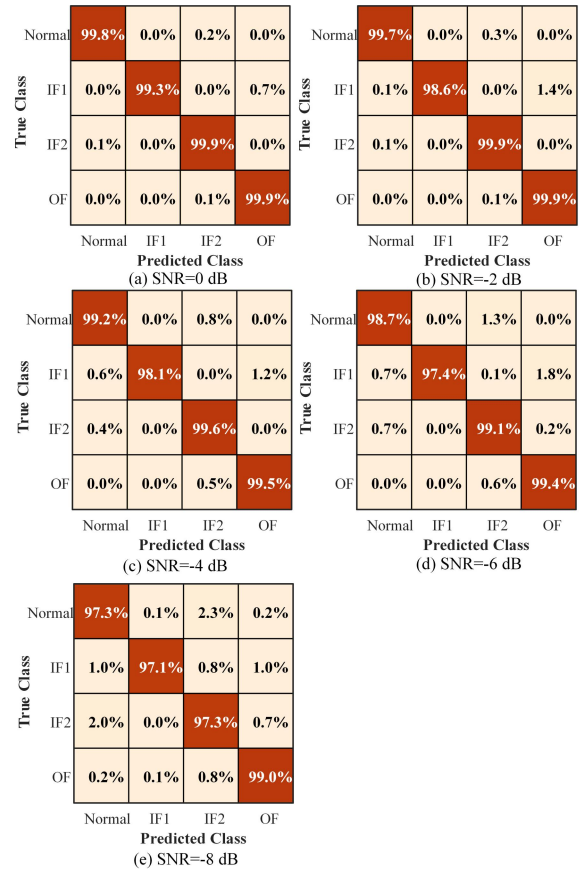


Fig. 11. Confusion matrices at different SNRs.

At SNR=0 dB, the proposed PCRRN achieves nearly perfect classification performance. Most samples are concentrated along the main diagonal, indicating that the learned prototype-response representation effectively separates the spectral distributions of Normal, IF1, IF2, and OF. Only a few isolated misclassifications can be observed, demonstrating the high discriminative capability of the proposed network even under mild noise contamination.

As the SNR gradually decreases from 0 dB to -8 dB, the diagonal dominance of the confusion matrices remains almost unchanged. The classification accuracy

remains consistently high, while only a limited number of samples are incorrectly assigned to neighboring fault categories. In particular, the two inner-race fault conditions, which exhibit relatively similar spectral characteristics, remain well distinguished throughout all noise conditions. This observation indicates that the proposed prototype-constrained representation is capable of capturing subtle structural differences between similar fault patterns rather than relying solely on local spectral amplitudes.

Overall, the experimental results demonstrate that the proposed PCRRN not only achieves the highest diagnostic accuracy but also exhibits the strongest robustness and the smallest performance variation across different operating speeds and noise levels. These characteristics indicate that the proposed prototype-response learning framework is well suited for practical aero-engine fault diagnosis under complex and noisy operating environments.

4.4 Ablation analysis

To investigate the contribution of the key components in PCRRN, an ablation study was conducted by constructing three variants with different prototype learning strategies and radial response modeling schemes. The regularization coefficient of the output-layer optimization was fixed as $\lambda = 10^{-3}$ for all variants to ensure a fair comparison. The following three variants were considered.

Ablation1: K-means prototype with unified radial scale. In this variant, the operating-state prototypes were obtained using the K-means clustering algorithm. The radial scale parameter was uniformly determined based on the average distance among all learned

prototypes. This variant represents a conventional prototype-based radial representation without considering the intrinsic distribution characteristics of individual operating states.

Ablation2: SVDD prototype with unified radial scale. In this variant, the K-means prototypes were replaced by SVDD-derived prototypes, while the same unified radial scale strategy was retained. By comparing V1 and V2, the influence of the prototype learning strategy can be evaluated, i.e., whether distribution-constrained prototypes provide more representative descriptions than centroid-based prototypes.

Full model: This model corresponds to the complete PCRRN framework. Specifically, each operating state was represented by an SVDD-derived prototype, and an individual radial scale parameter was determined according to the corresponding SVDD distribution radius. Therefore, different operating states can possess adaptive response ranges according to their intrinsic distribution compactness.

The comparison results are shown in Fig. 12. It can be observed that Ablation1 achieves the lowest diagnostic performance among all variants, indicating that directly using K-means centroids as prototypes cannot sufficiently characterize the intrinsic distribution structures of different aero-engine bearing states. Although K-means centers provide the average location of each class, they mainly describe the global mean feature distribution and ignore the compactness and boundary characteristics of individual operating states.

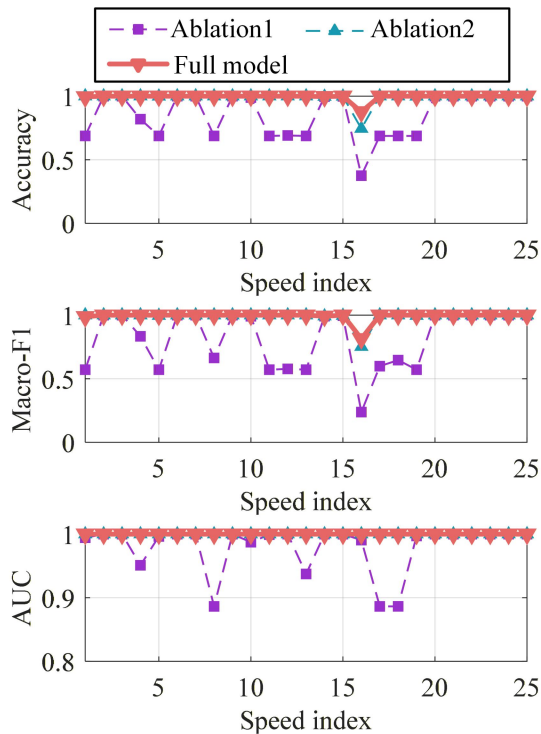


Fig. 12. The comparison results among different models.

Compared with Ablation1, Ablation2 achieves improved diagnostic performance after replacing K-means centers with SVDD-based prototypes. This improvement demonstrates that distribution-constrained prototype learning provides more discriminative state representations than conventional clustering-based centroids. The SVDD prototype considers the distribution geometry of each operating state and therefore provides a more reliable reference for measuring the similarity between testing samples and operating conditions.

Furthermore, Full model achieves the best overall performance among all variants. Compared with Ablation2, the only difference is the introduction of class-adaptive radial scales. The improved performance indicates that different operating states exhibit different distribution

characteristics in the feature space. A unified radial scale cannot accurately describe the response range of all states, especially when the intra-class compactness and inter-class separability are inconsistent. By assigning adaptive radial scales according to the SVDD-derived distribution radius, PCRRN can generate more informative response vectors and enhance the discrimination capability of the subsequent classifier.

Overall, the ablation results verify that both distribution-aware prototype learning and adaptive radial response modeling contribute to the effectiveness of PCRRN. The prototype learning mechanism provides meaningful geometric references for different operating states, while the adaptive radial response strategy further improves the representation capability by considering state-specific distribution characteristics.

5. Conclusions

This paper proposed a prototype-constrained radial response network for aero-engine fault diagnosis using vibration spectrum analysis. Unlike conventional data-driven classification models that directly learn decision boundaries from the original feature space, the proposed framework constructs representative prototypes for different operating states and transforms the original spectral features into a similarity-based response space. By integrating prototype learning mechanism, radial response modeling, and decision-making strategy into a unified analytical framework, PCRRN establishes an interpretable fault diagnosis model with an efficient analytical response-space decision mechanism and enhanced robustness against noise interference.

From a methodological perspective, the proposed framework exhibits three notable characteristics. First, representative prototypes are learned to characterize the intrinsic distribution structures of different operating states, providing compact geometric descriptions of spectral data. Second, the radial response modeling converts the nonlinear relationships between spectral samples and operating-state prototypes into discriminative response vectors, effectively reducing the influence of spectral fluctuations and measurement uncertainty. Third, the output-layer parameters are determined through a regularized least-squares optimization with a closed-form analytical solution, eliminating the need for iterative gradient-based training while improving computational efficiency and generalization capability.

Experimental validation was conducted using the HIT aero-engine bearing fault dataset under five noise levels ranging from 0 dB to -8 dB. Comparative studies against SVM, SMOTE+SVM, 1D-CNN, and LSTM demonstrated that the proposed PCRRN consistently achieved the highest diagnostic performance in terms of Accuracy, Macro-F1, and AUC. Moreover, the confusion matrix analysis further confirmed that PCRRN maintained excellent class separability and balanced recognition performance for all operating states, even under severe noise contamination. These results verify that the proposed prototype-response representation provides improved robustness and discrimination capability for aero-engine fault diagnosis under the investigated noisy operating conditions.

Although the proposed PCRRN demonstrates promising diagnostic performance, several limitations and

challenges remain. First, the current framework represents each operating state using a single learned prototype, which may be insufficient for characterizing complex operating states with multi-modal distributions or large intra-class variability caused by varying operating conditions and measurement uncertainties. Second, the prototype learning process is conducted under a supervised learning framework and assumes that representative labeled samples are available for all operating states. Consequently, its applicability to unseen fault types or previously unobserved operating conditions still requires further investigation. Moreover, although the proposed method adopts a closed-form optimization strategy for the decision layer, its overall computational efficiency has not been quantitatively evaluated through direct training and inference time measurements, and further analysis is required to verify its computational advantages. Future work will therefore focus on developing adaptive multi-prototype learning strategies to better capture complex distribution characteristics, incorporating domain adaptation and continual learning techniques to improve cross-domain and cross-operating-condition generalization, and validating the proposed framework on larger-scale industrial datasets under practical aero-engine operating conditions.

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