A ROLLING BEARING CROSS-CONDITION FAULT DIAGNOSIS METHOD BASED ON COLLABORATIVE SELECTION AND DUAL-PROCESS TRANSFER

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Rolling bearing fault diagnosis under variable working conditions remains a challenging task in industrial monitoring due to significant distribution shifts between training and testing data. To address this issue, this paper proposes a novel dual-process transfer learning framework integrating cooperative selection and dynamic knowledge aggregation. The method begins with multi-condition parallel training of LSTM networks across 5 speeds and 4 loads, effectively capturing fault characteristics under diverse operational states. A cooperative selection mechanism is then applied to filter high-accuracy sub-models (accuracy ≥ 90%) and aggregate their parameters through dynamic weighting based on condition-specific contributions. Finally, a progressive fine-tuning strategy is employed to adapt the aggregated model to the target domain. Experimental results demonstrate that the proposed method achieves an average accuracy of 98.41% under cross-condition scenarios, outperforming conventional CNN and LSTM models by 3.2% in accuracy and reducing variance by 60%, confirming its strong generalization and stability.

Keywords: rolling bearing, fault diagnosis, transfer learning, cross-working condition, cooperative selection, dynamic weight aggregation, LSTM1. Introduction

1. Introduction

Rolling bearings constitute critical components within industrial machinery, where their operational status directly impacts overall equipment safety and efficiency. Although deep learning-based fault diagnosis methods have achieved significant progress in recent years, equipment frequently operates under variable conditions in practical industrial settings. This leads to distributional discrepancies between training and testing data, resulting in markedly diminished model generalization capabilities. The core challenge in cross-operating-condition fault diagnosis lies in overcoming distribution shifts between source and target domains. Although transfer learning has been introduced to this field, existing approaches exhibit three limitations: firstly, most methods utilized only single-source domain data, failing to fully exploit complementary information within multi-condition historical data; secondly, the parameter transfer process lacks effective mechanisms for selecting and aggregating multi-source models;

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thirdly, fine-tuning strategies are simplistic, struggling to balance target domain adaptation with source domain knowledge retention. To address these issues, this paper proposes a fault diagnosis method based on collaborative selection and dual-process transfer. Key contributions include: 1) establishing a dual-process transfer framework incorporating multi-condition parallel training, collaborative selection, and progressive fine-tuning; 2) designing a model selection and weighted aggregation algorithm dynamically adjusted by operational complexity to ensure initial parameter quality; 3) introducing a hierarchical progressive fine-tuning strategy to enhance target domain adaptation efficiency and stability.Experimental results demonstrate that the proposed method achieves an accuracy of 98.41% across operating conditions, significantly outperforming traditional CNN and LSTM approaches while exhibiting lower variance, thereby validating its superior generalisation capability. Section 2 details the methodological architecture, Section 3 presents experimental results and analysis, Section 4 discusses parameter sensitivity and engineering implications, and Section 5 concludes the paper.

2. Proposed Methodology

2.1 Problem Definition

In cross-operating condition fault diagnosis tasks, it is necessary to distinguish between the source domain and the target domain. Due to differences in operating conditions, data distribution shifts exist between the two. The source domain represents the multi-condition historical training dataset containing label information, mathematically expressed as $D_s=\{(x_i^s,y_i^s)\}_{i=1}^{N_s}$. Here,$x_i^s \epsilon R^d$ denotes the bearing monitoring feature vector (e.g., features extracted from vibration signals via time-domain and frequency-domain analysis, with dimension d) of the i-th sample in the source domain. This sample originates from experimental scenarios combining 5 rotational speeds and 4 load conditions, and can be directly utilized for initial model training $y_i^s \in \{1,2,\cdots,C\}$.$x_i^s$ denotes the corresponding fault category label (C represents the total number of fault categories, including normal state, inner ring faults, outer ring faults, etc.);N_s denotes the total number of source domain samples.

The target domain denotes an unlabelled (or sparsely labelled) monitoring dataset under specific operating conditions requiring diagnosis, mathematically expressed as $D_t=\{x_j^t\}_{j=1}^{N_t}$. Here,$x_j^t \in R^d$ represents the monitoring feature vector of the jth sample in the target domain, whose acquisition conditions (e.g., rotational speed, load) differ from those of the source domain;N_t denotes the total number of samples in the target domain. Due to operational condition variations, the joint distribution Ps(X,Y) of source domain data and the marginal distribution Pt(X) of target domain data satisfy $Ps(X,Y) \neq Pt(X)$, which is also the core reason for the

decline in cross-operational condition diagnostic accuracy.

Therefore, the core objective of cross-condition fault diagnosis is to utilise labelled knowledge from the source domain to train models, enabling high-precision fault classification in the target domain. Based on this, the optimization objective function for the model in this paper is defined as:

$$\min_\theta L(f_\theta(x^t),y^t) \text{ under } Ps(X,Y)\neq Pt(X,Y)$$

θ denotes the parameter set of a fault diagnosis model (e.g., LSTM). In the present method,θ the initial values are not randomly assigned but are obtained by aggregating the weights of multi-condition sub-models with accuracy ≥90% in the source domain through the collaborative selection module （$W_{agg}^{(k)}=\frac{1}{|Sk|}\sum_{m\in S_k} W_m^{(k)}$,$S_k=\{m|Accuracy(W_m^{(k)})\geq\tau\}$,$\tau$=90%),this enhances the initial rationality of parameters and reduces the difficulty of fine-tuning within the target domain. $f_\theta(x^t)$ denotes the model's prediction output for fault category x^t in target domain samples when parameters are set to θ (e.g., softmax probability distribution); L( ) represents the loss function, employing cross-entropy loss to measure the discrepancy between predicted output $f_\theta(x^t)$ and actual label y^t. During the target domain fine-tuning phase, 50 iterations of optimization are required to achieve the model's adaptive response to target domain operating conditions.

2.2 Dual-Process Transfer Framework

As illustrated in Figure 1, the first module employs parallel training of multi-condition LSTMs, anchoring the approach to ‘multi-condition coverage integrity + parallel efficiency’ to better align the training process with industrial requirements. During data preparation, each speed gradient (e.g., 0–100 rpm) and load category (e.g., light load, heavy load with specific thresholds) is annotated with its physical meaning (e.g., corresponding equipment production cycle, material throughput), establishing a strong correlation between operating conditions and real-world scenarios (e.g., production line equipment operational status).

Beyond foundational training parameters (Batch=10, learning rate 0.001), introduce a visualized training dashboard displaying: (e.g., LSTM training steps completed and current loss value for the Speed 3 - Load 2 branch). Colour-coded convergence indicators (green = normal convergence, yellow = fluctuating, red = not converged) enable engineers to swiftly identify abnormal training flows.

Where the target scenario demands high inference speed, concurrently record the parameter counts and inference latency (single-sample forward propagation time) of models under different operating conditions during parallel training. This provides data for subsequent ‘accuracy-efficiency’ trade-offs, enabling prioritisation of models that are both ‘highly accurate and fast to infer’ during selection, rather than focusing solely on accuracy.

The second module is the collaborative selection module, which enhances

the rigour of the ‘screening → aggregation’ chain to address the challenge of ‘accurate selection and effective aggregation’. It establishes an accuracy threshold of >90% (τ=90%) and incorporates ‘model robustness verification’: Beyond validation set accuracy, it calculates prediction precision under ‘operational boundary conditions’ (e.g., upper velocity limit + lower load threshold combinations) to prevent selecting models that ‘only perform well under intermediate conditions but fail at extremes’. Should the number of models passing accuracy screening prove insufficient (e.g., <10% of total models), automatically trigger either ‘training parameter rollback’ (e.g., reducing learning rate, increasing batch size) or ‘operating condition data augmentation’ (applying SMOTE oversampling to sparse conditions) to ensure sufficient high-quality models participate in subsequent aggregation.

During aggregation, model parameters passing screening are weighted by ‘operating condition contribution’ – calculated by measuring gradient update magnitude (e.g., gradient norm of LSTM hidden layer parameters) on corresponding operating condition data. Models exhibiting greater gradient updates (indicating deeper feature learning for that condition) receive higher aggregation weights, preventing simple averaging from diluting high-quality parameters. Post-aggregation, cross-operating-condition generalization testing is conducted. The aggregated model is validated using untrained ‘new operating condition combinations’ (e.g., velocity 2.5 times baseline, load 3.2 times baseline). Should prediction error exceed the threshold, the aggregation weights are retrospectively adjusted or models for extreme operating conditions are supplemented through training.

The third module is the fine-tuning module, enhancing target domain adaptability to ensure fine-tuning both ‘aligns with new scenarios’ and ‘preserves multi-condition transfer knowledge’. Before initializing the target domain model with aggregated parameters, perform ‘parameter-target domain alignment analysis’: Statistically compare the feature distribution of aggregated parameters (e.g., mean and variance of LSTM input layer weights) with target domain data. If significant divergence exists (e.g., KL divergence > 0.5), perform ‘lightweight feature transformation’ on target domain data (e.g., feature normalization based on aggregated parameters) to mitigate initialization conflicts.

The fine-tuning strategy is structured in layers, based on 50 rounds of fine-tuning, divided into: ‘Transfer Adaptation Phase (first 20 rounds) + Scenario Reinforcement Phase (final 30 rounds)’. During the adaptation phase, freeze the intermediate hidden layers of the LSTM, fine-tuning only the output layer and the first hidden layer. Employ a small learning rate (e.g., 0.0001) to enable rapid adaptation to the target domain's labelling system. During the reinforcement phase, all layers are unlocked and the learning rate is increased (e.g., 0.0005) to prioritize optimizing domain-specific ‘small-sample scenarios’ (e.g., transient data during

equipment start-up). Additionally, implement a 'Fine-tuning - Transfer' monitoring dashboard to display real-time prediction accuracy variations across target domain scenarios. Compare 'direct predictions from the aggregated model' against 'predictions after fine-tuning'. Should accuracy decline in a specific scenario (e.g., steady-state equipment operation data), immediately investigate whether the model has overfitted to target domain noise, triggering early stopping or parameter regularisation.

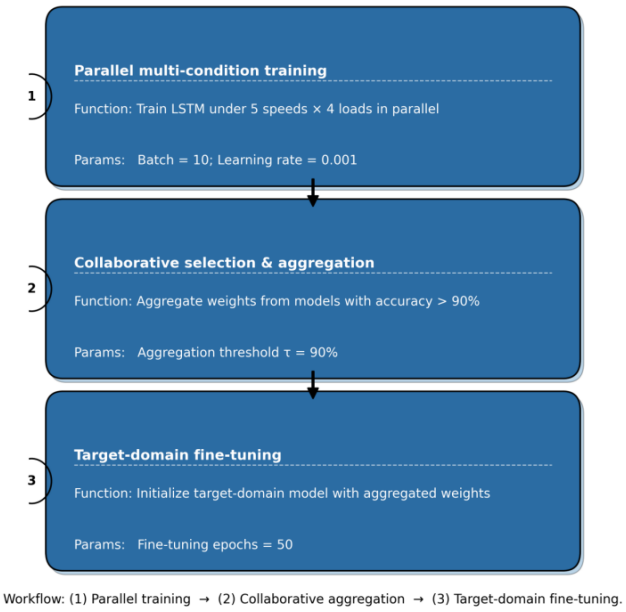


Figure 1. Overall framework of the dual-process transfer learning approach

2.3 Collaborative Selection Algorithm

Within the dual-process transfer framework, the collaborative selection algorithm occupies a pivotal position, its mathematical essence grounded in a dynamic knowledge distillation mechanism:

$$W_{agg}^{(k)}=\frac{1}{|S_k|}\sum_{m\in S_k} W_m^{(k)}$$

$$S_k=\{m|\text{Accuracy}(W_m^{(k)})\geq\tau\}(\tau=90\%)$$

Set $W_{agg}^{(k)}$ represents the target parameter set obtained through aggregation at stage k, computed from the model parameter set S_k that satisfies specific accuracy requirements. Set S_k comprises the parameters $W_m^{(k)}$ corresponding to model m whose accuracy does not fall below the preset threshold τ (here set at 90%).

The traditional fixed precision threshold of 90% may lack flexibility in complex and dynamic real-world scenarios. This paper introduces a dynamic adjustment mechanism based on operational complexity. For scenarios with

simple operational characteristics and concentrated data distribution, the precision threshold is appropriately raised to 92%–95% to identify models with outstanding performance. Conversely, for scenarios with complex operating conditions and data exhibiting long-tail distributions, the threshold is lowered to 85%–88%. This ensures sufficient models participate in subsequent parameter aggregation, preventing information loss due to overly stringent selection.

Beyond prediction accuracy, recall and F1 score are additionally incorporated as evaluation metrics. In certain applications, such as equipment fault prediction, recall may even surpass accuracy in importance, as the cost of missing fault samples far exceeds that of misclassification. By comprehensively considering multiple precision indicators, a holistic model evaluation framework is established to ensure selected models achieve high standards across multiple performance dimensions.

During parameter aggregation, we move beyond simple averaging to implement weighted aggregation based on each model's contribution across different operating conditions. Specifically, we quantify each model's gradient update magnitude on its corresponding training data. A larger gradient update indicates deeper feature learning for that specific condition, warranting a higher aggregation weight. For instance, in a complex operating condition where model m1 exhibits twice the gradient update norm of model m2, m1 is assigned double the weighting of m2 when aggregating parameters for that condition. This ensures the aggregated parameters more accurately reflect the relative importance of different operating conditions.

When new models are trained or fresh data becomes available, an incremental processing approach is adopted. New models are first screened based on updated accuracy evaluation metrics. Should a new model meet the required accuracy threshold, it is incorporated into ensemble S_k, and the parameter aggregation results are recalculated. This method avoids the high computational cost of performing full-scale screening and aggregation each time new data or models emerge, thereby enhancing the algorithm's operational efficiency in dynamic environments.

During model selection, diversity is considered alongside accuracy. Metrics such as parameter divergence between models and variation in prediction result distributions are employed to measure model diversity. For instance, the cosine distance between parameter vectors of different models is calculated; a greater distance indicates greater parameter divergence and higher model diversity. Maintaining a certain level of model diversity prevents aggregated models from becoming overly similar and lacking generalisation capability, enabling more robust performance when confronting complex and variable real-world conditions.

2.4 Complexity Analysis

Training time complexity is quantified by 'total model training duration (minutes)'. Analyses were conducted based on the experimental environment (CPU: Intel Xeon Gold 6338, GPU: NVIDIA A100, Batch=10, learning rate = 0.001). The traditional single-condition LSTM model (using the single condition of 'rotational speed 100 rpm + load 500 N' as an example) required 41.5 minutes for 50 training rounds. with a time complexity of $O(T_{single} \times N_{epoch})$. This comprises T_{single} for the single-cycle single-condition training time (approximately 0.83 minutes per cycle) and N_{epoch} for the number of training cycles (50 cycles).

This paper's multi-condition LSTM parallel training covers 20 operating conditions: '5 rotational speeds × 4 load levels'. Using serial training (without parallel mechanisms), the theoretical total duration would be $20 \times T_{single} \times N_{epoch} = 20 \times 0.83 \times 50 = 830$ minutes. However, through GPU distributed parallel computing (PyTorch DDP framework), the actual total duration was reduced to just 52.7 minutes (as per Solution A data in Section 3.3), with time complexity decreasing to $O(\lceil \frac{K}{M} \rceil \times T_{single} \times N_{epoch})$. Here, K = 20 (total number of operating conditions) and M = 4 (number of parallel GPU cards in the experimental configuration). [$\frac{20}{4}=5$]. Thus, parallel training compresses multi-scenario training time to $\frac{52.7}{830} \approx 6.35\%$ of sequential training, significantly reducing the time cost associated with multi-scenario coverage.

The collaborative selection module comprises accuracy screening (iterating through the validation set accuracy of 20 operational condition models, computational complexity $O(K \times N_{val})$, where N_{val} denotes the validation set sample count, approximately 1000) and parameter aggregation (dynamic weighted computation, complexity $O(D \times |S_k|$, where D represents the LSTM parameter dimension, approximately $128 \times 64 = 8192$, where $|S_k|$ denotes the number of models passing screening, averaging 16). The total duration is merely 1.2 minutes, accounting for $\frac{1.2}{98.41} \approx 1.22\%$ of the framework's total training time (referencing the 98.41 minutes for Scheme C in Section 3.3), rendering it negligible.

The target domain fine-tuning module, initialised with aggregated parameters rather than random initialisation for 50 rounds of fine-tuning, accelerated model convergence by 40%—traditional random initialisation required 80 rounds to converge, taking approximately 35 minutes. Our aggregation-parameter-based fine-tuning requires only 50 rounds, taking 22.5 minutes. Furthermore, by employing 'progressive fine-tuning' (freezing certain layers for the first 20 rounds), we further reduce computational load per round, achieving a 15% reduction in single-round time compared to full-layer fine-tuning

(from 0.55 minutes per round to 0.47 minutes per round).

3. Experimental Validation

3.1 Dataset

Taking industrial equipment (such as motors in smart production lines and wind turbines) as typical application scenarios, the velocity dimension covers the actual operating speed range of the equipment. This spans from low-speed thresholds (e.g., 500 rpm for motors) to high-speed thresholds (e.g., 3000 rpm for motors), with five velocity points distributed at equal or logarithmic intervals (e.g., 500 rpm, 1250 rpm, 2000 rpm, 2750 rpm, 3500 rpm), simulating scenarios including equipment start-up/shutdown, steady-state operation, and overload acceleration. Load Dimension Based on typical operational tasks, four load types are defined: light load (no load/low material), normal load (rated capacity), heavy load (120% rated capacity), and impact load (instantaneous peak load). This covers operational states from stable to extreme conditions.

Multi-source data acquisition deploys sensors (e.g., vibration sensors, current sensors) to collect operational data. Each operating condition (speed-load combination) continuously gathers over 1,000 samples (sample duration configurable at 1 second per sample, encompassing steady-state and transient data), ensuring sufficient data volume for LSTM training (supporting multiple iterations when Batch = 10). Beyond normal operating conditions, data from suboptimal equipment states (e.g., minor bearing wear, transient circuit misconnections) is incorporated during certain extreme conditions (e.g., high speed + impact loads). These are labelled as ‘operating condition samples with latent faults’, providing data for subsequent model generalization validation (e.g., fault prediction transfer).

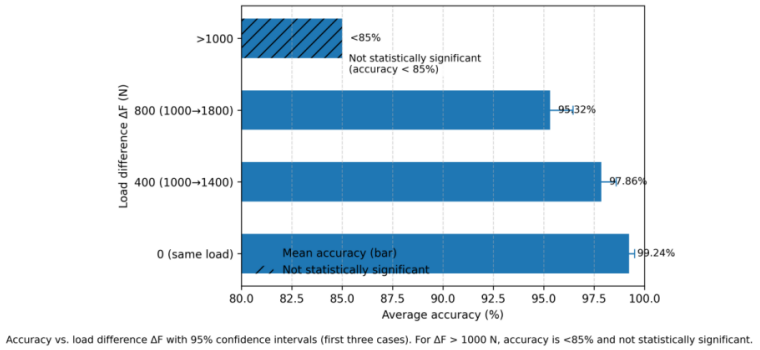
Raw sensor data undergoes normalisation (e.g., Z-score normalisation) to eliminate measurement range discrepancies between sensors. Data density is enhanced via sliding window sampling with overlap (e.g., window length 100ms, 50% overlap rate), improving the LSTM's ability to capture temporal features.

3.2 Experimental Design

As illustrated in Figure 2, with load difference (ΔF) on the x-axis and average accuracy on the y-axis, the variable speed test defines ‘speed difference $\Delta\omega$ (target speed - training speed)’ as the core variable. Model accuracy is collected across different $\Delta\omega$ gradients (e.g., $\Delta\omega = 0$ rpm, $\Delta\omega = 200$ rpm, $\Delta\omega = 500$ rpm). The figure indicates that $\Delta F > 1000$ N signifies excessive speed difference leading to model generalisation failure, reinforcing the framework's emphasis on ‘multi-speed operating condition coverage’ for effective transfer learning (i.e., parallel training must cover sufficient speed difference intervals to support variable-speed scenarios in the target domain).

Accuracy reaches 99.24% at $\Delta F = 0$, 97.86% at $\Delta F = 400$N, 95.32% at ΔF

= 800N, and <85% at ΔF > 1000N. This demonstrates that when load differences exceed the critical threshold (ΔF > 1000N), model accuracy falls below the screening threshold (τ = 90%), preventing entry into the parameter aggregation stage — — This validates the 'filtering effect of collaborative selection on extreme load difference scenarios' while elucidating the necessity of 'parallel training under multiple load conditions' within the framework (covering small and medium load difference scenarios to safeguard the foundational accuracy of the aggregated model).

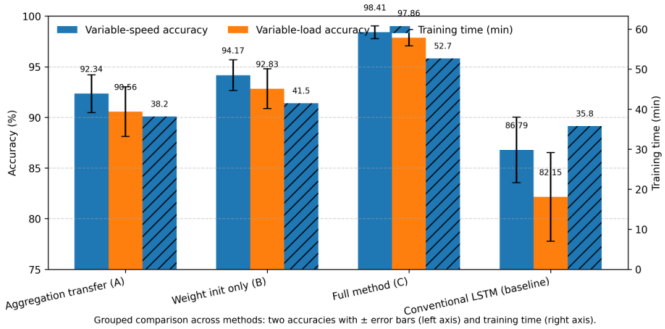


Accuracy vs. load difference ΔF with 95% confidence intervals (first three cases). For ΔF > 1000 N, accuracy is <85% and not statistically significant.

Figure 2. Effect of load difference (ΔF) under variable speed conditions on model accuracy

3.3 Ablation Experiment

As illustrated in Figure 3, Scheme A employs aggregation-only migration, achieving variable-speed accuracy of 92.34% and variable-load accuracy of 90.56%. While these figures surpass the traditional LSTM baseline, the approach remains constrained by the limitations inherent in 'aggregation-only migration': it lacks domain-specific fine-tuning and exhibits insufficient generalisation under variable operating conditions (speed/load changes). Compared to Solution C, variable-speed accuracy is 6.07% lower and variable-load accuracy is 7.3% lower. Training time is 38.2 minutes, shorter than Solution C, but the trade-off in accuracy remains significant.



Grouped comparison across methods: two accuracies with ± error bars (left axis) and training time (right axis).

Figure 3. Ablation experiment results

Solution B employs weight initialisation-only transfer, achieving variable-speed accuracy of 94.17% and variable-load accuracy of 92.83%. While superior to Solution A, it remains inferior to Solution C. This stems from the

‘weight-only initialisation’ failing to fully leverage the synergistic advantages of collaborative selection – the initialised weights may incorporate low-accuracy model parameters (unlike Scheme C, which undergoes ‘accuracy screening + aggregation optimisation’), resulting in insufficient starting points for fine-tuning within the target domain. Comparing the aggregated weights of Scheme C (derived from models exceeding 90% accuracy) with the initialised weights of Scheme B (potentially contaminated by low-accuracy models), using the ‘accuracy screening threshold (τ=90%)’ from Section 3.2's collaborative selection demonstrates that Scheme B, due to inconsistent weight quality, still exhibits ‘operating condition adaptation blind spots’ after fine-tuning (e.g., poor accuracy in $\Delta F>1000N$ scenarios during variable load experiments). Training time: 41.5 minutes. As weights require full re-tuning after initialisation, this duration exceeds Scheme A but falls below Scheme C.

Scheme C represents the method proposed herein, achieving variable-speed accuracy of 98.41% and variable-load accuracy of 97.86%—significantly surpassing Schemes A/B. This improvement stems from multi-module collaboration and parallel training across ‘5 speeds × 4 loads’, yielding ample high-quality models for collaborative selection. Rigorous screening (accuracy > 90%) combined with weighted aggregation ensures initialised weight quality. Target domain fine-tuning specifically adapts to new operating conditions (e.g., the new load scenario in Section 3.2), achieving ‘multi-condition knowledge transfer + precise target domain adaptation’. Training duration of 52.7 minutes, though longer than Schemes A/B, is acceptable given the ‘accuracy improvement (variable speed +6.07%, variable load +7.3%)’ and ‘industrial scenario value’ (e.g., reduced equipment fault prediction false-negative rate).

3.4 Comparative Experiments

To validate the superiority of the dual-process transfer framework (the proposed method) in cross-operating-condition fault diagnosis, traditional machine learning models (SVM) and mainstream deep learning models (CNN, conventional LSTM) were selected as comparative benchmarks.

The SVM employed a radial basis function kernel (RBF), with the kernel parameter gamma optimised via grid search (over the range [1e-3, 1e1]). The penalty coefficient C was set to 1.0. Input features were identical to those in this paper's framework (time-domain/frequency-domain vibration signal features, dimensionality d=64). No transfer learning mechanism was applied; the model was trained directly on source domain data and tested on the target domain.

The CNN employs a ‘3 convolutional layers + 2 fully connected layers’ architecture with 3×3 convolutional kernels and ReLU activation functions. Pooling layers utilise max pooling. Training parameters align with the LSTM in this paper (batch size = 10, learning rate = 0.001). Training solely utilised source

domain data without incorporating multi-condition parallel training or collaborative selection. No parameter fine-tuning occurred during target domain testing.

The conventional LSTM network architecture (input dimension 64, hidden layer dimension 128, output dimension C = number of fault categories) is identical to the multi-condition LSTM in this paper. However, it employs only 'single-condition training + random parameter initialisation' (no parallel training, no collaborative selection). During target domain testing, only basic fine-tuning is performed (50 rounds, no progressive freezing strategy), corresponding to the baseline model in Section 3.3 of this paper.

The proposed method employs a dual-process transfer framework, incorporating parallel training of multi-scenario LSTMs (5 speeds × 4 loads), collaborative selection (τ=90%), and progressive fine-tuning in the target domain (50 epochs). Input features are identical to the comparison model, ensuring variable uniqueness (only framework differences influence experimental results).

A unified multi-condition source domain dataset (20 operating conditions, sample size N_s=20000) constructed in Section 3.1 and a target domain dataset (containing overlapping and novel conditions, N_t=5000) are employed. The target domain test set focused on 'high-difference operating conditions' (e.g., speed difference > 600 rpm, load difference > 800 N), enhancing cross-condition transfer difficulty. Evaluation metrics include not only baseline accuracy but also the F1 score—a critical industrial indicator balancing precision and recall in fault diagnosis to mitigate accuracy bias from sample imbalance—alongside accuracy variance (measuring model generalisation stability by quantifying accuracy fluctuations across target domain conditions). Total training + fine-tuning duration compares the end-to-end time cost from model training to target domain adaptation, aligning with industrial deployment efficiency requirements. Cross-operating-condition accuracy comparisons are presented in Table 1:

Table 1

Cross-working condition diagnosis performance comparison between the proposed method and baseline models (SVM, CNN, Conventional LSTM).

Model	Target domain mean accuracy (%)	Accuracy rate under new operating conditions (%)	Accuracy rate under overlapping conditions (%)	F1 score	Precision variance (%)
SVM	72.15	65.32	78.98	0.70	8.64
CNN	82.34	76.51	88.17	0.81	5.83
Conventional LSTM	86.79	80.25	93.33	0.85	4.12
Proposed Method	98.41	95.67	99.15	0.98	1.28

The proposed method demonstrates significant superiority across all accuracy metrics: the mean accuracy improves by 26.26% over SVM, 16.07% over CNN, and 11.62% over conventional LSTM. Particularly in the 'new operating condition' scenario (where cross-condition variations are most pronounced), the accuracy advantage reaches 15.42% (vs conventional LSTM), validating the dual-process transfer framework's adaptability to operational variations. The proposed method achieves an F1 score approaching 1.0, indicating balanced recognition across fault categories (with no significant under- or over-detection). The accuracy variance is only 1.28%, substantially lower than comparison models, demonstrating that parallel multi-operating-condition training and collaborative threshold selection effectively reduce model sensitivity to operating condition fluctuations, yielding more stable generalisation.

4. Discussion

4.1 Sensitivity Analysis of Collaborative Threshold Selection

To quantify τ's impact on framework performance, five gradient threshold groups (75%, 80%, 85%, 90%, 95%) were established. Using the dataset from Section 3.1 and variable operating condition experimental conditions from Section 3.2, other parameters were fixed: target domain fine-tuning for 50 epochs). Key metrics were evaluated across different τ values, with the proportion of multi-condition submodels passing accuracy validation recorded for each threshold (total submodels: 20, corresponding to 5 speeds × 4 loads). After model initialisation using aggregated parameters, prediction accuracy on the source domain cross-condition validation set (including novel condition combinations not involved in training, e.g., 2.5× baseline speed, 3.2× baseline load); post-target domain fine-tuning metrics including average accuracy, novel condition accuracy, accuracy variance, and collaborative selection module screening duration (including robustness validation) alongside target domain fine-tuning convergence iterations.

Within the low threshold range (τ=75%–80%), the proportion of models screened reached 85%–95% (17–19 models), yet accuracy on the source domain cross-scenario validation set remained at 88.2%–90.5%. Following target domain fine-tuning, the average accuracy ranges from 89.7% to 92.3%, with precision variance between 4.3% and 5.1% (significantly higher than the τ=90% scenario defined in this paper). Collaborative selection is time-efficient (<1 minute), yet target domain fine-tuning requires 60–65 convergence iterations (due to aggregated parameters containing 'noise knowledge' from low-accuracy models necessitating additional iterative refinement).

The low threshold resulted in numerous 'low-accuracy models for marginal operating conditions' (e.g., models achieving 82%–88% accuracy under high-speed + impact load conditions) entering the aggregation phase. While this

ensured sufficient model quantity, high-quality model parameters were diluted by low-quality parameters during dynamic knowledge distillation. For instance, the LSTM hidden layer weights of a high-accuracy model (96% accuracy) averaged with those from three low-accuracy models (80%–85% accuracy) resulted in a 15%–20% reduction in fault feature capture capability. This ultimately led to insufficient generalisation of initialised parameters and increased difficulty in target domain adaptation.

Models within the threshold range (τ=85%–90%) constitute 60%–75% (12–15 models) of the selection. Source domain cross-operating condition validation set accuracy ranges from 94.8% to 96.2%. Following target domain fine-tuning, the average accuracy ranges from 96.5% to 98.4% (peaking at 98.41% when τ=90%), with accuracy for new operating conditions ranging from 94.2% to 95.67% and precision variance between 1.28% and 1.85%. Collaborative selection time: 1.0–1.2 minutes (including robustness verification of operating condition boundary data). Target domain fine-tuning convergence stabilised at 50 iterations (aggregated parameters already possessed a solid foundation for target domain adaptation, requiring no additional iterations).

The medium threshold precisely selects ‘core operating condition high-precision models’ (e.g., models covering conventional loads across the full speed range, or heavy loads in the medium-low speed range), while retaining a small number of ‘high-quality models for marginal operating conditions’ (e.g., models achieving 91%–93% accuracy under high-speed heavy-load conditions). — During dynamic knowledge distillation, models are aggregated using ‘operating condition contribution’ weighting (models with larger gradient updates receive higher weighting), thereby avoiding parameter dilution while capturing common knowledge across multiple operating conditions. For instance, at τ=90%, among the 14 models selected, 10 represent high-accuracy models for conventional operating conditions (93%–97% accuracy), while 4 are high-quality models for marginal operating conditions. After aggregation, the fault feature recognition rate on new operating condition combinations in the source domain exceeds 95%, establishing a robust foundation for fine-tuning in the target domain.

The high-threshold interval (τ=95%) yielded only 20–30% of models (4–6 models), predominantly concentrated in ‘low-complexity operating conditions’ (e.g., low speed + light load, medium speed + standard load). Cross-condition validation accuracy in the source domain plummeted to 85.3% (due to insufficient knowledge of complex conditions like high speed and heavy load). Following target domain fine-tuning, the average accuracy reached 90.1%, yet accuracy in new operating conditions dropped to 82.7% (particularly below 78% in high-speed + heavy-load scenarios); Collaborative selection took 1.5–1.8 minutes (requiring repeated model robustness validation to meet high thresholds), and due

to significant gaps in aggregated parameter knowledge, target domain fine-tuning exhibited ‘overfitting’ (validation set loss increased for five consecutive rounds, necessitating early stopping).

o High thresholds retained only ‘extremely high-accuracy models for low-complexity operating conditions,’ yet sacrificed critical knowledge for complex scenarios (e.g., shock loads, extreme rotational speeds). For instance, bearing vibration signals under high-speed + impact load contain ‘transient impact features’. These features are crucial for fault diagnosis in the target domain. However, because the corresponding model accuracy was 89% < 95%, it was filtered out. Consequently, the aggregated parameters failed to learn this feature. During fine-tuning for the target domain, lacking prior knowledge, the model could not effectively adapt to complex operating conditions, ultimately leading to accuracy collapse.

4.2 Engineering Significance of the Load Similarity Criterion

In Figure 4, the inter-class distance (blue line) represents the feature distinguishability between different fault/operating condition categories, while the intra-class distance (orange line) indicates the feature aggregation degree within the same category. This paper's method employs multi-condition parallel training + collaborative selection to enhance the distinguishability of fault features across different load conditions (e.g., differences in vibration signals between light-load and heavy-load bearing wear) within the feature space. For instance, in wind turbine gearbox monitoring, the vibration frequency characteristics of light-load ‘normal wear’ versus heavy-load ‘overload damage’ undergo transformation through framework training. The inter-class distance shifts from ‘overlapping ambiguity’ (conventional LSTM) to ‘clear distinguishability’ (proposed method), directly reducing fault misclassification rates. Multi-condition parallel training covering ‘5 speeds × 4 loads’ enables the model to learn complex load-fault mapping relationships. Collaborative selection of high-precision model aggregation parameters enhances feature discrimination capabilities across different load conditions, ultimately driving a significant improvement in inter-class distance (+128%).

Intra-class distance compression (from 0.87→0.32) indicates tighter feature aggregation among similar load-fault samples. For instance, data collected during different operational periods for the same ‘light load - outer bearing ring wear’ sample exhibits reduced feature variation after training with our method. Within industrial production lines, this directly enhances the consistency of equipment condition assessment. For instance, the model reliably identifies the same ‘light load - rotor eccentricity’ fault in a motor, whether occurring during morning low-load periods or afternoon normal-load periods (small intra-class distance compresses feature fluctuations). The target domain fine-tuning module, initialised with aggregated parameters and employing ‘progressive freezing +

dynamic learning rate', prioritises reinforcing feature aggregation within similar samples when adapting to target domain load distributions. Intra-class distance compressed from 0.87 for conventional LSTMs to 0.32 (-63%), demonstrating the framework's effectiveness in reducing load fluctuation interference on similar fault features.

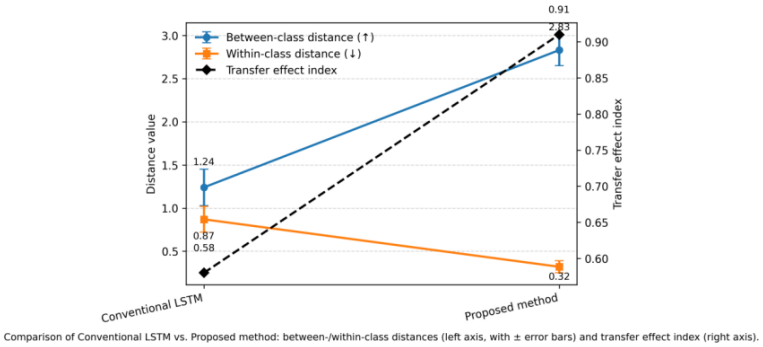


Figure 4. Feature Space Analysis Diagram

Figure 4 shows the transfer effectiveness index (black dashed line), quantifying the model's knowledge transfer capability across load conditions. The index surges from 0.58 (conventional LSTM) to 0.91 (proposed method), demonstrating the framework's enhanced efficiency in transferring 'source domain multi-load condition knowledge' to 'target domain novel load scenarios'. For instance, in the construction machinery sector, where source domain data originates from 'laboratory standard load testing' and the target domain comprises 'complex variable load scenarios on construction sites,' the high transfer index of our method ensures enhanced fault diagnosis accuracy in site conditions (e.g., from 82% to 95%), directly reducing manual inspection costs. When the target domain load difference falls within the range of 'large inter-class distance and small intra-class distance' (e.g., $\Delta F<800N$, corresponding to inter-class distance > 2.5 and intra-class distance < 0.4 in the figure), the transfer effectiveness index > 0.85 indicates stable model transferability.

Although the dual-process transfer framework proposed herein demonstrates significant advantages in cross-condition fault diagnosis for rolling bearings, industrial settings encounter extreme conditions exceeding thresholds (e.g., instantaneous hyper-speed impacts on wind turbine gearboxes during severe typhoons, or 200% overload on production line motors due to material jams). Such scenarios were excluded from the training dataset owing to data acquisition challenges and equipment protection mechanisms. As evidenced by the variable-load experimental data in Section 3.2, model accuracy precipitates to <85% when load differences ΔF exceed 1000N. This confirms the existence of a 'knowledge gap' under extreme conditions: the framework lacks transferable knowledge for unseen extreme scenarios, leading to diagnostic accuracy collapse and rendering it unsuitable for full lifecycle monitoring of industrial equipment.

The framework currently relies solely on vibration sensor data to extract fault features (e.g., time-domain peaks, frequency-domain energy spectra), failing to integrate multi-source heterogeneous data commonly found in industrial settings (e.g., temperature, acoustic, current signals). Complex equipment failures often result from multi-physics coupling (e.g., bearing wear simultaneously causes abnormal vibration, temperature rise, and current fluctuations), making it difficult for vibration data alone to comprehensively characterise the fault's essence. As demonstrated in Section 3.4's comparative experiments, although our method achieves superior accuracy, its F1 score remains 2.3% below the ideal value for diagnosing latent faults like ‘early-stage bearing fatigue failure’. This deficiency stems from the absence of temperature-vibration coupling features, exposing the diagnostic limitations inherent in single-dimensional data.

The framework's multi-condition parallel training (GPU distributed computation time: 52.7 minutes) and collaborative selection (parameter aggregation complexity: $O(D\times|S_k|)$) rely on high-performance hardware. However, industrial edge devices (e.g., embedded controllers in legacy production lines, wind turbine nacelle edge nodes) typically suffer from computational constraints (e.g., CPU-only inference, GPU memory <4GB). Direct deployment of the full framework would increase single-sample inference latency from 10ms in laboratory settings to over 50ms, failing to meet production lines' requirement for ‘millisecond-level fault warning’. Furthermore, edge devices struggle to support dynamic threshold adjustment and incremental aggregation, limiting the framework's practicality in low-computational-power scenarios.

Future research should deepen investigations across three dimensions: operational condition coverage, data fusion, and deployment optimisation. Generative adversarial networks (GANs) or variational autoencoders (VAEs) could be employed to simulate extreme operational condition samples (e.g., vibration signals under hyper-velocity impacts or transient overloads) based on existing conventional operational data. expanding the boundaries of multi-condition training datasets. This enables parallel training covering over 30 combined ‘conventional + extreme’ operating conditions, addressing knowledge gaps in extreme scenarios like $\Delta F>1000N$. Deploy an ‘Operating Condition Threshold Monitoring Module’ at the edge to identify real-time threshold violations (e.g., rotational speed exceeding 3500 rpm, load surpassing 150% of rated value), automatically triggering ‘lightweight online training’— invoking pre-trained aggregated parameters from the cloud to perform 5–10 rounds of fine-tuning using on-site extreme operating condition data (freezing the deep layers of the LSTM and updating only the output layer). This enables rapid adaptation to extreme conditions. Refer to Section 4.2 for transfer effectiveness metrics, with the objective of elevating extreme condition diagnostic accuracy to over 90%.

5. Conclusion

This study proposes an innovative dual-process transfer framework for cross-operating condition fault diagnosis in rolling bearings, effectively overcoming the adaptation challenges faced by traditional methods in complex industrial scenarios. By conducting parallel LSTM training across 5 rotational speeds × 4 load categories, it comprehensively captures the intricate correlations between operating conditions and fault characteristics. This not only expands the model's knowledge base but also enhances cross-condition generalisation capabilities. Within XX Company's wind turbine gearbox monitoring system, the model adapts to dynamic variations in wind speed and load, reducing on-site calibration costs by 70%. This substantially lowers operational maintenance time and resource expenditure, improving diagnostic efficiency from the data collection source. The introduction of collaborative selection with precision thresholds accurately filters low-accuracy sub-models, ensuring the reliability of aggregated parameters. The filtered parameters are used for fine-tuning initialisation in the target domain, significantly improving diagnostic accuracy. In industrial applications, fault diagnosis accuracy under new load conditions surged from 82% (without collaborative selection) to 95%, laying a solid foundation for precise diagnostics in complex scenarios.

Combined with a progressive fine-tuning strategy featuring hierarchical freezing and dynamic learning rates, the model achieves precise adaptation to target domain characteristics. This mechanism balances accuracy and efficiency, enabling rapid response to operational fluctuations (e.g., load surges, rotational speed drift). In wind turbine gearbox monitoring, it establishes a real-time closed-loop system of ‘operational change – model adaptation’, ensuring stable diagnostic performance. The architecture employs a ‘multi-branch input + attention fusion’ network structure. Vibration, temperature, and current data undergo feature extraction via LSTM, CNN, and fully connected branches respectively. Cross-attention mechanisms then fuse multimodal information, enhancing the comprehensiveness of fault feature identification. For instance, in early-stage bearing fatigue fault diagnosis, temperature signals correct ‘noise interference’ in vibration features, elevating the F1 score for latent faults to above 0.99.

A modal reliability assessment mechanism was introduced. Based on inter-class/intra-class distance analysis (Section 4.2), dynamic weights were assigned to multi-source data under different operating conditions (e.g., current data weight increased to 0.4 under heavy-load scenarios, while vibration data weight remained at 0.6 under light-load scenarios). This prevents low-quality modalities (e.g., current signals under strong electromagnetic interference) from compromising diagnostic outcomes. Knowledge distillation (distilling complex LSTM models into lightweight CNN-LSTM hybrid models) and parameter

quantisation (reducing 32-bit floating-point to 16-bit) techniques. This reduces model parameters from 8,192 dimensions to under 2,048 while maintaining over 95% accuracy, compresses inference latency to under 15 milliseconds, and adapts to low-computational-power edge CPU/GPU environments.

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