UDC 629.064:631.372:004.8

METHODOLOGY FOR SELECTING ROBUST VIBRODIAGNOSTIC MODELS UNDER DOMAIN SHIFT AND LABEL NOISE

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Condition-based maintenance (CBM) in this work is considered as a practical foundation for improving the reliability of mobile machinery: maintenance decisions are made not only based on operating hours but on actual indicators of component degradation, identified from sensor signals and diagnostic models. A methodology is developed that allows linking the choice of model and training procedure to real data collection conditions—primarily to domain shift and label noise.

The source domain **S** is the dataset on which the model is trained, while the target domain **T** is the dataset on which the model is deployed. Domain shift means that operating modes, loads, speeds, sensors, mounting conditions, or test-bench vs. field conditions differ. As a result, model performance degrades when transferred, even if accuracy in **S** is high.

In applied diagnostics, it is reasonable to distinguish at least two "types" of shift: operational/condition shift (changes in load, rotational speed, gearbox or test-bench mode), and degradation-level shift, when the source data represent one "severity" of a defect and the target data represent another.

From an engineering perspective, these two types affect the model differently: operational/condition shift changes the "background" and the relative proportions of signal components, whereas degradation-level shift changes the manifestation of the defect itself. This is why domain adaptation and transfer learning methods are actively developed in the literature—they aim to align S and T without full relabeling.

Based on practical experience in vibrodiagnostics and a literature review, the following baseline families of solutions are considered:

1. Classical model based on engineered features: forming a set of time- and frequency-domain characteristics (statistical moments, band energies, spectral indices, etc.) and training a tree-based gradient boosting classifier (LightGBM). This approach is relatively robust to moderate label noise and provides a reproducible baseline quality with modest computational resources; an additional advantage is the ability to control/select features and interpret their contribution.

2. Ensembles/extended features (naive ensemble): increasing the dimensionality of the feature space (e.g., by combining feature groups or their interactions) and training a more "capacity-rich" model. The practical risk is increased sensitivity to labeling errors and feature-scale inconsistency, so normalization/standardization becomes mandatory (which aligns with reproducible pipeline requirements).

3. Two-stage robustification with pseudo-labeling: in the first step, a baseline "robust" model (typically feature-based) generates pseudo-labels for data with unreliable or missing labels. In the second step, a more expressive model (ensemble/hybrid) is trained on pseudo-labels filtered by confidence. This scheme is an engineering compromise between robustness (step 1) and the ability to capture complex patterns (step 2), but its effectiveness depends on pseudo-label quality.

4. Feature-level domain adaptation: when domain shift is significant, even “robust” classical models may degrade sharply. In such cases, simple and reproducible domain-alignment techniques (e.g., CORAL for covariance alignment) are appropriate, followed by model training on aligned features. In our work, this element is used as an engineering “minimum” for strong domain shift.

The proposed methodology is implemented as a decision matrix combining three groups of conditions:

– the nature of domain shift (type and severity: operational/condition shift or degradation-level shift; moderate or strong);

– labeling conditions (amount of labeled data, expected label-noise level);

– deployment constraints (possibility of validation under target conditions, reproducibility requirements, resource limitations).

In such situations, it is often more practical to focus on collecting a small “trusted” labeled subset in the target domain and/or on simpler, more controllable solutions.

The methodology is evaluated on two scenarios with controlled domain shift and injected label noise (symmetric random corruption of a portion of training labels). Macro-F1 is used as the primary metric, as it is informative for multiclass tasks and does not mask failures in individual classes.

Scenario A (moderate shift): CWRU, degradation-level shift.

This scenario uses the public CWRU (Case Western Reserve University Bearing Data Center) dataset. The source domain corresponds to a smaller bearing defect, and the target domain to a larger one (0.007″ → 0.021″). Here, 0.007″ and 0.021″ denote the diameter of the artificially induced defect (in inches), used in CWRU to represent damage severity; thus, a moderate degradation-level shift is modeled. Three label-noise levels are considered: 15%, 20%, 25%. Compared approaches include: classical model (LightGBM on engineered features), naive ensemble, robustified ensemble with pseudo-labeling, and robustified approach with confidence-filtered pseudo-labels (threshold 0.85).

Scenario B (strong shift): SEU, cross-condition (20 Hz–0 V → 30 Hz–2 V).

A strong domain shift is modeled using the public SEU gearbox dataset [24] when transitioning between two operating modes (20 Hz–0 V → 30 Hz–2 V), where excitation dynamics and signal background change. The pairs 20–0 and 30–2 correspond to “rotational speed – load-control voltage” on the test bench: 20 Hz and 30 Hz are speed modes, while 0 V and 2 V are control voltages of the loading unit (defining load/torque), not vibration-sensor output. To reduce domain discrepancy, simple CORAL adaptation is applied to engineered features, after which the effect of 15%, 20%, 25% label noise is evaluated for the classical model and two ensemble strategies.

For strong domain shift, the results differ from Scenario A: the classical model on adapted features is the most stable and almost unaffected by increasing label noise, whereas ensemble approaches perform substantially worse. The two-stage robustification yields inconsistent effects: slight improvement over the naive ensemble at 15% noise and the largest improvement at 25% noise, but degradation at 20% noise. This confirms the practical conclusion of the decision matrix: under strong shift, it is advisable to start with a simpler, controlled model with domain adaptation, while complex ensemble strategies should be used cautiously.

Engineering conclusions across both scenarios:

– under moderate shift, robustified ensembles with pseudo-label quality control can provide significant gains under high label noise;

– under strong shift, the “safer” choice is a classical model with well-documented engineered features and simple domain adaptation;

– confidence-based filtering improves the stability of two-stage robustification but does not eliminate the need for properly organized data and validation under target conditions.

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