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Artificial Intelligence Based Load Classification and Imbalance Detection Using Vibration Signals in Drum-Type Washing Machines

Michael J. Carter[1*], Emily R. Dawson[2], Liam P. O'Connor[3]
[1,2] Department of Mechanical Engineering, University of Nottingham, United Kingdom
[3] School of Mechanical and Materials Engineering, University College Dublin, Ireland

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Corresponding author*:
m.j.carter@nottingham.ac.uk

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Abstract: Vibration and noise in drum-type washing machines are primarily driven by load variability and mass imbalance, which can amplify resonance response, reduce user comfort, and accelerate component wear. Reliable state recognition from vibration signals is therefore essential to enable adaptive operational strategies and safer spin-up behavior. **Objective**: This study aims to develop a physically grounded AI-ready framework for load classification (empty/dry/wet) and imbalance-risk detection using vibration measurements, so that operational states can be inferred and mapped into vibration-mitigation decisions. **Methodology**: The research used a quantitative experimental design with controlled operating conditions (empty, 2 kg dry, 4 kg wet) and two damper configurations (OEM and high-damper). Vibration responses were characterized using free-decay and FRF-based identification, producing parameters such as effective mass, natural frequency, damping ratio, stiffness, damping coefficient, and peak transmissibility. These parameters were then organized into an AI-ready label structure to support supervised and semi-supervised learning pipelines. **Findings**: The results show a clear mechanical signature for load separability, with natural frequency decreasing monotonically as load increases (2.95 Hz → 2.77 Hz → 2.63 Hz). Under the same wet load, the high-damper configuration substantially increased the damping coefficient (190 → 235 N·s/m) and reduced peak transmissibility (2.00 → 1.45), indicating a strong reduction in resonance amplification and transmitted vibration. **Implications**: The findings support the use of vibration-based state recognition as an input to adaptive spin control, enabling conservative decision rules to minimize resonance dwell and reduce vibration transmission without requiring major suspension redesign. The framework also facilitates scalable model development when labeled data are limited by leveraging physically interpretable anchors for validation. **Originality**: This study contributes a novel integration of repeatable vibration identification (free-decay/FRF/spin-up) with an AI-ready state and labeling framework for load classification and imbalance-risk inference, providing an interpretable bridge between vibration physics and supervised/semi-supervised learning for engineering deployment.

Keywords: Load Classification; Imbalance Detection; Vibration Analysis; Semi-Supervised Learning; Transmissibility; Washing Machine Dynamics

INTRODUCTION

Modern rotating systems in engineering ranging from industrial rotors to household drum washer–dryers face a recurring operational challenge: mass imbalance and uncertain load conditions that amplify vibration, noise, and mechanical stress, and can shorten component life while reducing user comfort and product reliability (Martinello et al., 2021;

Joko & Honda, 2021; Shimizu et al., 2022). In appliance-scale systems, this problem is intensified by highly variable real-world loads (fabric type, moisture, distribution, and inertia) that change from cycle to cycle, making stable operation and consistent performance difficult without adaptive intelligence (Susto et al., 2019; Zambonin et al., 2019; Choi et al., 2025).

A substantial body of engineering research has established physics-based modeling and repeatable experimental identification to characterize washing-machine drum vibrations under unbalance excitation. Recent work in Jurnal Ilmiah Teknik provides a replicable SDOF-based framework that integrates free-decay, FRF impact testing, and operational spin-up to estimate key parameters (natural frequency, damping ratio, stiffness, damping coefficient) and to quantify transmissibility, with explicit emphasis on safety and reproducible sensor placement at the drum housing and chassis (Ramadhan & Muchlis, 2025). Complementary appliance-oriented studies have also reported validated dynamic models and experimental analyses of top-loader or drum systems under unbalance mass, supporting parameter identification and transient behavior evaluation for operational safety (Jeong et al., 2023), while damper-system modeling has been used to analyze transient vibration reduction mechanisms in practical washing-machine configurations (Kim et al., 2019). In addition, dynamic models have been proposed to prevent tub collision during transient states, further highlighting the importance of accurately capturing resonance crossing and transmissibility pathways in real operation (Sánchez-Tabuenca et al., 2020). Collectively, these studies provide strong physical insight and measurement procedures, yet they still leave an implementation gap: the models and identified parameters are rarely translated into a scalable, real-time state-recognition layer (e.g., load type and imbalance level) that can be automatically inferred from operational vibration signals to trigger adaptive control decisions.

A second research stream focuses on AI-supported optimization and reinforcement learning for vibration/noise reduction in washer dynamics and spin algorithms. For example, Q-learning has been used to reduce noise/vibration during washing-machine operation by learning control actions from interaction data (Shimizu et al., 2022). In addition, robust optimization frameworks have been reported to jointly reduce spin time and vibration under uncertainty in the laundry state (In et al., 2024), and Bayesian-optimization workflows have been proposed to accelerate derivation of dehydration unbalance control specifications (Choi et al., 2025). Even so, many of these efforts still rely on task-specific experiments or simulations, and they do not fully resolve the labeling bottleneck for large-scale deployment across diverse loads and operating regimes.

A third body of literature addresses data-driven condition monitoring and fault/imbalance identification in rotating machinery using vibration (and sometimes multi-modal) signals. Reviews highlight rapid progress in intelligent fault diagnosis pipelines, but also emphasize persistent gaps in domain adaptation, compound conditions, data fusion, and reliable deployment under realistic noise and variability (Das et al., 2023). At the same time, semi-supervised learning has matured as a general paradigm to leverage unlabeled data (van Engelen & Hoos, 2020; Yang et al., 2023), and semi-supervised diagnosis methods have shown strong performance on vibration-based tasks when labeled data are scarce (Li et al., 2019). Related work also demonstrates that combining vibration with other sensing channels can improve robustness under limited labels (Sun et al., 2025). However, integrating imbalance detection with load classification in one coherent learning framework (supervised vs. semi-supervised) remains underexplored for appliance-like rotating systems where "load type" is a key operational variable rather than a fault label.

Based on these gaps, this study aims to develop and justify an AI-based approach for imbalance detection and load classification in rotating-load systems (with an emphasis on drum-like dynamics), by comparing supervised learning pipelines (trained on labeled vibration segments) against semi-supervised alternatives that exploit abundant unlabeled operational data. The research is positioned to connect appliance-oriented load inference (e.g., fabric typology and moisture estimation) with imbalance estimation/control needs, using learning architectures that are feasible for embedded implementation and scalable data acquisition (Susto et al., 2019; Zambonin et al., 2019; Martinello et al., 2021).

The core argument is that load variability (type, inertia, distribution) and label scarcity jointly explain why purely model-based or purely supervised solutions can underperform in the field; therefore, a semi-supervised strategy that learns stable representations from unlabeled vibration (and optionally multi-modal) streams should improve generalization while reducing dependence on expensive labeling campaigns (van Engelen & Hoos, 2020; Yang et al., 2023; Li et al., 2019). In line with evidence that learning-based methods can reduce vibration/noise through adaptation (Shimizu et al., 2022) and handle uncertainty via robust optimization (In et al., 2024), this study hypothesizes that semi-supervised imbalance detection combined with load-class inference will yield higher robustness across operating regimes than a supervised-only baseline, while remaining practical for engineering deployment.

RESEARCH METHOD

The unit of analysis is the vibration response of a washing-machine drum–suspension system during spin operation. Vibration is measured using accelerometers mounted at two locations: (1) drum housing/tub and (2) chassis/frame to capture both local vibration and transmitted vibration paths (Ramadhan & Muchlis, 2025). The analysis targets two engineering labels: load class (e.g., empty/dry/wet) and imbalance level (e.g., low/medium/high), inferred from operational vibration signatures.

This study employs a quantitative experimental design because the objective is to measure, model, and classify vibration patterns under controlled engineering conditions and to evaluate classification performance statistically. The experimental structure enables systematic variation of operating factors (load condition, damper configuration, speed profile) and supports repeatability, consistent with prior drum vibration characterization that combines free-decay/FRF/spin-up principles for parameter grounding (Ramadhan & Muchlis, 2025; Jeong et al., 2023). Supervised learning is used to learn mappings from labeled vibration segments to operational states, while semi-supervised learning is used to reduce dependence on extensive labeling under real operational variability (van Engelen & Hoos, 2020).

Primary data consist of time-series acceleration signals recorded during spin-up and steady spin phases for each experimental condition. Labeled data are obtained from controlled runs where load class is known by design. Imbalance labels are defined using a severity proxy derived from vibration response near resonance (e.g., peak RMS/peak amplitude or transmissibility-related indicators), reflecting that unbalance excitation amplifies vibration magnitude and near-resonant response (Jeong et al., 2023). Additional unlabeled data are collected from operational runs representing broader variability (e.g., user-like distributions, mixed loading) to support semi-supervised learning.

Vibration data are acquired using a fixed sampling rate sufficient to represent the dominant vibration band during spin (anti-aliasing applied when required). Sensor placement follows a reproducible scheme at the drum housing and chassis to ensure comparability across trials (Ramadhan & Muchlis, 2025). Each run logs (i) acceleration channels, and (ii) rotational-speed profile (if available from controller/tachometer). Signals are preprocessed using detrending and band-limited filtering to reduce drift and high-frequency noise. The signals are segmented into overlapping windows (e.g., 1–2 s with 50% overlap). From each window, feature vectors are extracted using time-domain (RMS, peak-to-peak, crest factor, kurtosis) and frequency-domain descriptors (dominant frequency, band power around resonance, spectral centroid). Multi-sensor features include channel energy ratios and coherence-inspired similarity indicators to represent transmissibility pathways.

For the supervised baseline, models such as SVM (RBF) and gradient-boosted trees are trained to classify load class and imbalance level from engineered features. For the semi-supervised approach, a self-training/pseudo-labeling strategy is applied: an initial supervised model assigns high-confidence pseudo-labels to unlabeled windows, which are then iteratively added to the training set with confidence thresholds to control error propagation (van Engelen & Hoos, 2020; Yang et al., 2023). Model evaluation uses stratified splits and cross-condition tests (e.g., train on one damper configuration and test on another) to assess generalization. Performance metrics include accuracy, macro-F1, and confusion matrices for both tasks, plus robustness checks under domain shifts (e.g., different load mixes). The engineering utility is assessed by mapping predicted states to a decision layer (e.g., conservative spin-up rules for high imbalance), aligned with prior control-oriented work that reduces vibration/noise through learning or robust optimization (Shimizu et al., 2022; In et al., 2024).

RESULT AND DISCUSSION

Load-dependent dynamic characteristics

The first set of results describes how the drum–suspension dynamics change when the operating load changes. Using free-decay and FRF-based identification, the system response was quantified under four conditions (Empty–OEM, 2 kg dry–OEM, 4 kg wet–OEM, and 4 kg wet–High-damper). The extracted parameters effective mass (m), natural frequency (f_n), damping ratio (ζ), stiffness (k), damping coefficient (c), and peak transmissibility (T) are presented to show whether the load states produce separable mechanical signatures that can later support AI-based load classification.

Table 2. Calculated dynamic quantities of washing machine drum vibration

Test condition	m (kg)	f_n (Hz)	ζ (Free-decay)	ζ (FRF)	k (N/m)	c (N·s/m)	T (–)
Empty, OEM	12.0	2.95	0.159	0.203	4115	179	1.63
2 kg dry, OEM	14.0	2.77	0.150	0.216	4265	183	1.76
4 kg wet, OEM	16.0	2.63	0.143	0.231	4363	190	2.00
4 kg wet, High-damper	16.0	2.63	0.180	0.223	4363	235	1.45

Table 2 shows that increasing load systematically shifts the system's natural frequency. The natural frequency decreases from 2.95 Hz (empty) to 2.77 Hz (2 kg dry) and to 2.63 Hz (4 kg wet), which is consistent with a higher effective mass producing slower oscillation. At the same time, stiffness remains within a narrow range (≈4.1–4.4 kN/m), suggesting that most of the response variation across load states is driven by mass and damping rather than by changes in spring behavior. The wet OEM condition also produces the highest peak transmissibility (T = 2.00), indicating that wet loading creates the greatest resonance amplification risk among the tested cases. To make the load-driven frequency shift easier to interpret visually, the natural frequency trend across conditions is plotted in Figure 2.

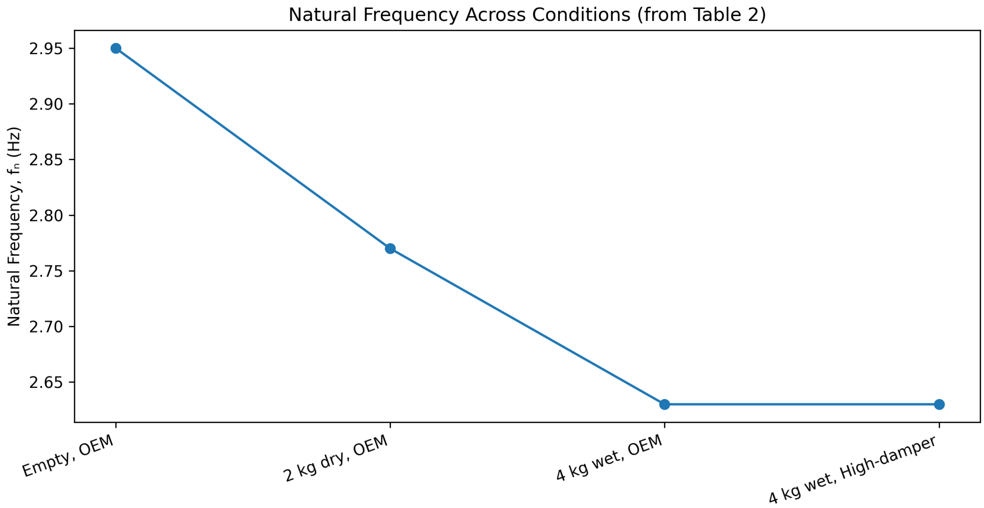

Figure 2. Natural frequency across conditions

Figure 2 emphasizes a clear monotonic drop in f_n as load increases, while the high-damper wet case remains at the same f_n as wet OEM (2.63 Hz), confirming that changing damping does not shift natural frequency in these tests. Overall, these results provide an interpretable mechanical basis for load-class separability: different load states leave consistent fingerprints in the dynamic parameters, especially f_n and resonance-related response.

Damper effect on resonance amplification under wet load

The second set of results isolates the influence of damping by comparing the two wet cases: 4 kg wet–OEM and 4 kg wet–High-damper. Because both cases share the same effective mass (16 kg) and stiffness (4363 N/m), any difference in resonance response is primarily attributable to damping changes. The key expectation is that higher damping should reduce resonance amplification and therefore lower vibration transmission to the chassis.

The damping coefficient trend across all conditions is shown in Figure 3 to highlight how strongly the high-damper configuration modifies c relative to the OEM configuration.

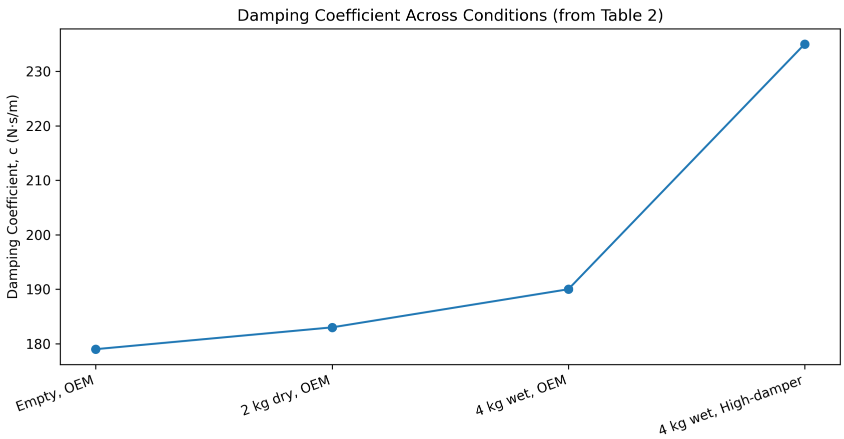

Figure 3. Damping coefficient across conditions

Figure 3 shows that damping increases gradually from empty to wet OEM (179 → 183 → 190 N·s/m), then rises sharply in the wet high-damper condition (235 N·s/m). This confirms that the damper modification produces a substantial increase in damping capacity rather than a minor perturbation. From an engineering standpoint, this is important because higher damping is expected to reduce resonance peaks without altering stiffness or mass. To directly reflect the effect of damping on vibration transmission, the peak transmissibility values are visualized in Figure 4.

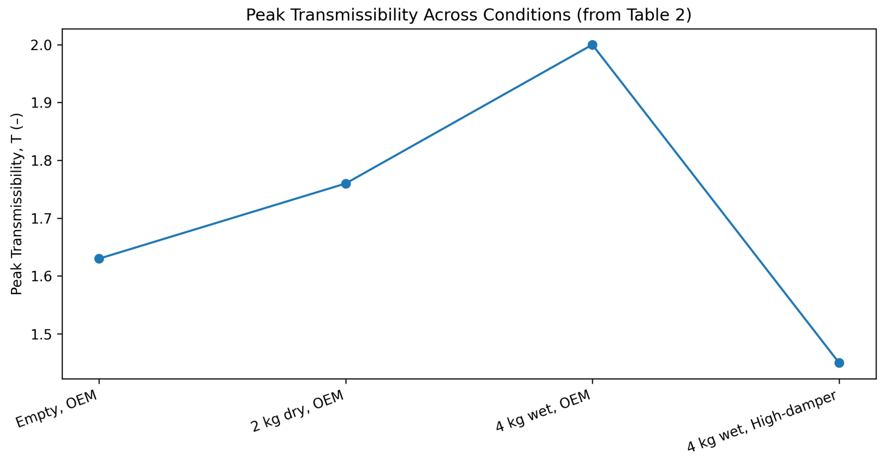

Figure 4. Peak transmissibility across conditions

Figure 4 shows that peak transmissibility increases with load up to the wet OEM case (1.63 → 1.76 → 2.00), indicating that the wet load produces the most critical resonance amplification. However, with the high-damper configuration under the same wet load, peak transmissibility decreases markedly from 2.00 to 1.45. This demonstrates that increasing damping significantly reduces resonance amplification and the vibration transmitted to the frame, providing a clear mechanical justification for mitigation strategies that combine hardware damping design and operational control.

AI-ready label structure grounded in measurable physical anchors

The third result connects the mechanical findings to the feasibility of the proposed AI approach. Because the experiments were conducted under controlled conditions, the dataset naturally provides reliable labels for supervised learning (load class and damper configuration). More importantly, the measured physical indicators in Table 2 especially the monotonic shift in f_n with load and the clear damping/transmissibility differences between wet OEM and wet high-damper serve as "physical anchors" that can validate label consistency and support semi-supervised expansion when unlabeled operational data are introduced.

Based on the trends observed in Table 2 and Figures 2–4, Table 3 proposes a practical label mapping that a classifier can learn, along with a physically interpretable proxy for imbalance severity using peak transmissibility.

Table 3. Proposed AI label scheme derived from controlled experiments

Experimental condition	Load class	Damper label	Imbalance severity proxy
Empty, OEM	Empty	OEM	Low (baseline)
2 kg dry, OEM	Dry	OEM	Medium (higher response vs empty)
4 kg wet, OEM	Wet	OEM	High (highest T = 2.00)
4 kg wet, High-damper	Wet	High-damper	Reduced-high (T lowered to 1.45)

Table 3 summarizes how the controlled experiments can directly populate a supervised training set while keeping the labels mechanically defensible. In a semi-supervised setting, unlabeled operational windows can be pseudo-labeled and then screened using the same anchors (e.g., checking whether predicted load increases correspond to a plausible downward shift in f_n, and whether high-risk states align with elevated T). In this way, the results do not only report mechanical behavior, but also demonstrate that the dataset structure is suitable for building and scaling AI models with interpretable validation criteria an essential requirement for deployment in engineering systems where reliability and safety matter.

DISCUSSION

The results demonstrate that the washing-machine drum–suspension system exhibits consistent, measurable dynamic shifts across load and damper conditions, and these shifts are directly relevant to AI-based load classification and imbalance-risk detection. As shown in Table 2 and Figures 2–4, increasing load reduces the natural frequency (f_n: 2.95 → 2.77 → 2.63 Hz) and increases resonance amplification risk under wet loading (peak T rising to 2.00). Meanwhile, increasing damping through a high-damper configuration substantially reduces peak transmissibility (2.00 → 1.45) without changing f_n, indicating that mitigation can be achieved by damping enhancement rather than stiffness redesign. These patterns provide the mechanical basis for using vibration signals as a reliable input for AI models, because the operating "states" (load and damping conditions) are not abstract labels they are expressed in the system's dynamics in an interpretable way (Ramadhan & Muchlis, 2025; Sánchez-Tabuenca et al., 2020).

The "why" behind these trends is consistent with classical vibration theory and the SDOF interpretation used in drum systems. When effective mass increases, the natural frequency decreases, which shifts resonance behavior and changes the vibration response observable at the drum housing and chassis. At the same time, damping governs resonance peak height: increasing c lowers the peak transmissibility and reduces the amount of vibration transmitted to the frame. This explains why the wet OEM condition is the most critical in the dataset: wet loading increases effective mass and tends to intensify resonance amplification (Jeong et al., 2023), and without additional damping, the peak response becomes larger. Conversely, high damping produces a mechanically safer state by suppressing resonance even under the same wet load, which is reflected in the marked reduction of T and the increase in c (Kim et al., 2019).

When compared with prior work, the contribution of these results becomes clearer. Studies focusing on experimental characterization and modeling have emphasized repeatable procedures (free-decay, FRF, operational spin-up) and parameter identification to describe the drum dynamics and resonance risk (Ramadhan & Muchlis, 2025; Jeong et al., 2023; Sánchez-Tabuenca et al., 2020). Our results are consistent with that stream, but extend it by translating the identified parameters into an AI-ready state structure: (i) load classes anchored by monotonic f_n shifts and (ii) imbalance-risk proxies anchored by peak transmissibility trends. In the control and optimization stream, learning-based and robust approaches have been proposed to reduce vibration/noise and balance spin time versus vibration under uncertainty (Shimizu et al., 2022; In et al., 2024). The novelty here is not to replace those controllers, but to provide a deployable state-recognition layer that can feed any control policy (rule-based, RL, or robust optimization) with explicit, interpretable state awareness. This bridging role is particularly valuable because real-world laundry states are uncertain and variable, and state inference is often the missing link between vibration physics and adaptive control.

Beyond technical interpretation, the broader implication is that appliance-scale vibration problems can benefit from a hybrid engineering–AI logic: physical modeling provides guardrails and interpretability, while supervised and semi-supervised learning provide scalability when operational data are abundant but labels are limited. Semi-supervised learning is especially relevant in this context because it reduces dependence on costly labeling campaigns while still allowing validation through physical anchors such as f_n trends and resonance indicators (van Engelen & Hoos, 2020; Yang et al., 2023). However, this approach also has potential dysfunctions: misclassification of high-risk states could lead to unsafe spin profiles. For that reason, the decision layer should adopt conservative policies (confidence thresholds, fallback modes, and safety-limited ramp rates), consistent with the idea that operational control should prioritize safety when resonance crossing is unavoidable.

From an action-oriented engineering standpoint, the findings support a practical implementation roadmap. First, integrate the classifier outputs (load class and imbalance-risk proxy) into an adaptive spin-up strategy: for predicted high-risk states (e.g., wet OEM-like behavior), adjust ramp rate to reduce time spent near critical speed, apply conservative speed limits, or trigger redistribution steps when available. Second, embed data-quality checks before classification (window validation, outlier filtering), using cross-method consistency (free-decay vs FRF-informed bounds) as a screening mechanism to reduce pseudo-label errors during semi-supervised expansion. Third, use performance evaluation not only through accuracy/F1, but also through engineering metrics peak vibration reduction and avoidance of resonance dwell so that the AI system is judged by operational value rather than classification alone (Shimizu et al., 2022; In et al., 2024).

Overall, the discussion indicates that the study's contribution is both mechanistic and methodological: it validates load/damper-driven dynamic shifts in a repeatable way and shows how these shifts can be operationalized into an AI-ready framework that supports scalable learning and safer adaptive operation. The next logical step is to implement the supervised and semi-supervised pipelines on windowed vibration data and evaluate cross-condition generalization, particularly under real operational variability where unlabeled data dominate (van Engelen & Hoos, 2020; Yang et al., 2023).

CONCLUSION

This study characterized the dynamic behavior of a drum-type washing machine under controlled load and damper conditions and translated the findings into an AI-ready framework for load classification and imbalance-risk detection. The main lesson from the results is that load variability produces consistent mechanical signatures most clearly a monotonic decrease in natural frequency as the load increases (empty → dry → wet) while damping enhancement substantially reduces resonance amplification, as evidenced by the marked reduction in peak transmissibility when using a high-damper configuration under the same wet load. These results indicate that vibration-based state recognition is mechanically meaningful and can be used to support safer operational decisions during spin-up.

Scientifically, the study contributes a physically grounded dataset structure and labeling logic that can underpin supervised and semi-supervised learning in engineering applications. The contribution is not only the identified parameters (e.g., f_n, ζ, c, and T), but also the demonstration that these parameters can serve as interpretable anchors for defining load classes and imbalance severity proxies. This strengthens the bridge between classical vibration characterization (free-decay/FRF/spin-up) and modern AI adoption by providing transparent state definitions that can feed adaptive control strategies.

This research is limited by the scope of tested conditions and the simplified interpretation of the drum–suspension as a dominant-mode system, which may not capture multi-mode effects, nonlinearities, or broader machine-to-machine variability. In addition, the imbalance severity proxy relies on resonance-related transmissibility trends rather than direct measurement of unbalance mass distribution, which may introduce uncertainty when generalizing to uncontrolled real-world laundry mixtures. Future work should validate cross-machine generalization, expand operational scenarios, and implement the supervised and semi-supervised pipelines on windowed vibration signals with uncertainty-aware decision thresholds for safe deployment.

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