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Non-invasive electrical detection of screw wear in an industrial extrusion system

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Reliable detection of mechanical wear is essential for maintaining operational stability and reducing unplanned downtime in industrial extrusion systems. This study investigates non-invasive detection of screw wear using operational electrical measurements acquired from a single-screw industrial extruder. Electrical parameters were recorded under steady-state processing conditions for healthy and worn screw configurations to determine whether measurable differences in electromechanical behaviour could support condition assessment. The collected signals were segmented into 1429 labelled samples and evaluated using statistical and time–frequency analyses. Mean electrical parameters were compared between technical states, and independent samples Welch t-tests confirmed statistically significant differences in phase voltage for all monitored phases ($p < 0.001$). Continuous wavelet transform was applied to capture non-stationary signal characteristics, enabling extraction of energy- and entropy-based descriptors associated with variations in mechanical load. The derived features were subsequently used for automated classification of machine condition. The results revealed consistent increases in phase voltage for the worn screw ranging from 0.50% to 0.61%, indicating a stable shift in the electrical operating characteristics of the drive system. Supervised classification achieved an accuracy of 96.2% (289 of 300 samples correctly classified in the testing subset), demonstrating reliable separability between technical states without the need for additional vibration instrumentation. These findings confirm that operational electrical signals provide diagnostically relevant information for screw wear detection and support scalable implementation of electrical condition monitoring in industrial extrusion systems.

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1. Introduction

Maintaining high operational reliability of industrial machinery requires effective methods for early detection of component degradation. In modern production environments, condition-based maintenance (CBM) strategies play a central role in reducing unexpected downtime, optimizing maintenance scheduling, and improving energy efficiency [1, 2]. The effectiveness of CBM frameworks depends fundamentally on the availability of measurable signals that reliably reflect changes in mechanical condition without excessive instrumentation complexity.

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Among various diagnostic approaches, motor current signature analysis (MCSA) has gained significant recognition as a practical and non-invasive tool for monitoring electromechanical systems. Electrical signals inherently reflect variations in mechanical load, enabling fault detection without the need for additional vibration or acoustic sensors [3, 4]. Early investigations demonstrated that bearing damage introduces characteristic components into stator current signals [5], while subsequent research confirmed the applicability of current-based diagnostics to gearbox faults and other rotating machinery defects [6]. These findings established electrical measurements as a viable medium for mechanical fault detection.

Because industrial drive signals are typically non-stationary and influenced by process variability, advanced signal-processing techniques are often required to extract diagnostically meaningful information. Wavelet transform methods provide simultaneous time–frequency localization, making them particularly suitable for analysing transient disturbances and load fluctuations [7, 8]. Their effectiveness has been demonstrated in bearing fault detection using wavelet packet transform [9] and in identifying motor misalignment through discrete wavelet decomposition [10]. Hybrid approaches combining autoregressive modelling with wavelet decomposition have further enhanced diagnostic sensitivity while maintaining computational feasibility for industrial applications [11]. Alternative adaptive decomposition techniques, such as empirical mode decomposition, have also been successfully applied to rotating machinery diagnostics [12], and model-based approaches have supported bearing damage detection through stator current monitoring [13].

In parallel with advances in signal processing, machine learning techniques have increasingly been integrated into diagnostic systems to automate feature interpretation and improve robustness to noise and operational variability [14, 15]. Comprehensive reviews highlight the growing role of intelligent algorithms in fault diagnosis of rotating machinery and emphasize the importance of combining physically meaningful features with data-driven classification frameworks [16, 17].

Despite substantial progress in electrical-based diagnostics of rotating machinery, extrusion systems remain comparatively underrepresented in measurement-driven condition monitoring research. In single-screw extrusion, mechanical wear alters friction conditions, material transport, and torque demand, thereby modifying the electromechanical response of the drive system. Previous studies have explored the use of wavelet analysis for evaluating wear of food extruder components [18], and continuous wavelet transform combined with motor current measurements has enabled detection of extruder element degradation [19]. However, systematic validation of non-invasive electrical diagnostics under real industrial processing conditions remains limited.

This study presents an industrially validated, non-invasive diagnostic framework for detecting extruder screw wear based exclusively on operational electrical measurements. Unlike sensor-intensive monitoring strategies, the proposed approach relies solely on signals already available within the electrical infrastructure of the machine, thereby supporting scalable deployment in industrial environments.

The main contributions of this study are threefold:

- industrial-scale validation of electrical signal–based wear diagnostics for single-screw extrusion systems;
- development of a physically interpretable health indicator derived from continuous wavelet transform features;
- demonstration of accurate automated classification between healthy and worn screw conditions using non-invasive measurements.

By establishing a direct and interpretable relationship between electrical signal behaviour and mechanical screw degradation, this work extends the paradigm of measurement-based diagnostics to extrusion systems and supports the broader transition toward intelligent, infrastructure-efficient condition monitoring in industrial processing equipment.

Accordingly, the study tests the hypothesis that operational electrical measurements obtained from an industrial extrusion system contain statistically distinguishable information enabling reliable differentiation between healthy and worn screw conditions.

2. Material and methods

2.1. Experimental framework

The study employed a comparative experimental design to determine whether operational electrical signals can differentiate between healthy and worn conditions of an industrial single-screw extruder. Two technical states were analysed:

- healthy screw (H), representing nominal operation,
- worn screw (W), characterized by significant surface degradation affecting material transport and friction.

All measurements were conducted under steady-state operating conditions to ensure comparability between machine states and to reduce process-induced variability.

2.2. Industrial extrusion system

Experiments were performed on an industrial single-screw food extruder driven by a 7.5 kW three-phase induction motor operating at a constant rotational speed of 500 rpm. The extrusion head was equipped with an 8 mm die, and the screw length-to-diameter ratio (L/D) was 5:1.

Wheat grain with a moisture content of approximately 15% was used to provide repeatable load conditions. The barrel exhibited negligible wear; therefore, observed electrical differences were attributed primarily to the technical condition of the screw.

2.3. Electrical data acquisition

Operational electrical measurements were acquired using a portable power quality analyser compliant with the EN 61000-4-30 Class S standard. Three-phase signals were recorded to capture the electromechanical response of the drive system during extrusion. Prior to analysis, the measurement setup was verified to ensure signal consistency and data completeness.

The monitored parameters included phase current, phase voltage, instantaneous active power, cumulative energy consumption, and barrel temperature. Data were sampled at 7 kHz to preserve transient phenomena associated with dynamic load variations and to ensure sufficient resolution for subsequent time–frequency analysis.

Measurements were performed under stable processing conditions to minimize external disturbances and support reliable comparison between healthy and worn screw configurations. This approach enabled the recorded electrical signals to reflect primarily the mechanical state of the extrusion system rather than short-term operational variability.

High-frequency current signals were retained for diagnostic analysis, while selected process variables were used to verify operating stability throughout the measurement campaign.

2.4. Dataset preparation

Continuous electrical signals were segmented into fixed-duration time windows to obtain analytically meaningful samples suitable for statistical and signal-based analysis.

The final dataset consisted of 1429 labelled segments representing healthy and worn screw conditions. Segment lengths were selected to capture stable operating behaviour while limiting temporal autocorrelation between samples.

Each segment reflected ongoing industrial operation rather than a controlled laboratory snapshot, preserving realistic process characteristics.

2.5. Signal preprocessing

Preprocessing was intentionally limited to retain diagnostically relevant signal components. The procedure included removal of outliers, elimination of DC components, z-score normalization, and verification of sampling consistency.

No aggressive filtering was applied in order to avoid suppressing degradation-related signal features.

2.6. Statistical evaluation of electrical parameters

An initial statistical comparison was conducted to determine whether screw wear produced measurable changes in electrical behaviour. Mean values and dispersion measures were computed for both technical states to identify systematic differences in the electromechanical response of the drive system, thereby establishing a quantitative baseline for subsequent signal-based diagnostics.

To formally verify whether the observed electrical differences represented a systematic effect rather than incidental variability, independent samples Welch t-tests were performed for the phase voltage measurements. Statistical significance was evaluated at the 95% confidence level.

2.7. Time–frequency analysis

Motor current signals were analysed using continuous wavelet transform (CWT) to capture non-stationary characteristics associated with dynamic mechanical loading.

The resulting time–frequency representations enabled identification of energy redistribution patterns and transient disturbances differentiating healthy and worn operating conditions.

2.8. Feature extraction and health indicator construction

Features were derived from the wavelet domain to quantify differences between machine states. The extracted descriptors included energy-related measures, entropy-based indicators describing signal complexity, and variance-related metrics reflecting load fluctuations.

These features were aggregated into a unified health indicator designed to enhance separability between technical states and support interpretable condition assessment.

2.9. Classification and performance metric

Automated differentiation between healthy and worn screw conditions was performed using a supervised classification approach trained on feature vectors derived from wavelet-based descriptors. The split was performed using random stratified sampling to preserve class balance. Classification outcomes were summarized using a confusion matrix describing the relationship between predicted and actual machine states (Table 1).

Table 1. Confusion matrix used for evaluating classification performance

	Predicted Healthy	Predicted Worn
Actual Healthy	TP (True Positive)	FN (False Negative)
Actual Worn	FP (False Positive)	TN (True Negative)

Model performance was quantified using classification accuracy, defined as the ratio of correctly classified samples to the total number of evaluated observations:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where
TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

The classification stage supported objective differentiation between technical states, while diagnostic interpretation remained grounded in measurable electrical behaviour.

2.10. Methodological workflow

The diagnostic procedure consisted of the following steps:
– acquisition of operational electrical signals,
– minimal preprocessing,
– statistical comparison of electrical parameters,
– time–frequency transformation using CWT,
– extraction of diagnostic features,
– construction of a health indicator,
– automated classification of screw condition.

This structured workflow enabled reproducible differentiation between technical states using exclusively non-invasive electrical measurements.

3. Results and discussion

3.1. Statistical differences in electrical parameters

The statistical comparison of electrical parameters was performed on 1429 labelled signal segments representing healthy and worn screw conditions. Mean phase voltage values were consistently higher for the worn configuration across all monitored phases (Table 2).

Table 2. Statistical comparison of phase voltage measurements for healthy and worn screw conditions

Parameter	Healthy_mean [V]	Worn_mean [V]	Δ [%]	Healthy_std [V]	Worn_std [V]
U12 (Avg)	390.74	392.70	0.50	1.32	1.02
U23 (Avg)	390.16	392.28	0.54	1.93	1.59
U31 (Avg)	392.53	394.93	0.61	1.35	0.90

Independent samples Welch t-tests confirmed statistically significant differences between healthy and worn screw conditions for all monitored phase voltages ($p < 0.001$), indicating that the observed voltage increases represent a systematic electrical response to mechanical wear rather than random process or supply variability.

The observed increases ranged from 0.50% to 0.61%. Although numerically moderate, these differences were systematic across phases U12, U23, and U31 and were accompanied by slightly reduced standard deviation for the worn state, indicating a stable shift in the electromechanical operating point rather than sporadic fluctuation.

From a physical perspective, increased phase voltage and current are consistent with elevated torque demand resulting from intensified friction and modified material transport inside the barrel. This observation aligns with established principles of motor current signature analysis, where mechanical loading variations are reflected in electrical quantities [3, 4].

While electrical-based diagnostics are widely reported for bearings and gearboxes [5, 6], their application to extrusion systems remains limited. The present results demonstrate that even relatively small but consistent electrical deviations can serve as measurable indicators of screw degradation under real industrial conditions.

3.2. Time–frequency characteristics of stator current signals

Time–frequency representations obtained using continuous wavelet transform revealed distinct differences between healthy and worn screw conditions (Fig. 1)

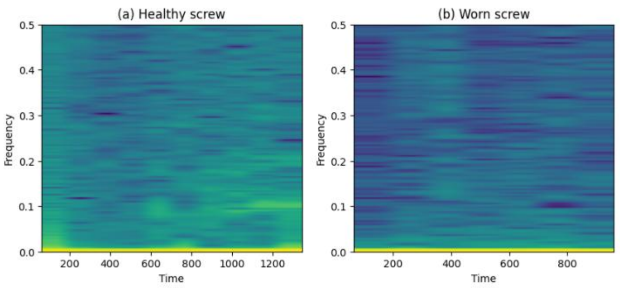

Fig. 1. Time–frequency representations of stator current signals for (a) healthy and (b) worn screw conditions

Signals recorded under nominal conditions exhibited relatively stable energy concentration within dominant frequency bands. In contrast, the worn configuration showed localized high-energy regions distributed across multiple scales, indicating increased variability of mechanical load.

Such redistribution of spectral energy is characteristic of non-stationary disturbances generated by irregular torque transmission. Similar phenomena have been reported in studies of bearing and gearbox faults using wavelet-based approaches [7-10]. The present findings extend these observations to extrusion processes, where material–screw interaction introduces additional complexity compared with conventional rotating machinery.

The results confirm that time–frequency analysis provides sensitivity to localized signal irregularities that are not readily observable using purely statistical measures.

3.3. Feature-based differentiation and health indicator behaviour

Features derived from the wavelet domain, including energy-related measures, entropy-based descriptors, and variance-related metrics, demonstrated consistent separation between technical states. For the worn screw, energy and entropy indicators reached higher values, reflecting increased signal complexity and load fluctuation.

The aggregation of these features into a unified health indicator enabled compact representation of degradation-related effects. The indicator maintained stable values for the healthy state and shifted toward higher levels for the worn configuration.

Rather than indicating progressive wear evolution, the indicator primarily differentiated between two discrete technical states. This distinction is important: the present framework supports condition identification rather than remaining useful life estimation.

The transformation of raw electrical signals into interpretable diagnostic features corresponds with current trends in intelligent condition monitoring, where physically meaningful descriptors are preferred over purely black-box representations [14-17].

3.4. Classification performance

Automated differentiation between machine states yielded an accuracy of 96.2% (289 correctly classified samples out of 300 in the testing subset). This level of performance indicates that the extracted wavelet-based features contained sufficient discriminatory information to distinguish healthy and worn conditions using exclusively electrical measurements. Importantly, the classification relied on features directly linked to measurable electromechanical behaviour, supporting interpretability of the decision process.

Machine learning has increasingly been applied in rotating machinery diagnostics [14-17], often using vibration or multi-sensor data. In contrast, the present study demonstrates that high classification accuracy can be achieved using non-invasive electrical signals alone. This has practical implications for industrial deployment, as electrical monitoring utilizes infrastructure already present in drive systems.

3.5. Integrated interpretation and relevance to global research

Across all analytical stages - statistical comparison, time–frequency analysis, feature extraction, and classification - the worn configuration exhibited characteristics associated with increased mechanical load and reduced process stability. The convergence of these independent analytical perspectives strengthens the reliability of the diagnostic conclusions.

The findings are consistent with global research trends emphasizing the use of electrical signals for machinery diagnostics [3-6], the application of wavelet-based techniques to non-stationary systems [7-10], and the integration of interpretable feature engineering with supervised learning [14-17]. However, extrusion systems remain comparatively underrepresented in this domain.

By validating electrical signal–based diagnostics under real industrial processing conditions, this study extends the paradigm of motor current–based monitoring beyond conventional rotating components to screw-based material processing equipment. The ability to detect degradation without additional vibration instrumentation supports scalable implementation within condition-based maintenance frameworks [1, 2].

3.6. Limitations and implications

The analysis compared two discrete technical states and did not track gradual wear progression. Therefore, the presented framework is suitable for condition discrimination rather than predictive lifetime modelling.

Additionally, measurements were conducted under steady-state conditions. Although this improved comparability, further investigation under variable process regimes would strengthen generalization capability.

Despite these limitations, the results demonstrate that operational electrical signals contain diagnostically relevant information about screw wear in industrial extrusion systems. The integration of statistical, time–frequency, and classification analyses provides a coherent pathway linking measurable electrical behaviour with mechanical degradation.

4. Conclusions

The analysis of operational electrical signals obtained from healthy and worn screw configurations revealed measurable differences in the electrical behaviour of the extrusion system. Mean phase voltage values were consistently higher for the worn screw across all monitored phases, with relative increases ranging from 0.50% to 0.61%. Although the magnitude of these changes was moderate, their repeatability across phases indicates a stable shift in the electromechanical operating conditions rather than incidental fluctuation. The worn configuration was therefore associated with a detectable increase in electrical load during extrusion.

The observed differences confirm that operational electrical parameters respond to variations in screw condition and are capable of capturing degradation-related effects under real industrial processing conditions. This sensitivity provides a quantitative basis for distinguishing between nominal and degraded machine states using measurements already available within the electrical infrastructure of the drive system.

Automated classification further supported the differentiation between technical states. Using feature vectors derived from wavelet-based descriptors, the supervised classification model achieved an accuracy of 96.2%, corresponding to 289 correctly classified samples out of 300 in the testing dataset. This level of predictive performance indicates a high degree of separability between healthy and worn conditions based exclusively on non-invasive electrical measurements.

The combined statistical and classification outcomes establish a direct relationship between electrical signal behaviour and mechanical screw degradation. Together, these results demonstrate that diagnostically relevant information extracted from operational electrical signals is sufficient to support reliable condition identification in industrial extrusion systems.

The proposed approach contributes to the advancement of scalable, infrastructure-efficient diagnostics for industrial processing equipment.

The presented results support the broader applicability of operational electrical measurements as a scalable and infrastructure-efficient foundation for condition monitoring in industrial processing systems.

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