

University of Wales Trinity Saint David

School of Engineering



Prifysgol Cymru

Y Drindod Dewi Sant

University of Wales

Trinity Saint David

Control Technology – Technical Report

Predictive Maintenance Strategies

ACMA6001

Meuryn Nelson

2308099

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1 Introduction

Predictive maintenance (PdM) seeks to identify developing equipment faults early enough for maintenance to be planned before failure. This is particularly important in continuous-process industries, where rotating equipment failure can interrupt production, affect process stability and create safety hazards. This report reviews maintenance strategy and condition-monitoring data, then uses a MATLAB/Simulink model of a refinery crude-charge pump P-2201A as a comparative case study. The model represents a motor-driven two-speed gearbox with casing vibration measurement and shaft tachometers. It also simulates three degradation mechanisms – gear-tooth damage, output-shaft wear, and vibration-sensor drift.

The objectives are to compare reactive, preventive and predictive strategies; critically assess conventional and AI-based fault diagnosis; compare a feature-based support vector machine (SVM) with raw-spectrum shallow neural networks and recommend a practical approach for deployment in the refinery scenario.

2 Maintenance Strategy in Industrial Operations

Maintenance is an operational decision rather than simply a repair activity because maintenance policies determine intervention timing and balance equipment reliability, failure risk, downtime and the utilisation of component life (Wang, 2002; Scarf, Dwight and Al-Musrati, 2005). According to Coanda et al (2020), reactive maintenance allows an asset to run until failure before any maintenance is performed. This creates a low initial cost and requires no need for complex planning (Gholipour, 2025). However, this strategy creates unplanned downtime, unpredictable production capacity and increased maintenance costs to repair failures (Swanson, 2001).

Preventive maintenance (PM) is a scheduled maintenance strategy carried out at fixed calendar or running-hour intervals to prevent damage or disruption to equipment before failures occur (Suprpto, 2025). Iwarue (2025) states that although PM has had a widely positive impact on industry, it can provide large upfront costs, be inefficient in complex systems, and some organisations struggle to find a balance between PM and operational demands which can lead to delays and disruptions in production. Hansen, Kulahci and Nielsen (2024) therefore describe a central attraction of predictive maintenance (PdM) as moving intervention closer to the point in which it is required, rather than relying on schedule.

PdM predicts trends, behavioural patterns and correlating data by using machine learning and statistical models for anticipating pending failures before they occur, improving the decision-making process for maintenance activity (Zonta et al. 2020). Reviews identify reduced downtime and maintenance cost as major motivations for PdM, but also stress the need for reliable sensors, data infrastructure, specialist skills and sufficient failure-related data (Huang et al. 2024). PdM should therefore be viewed as a risk-based complement to PM, rather than a replacement.

The effect of strategy extends beyond availability. Deterioration to equipment can increase process variation and affect output quality. Maintenance and quality decisions are consequently interdependent (Farahani and Tohidj, 2021). In a refinery, deterioration of pumps or gearboxes may cause increased vibration, reduced efficiency or unstable process flow, while an unexpected failure can interrupt feed to downstream operations. Condition monitoring provides an opportunity to recognise abnormal behaviour while equipment is still operating, so that developing faults can be investigated before they progress to functional failure. Vibration-based monitoring is particularly relevant to rotating machinery because changes in machine condition can produce identifiable patterns in measured vibration signals (Tiboni et al. 2022) The value of PdM therefore lies not just in

reducing downtime, but also in providing maintenance personnel with earlier evidence on which to determine inspection and intervention decisions.

Maintenance strategy should therefore be selected according to the criticality of the asset, the detectability of its failure modes, along with the economic and safety consequences of failure. This makes it a multi-criteria problem rather than a choice of one universally superior approach (Shafiee et al. 2019; Arjomandi et al. 2021). For low-criticality equipment, where failure has limited consequences and repair is simple, a run-to-failure strategy may remain economically reasonable. As asset criticality and failure consequences increase, preventive and condition-based approaches become more attractive as they can reduce exposure to unplanned failure (Polenghi et al. 2022). In oil-refinery applications, Arjomandi et al. (2021) found that condition-based and reliability-centred approaches were suitable for critical crude-oil distillation assets when economic, safety and sustainability considerations were evaluated together.

When deterioration can be detected before failure, condition monitoring can provide a planning window in which maintenance and spare-part requirements can be coordinated. This is important where replacement components have significant lead times, as predictive information can inform both the timing of the maintenance and the ordering of spare parts (Ma et al. 2024).

Strategy	Trigger	Main Advantage	Main Limitation
Reactive	Failure occurs	Low planning cost for non-critical items	Unplanned downtime, secondary damage, emergency spares
Preventive	Fixed time/usage interval	Planned work and predictable resource use	Can over-maintain healthy equipment and consume outage time
Predictive	Measured condition/predicted deterioration	Maintenance closer to actual need, earlier planning window	Needs reliable sensors, data, analytics and validation

Table 1 Maintenance strategies comparison.

3 Condition Monitoring and Fault Diagnosis

Industrial condition monitoring is not restricted to a single measurement technique. Equipment health can be assessed through vibration, temperature, acoustic emission, electrical-current and wear-debris measurements, with the appropriate technique depending on the failure mechanism being investigated (Liu et al. 2021). Vibration analysis is widely used for condition monitoring of rotating machinery because faults can produce changes in the amplitude and frequency content of the measured vibration signals (Zhou et al. 2023). Rotating-machinery fault diagnosis typically involves acquiring condition data, processing the measured signals and extracting fault-sensitive information before classification or diagnostic decisions are made. Time-domain statistical features can be used to characterise changes in vibration behaviour, while frequency-domain techniques such as the Fast Fourier Transform (FFT) reveal changes in spectral content associated with machinery condition (Das et al. 2023).

A key advantage of conventional vibration-based diagnostic methods is their connection to established machinery behaviour and fault mechanisms. Frequency-domain analysis can relate changes in vibration spectra to characteristic components associated with rotating speed, gears and bearings, allowing engineers to interpret diagnostic evidence using physical knowledge of the machine. However, conventional diagnosis relies on expert knowledge and manually designed signal-processing or feature-extraction methods, which may be tailored to specific fault types (Chen et al. 2024). Performance can also be affected by changes in operating conditions such as variations in rotational speed and load which can alter measured vibration characteristics and make fixed diagnostic features or limits less reliable (Liu et al. 2023).

Machine-learning methods can automate fault classification by learning relationships between condition-monitoring data and equipment health states. Feature-based methods such as SVMs use engineered signal characteristics as classifier inputs, whereas neural networks can learn more complex representations from higher-dimensional vibration data, reducing reliance on manual feature selection (Sanchez et al. 2024). However, data-driven models require sufficient representative training data, which can be difficult to obtain because industrial fault examples are often limited (Matania et al. 2024). Evaluation using previously unseen data is therefore important to assess generalisation and reduce the risk of overfitting (Leukel et al. 2021).

Synthetic data provides a practical way of generating labelled fault examples when real failure data is scarce. However, differences between simulated and real machinery can produce a domain gap, meaning that a model trained successfully on virtual data may not achieve the same performance on

physical machinery. Digital-twin research therefore increasingly combines simulated fault data with transfer-learning and domain-adaptation methods to improve applicability to real machinery (Zhang et al. 2023; Xia et al. 2024). Diagnostic performance demonstrated using simulated data should be validated by representative real-world measurements before industrial deployment.

Approach	Strength	Limitation	Role
Manual vibration analysis	Physically interpretable	Requires specialist expertise	Diagnosis and confirmation
Threshold monitoring	Simple and fast	Sensitive to operating conditions	Initial fault screening
Singal processing/statistics	Extracts fault-sensitive information	Requires appropriate feature selection	Feature extraction
Feature-based SVM	Compact engineered input	Dependent on selected features	Automated fault classification
Neural network	Learns complex patterns from high-dimensional data	Requires representative training data	Automated fault classification

Table 2 Comparison of conventional and machine-learning approaches to condition monitoring and fault diagnosis.

4 Case Study Model

4.1 Data Generation and Preparation

The case study used the supplied Simulink transmission model to generate vibration data representing three fault conditions: vibration-sensor drift, output-shaft wear and gear-tooth damage. These were controlled by the model variables SDrift, ShaftWear and ToothFaultGain, respectively. Systematic and randomised combinations of the fault parameters produced a total of 208 simulation runs. The first 10 seconds of each simulation were removed to exclude start-up transients, ensuring that subsequent analysis was based on the steady-state vibration response.

Two representations of the vibration data were then prepared for fault classification. For the feature-based approach, 18 time-, no linear- and frequency domain characteristics were extracted from each simulation. These were combined with the three individual fault labels and a composite FaultCode, producing a 208 x 22 dataset. For a neural-network approach, each steady-state vibration signal was resampled to 10.24 points and transformed using the FFT. The first 512 log-scaled magnitude-

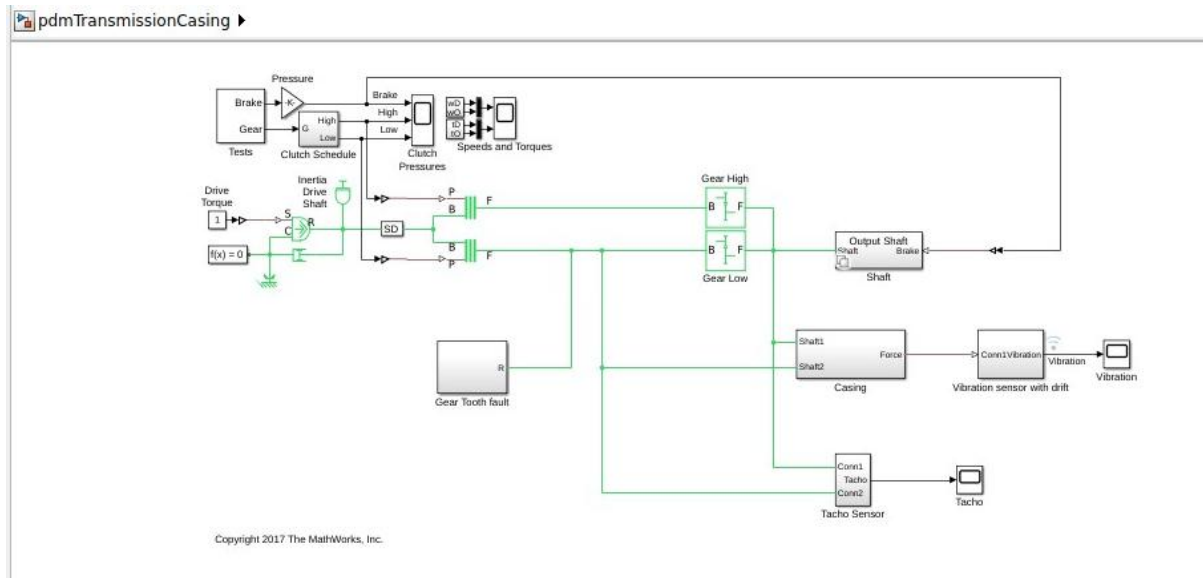


Figure 1 Simulink transmission-casing model used to generate the synthetic fault dataset.

spectrum values were retained as network inputs.

Case-study item	Value
Simulation runs	208
Engineered dataset	208 x 22 (18 features + 4 variables)
Neural-network input	208 x 512 spectral bins
Train / validation / test	146 / 31 / 31
Faults	Sensor drift, shaft wear, gear-tooth damage

Table 3 Summary of case-study data preparation.

4.2 Feature Exploration

Neighbourhood Component Analysis (NCA) was used to assess which of the 18 engineered vibration features provided the greatest discrimination for each fault. Sensor drift was most strongly associated with SigRangeCumSum and PeakSpecKurtosis.

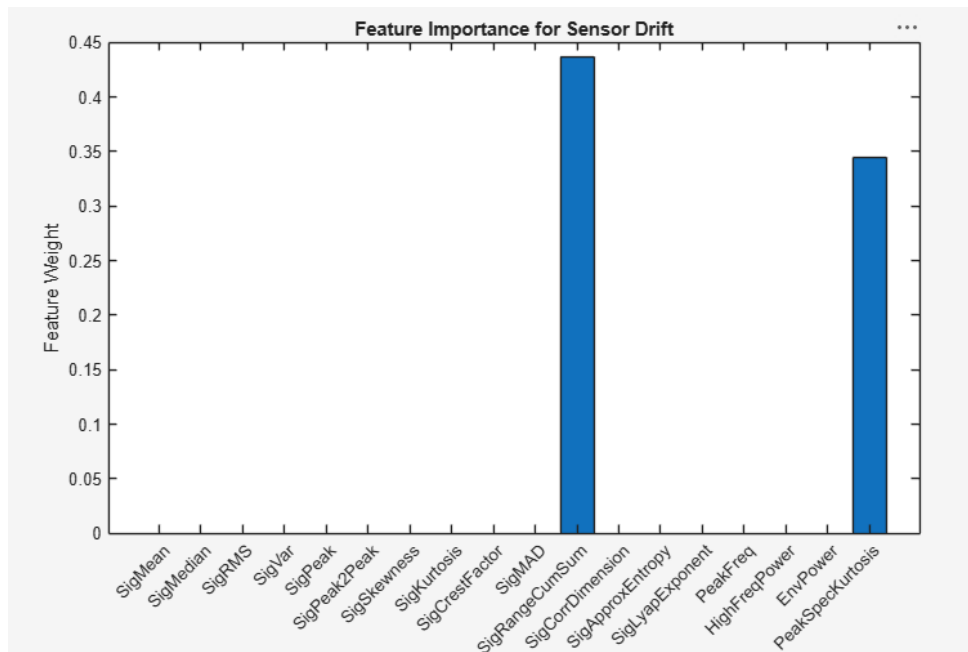


Figure 2 NCA feature importance for sensor drift classification.

Shaft wear was associated most strongly with SigLyapExponent, PeakFreq and PeakSpecKurtosis.

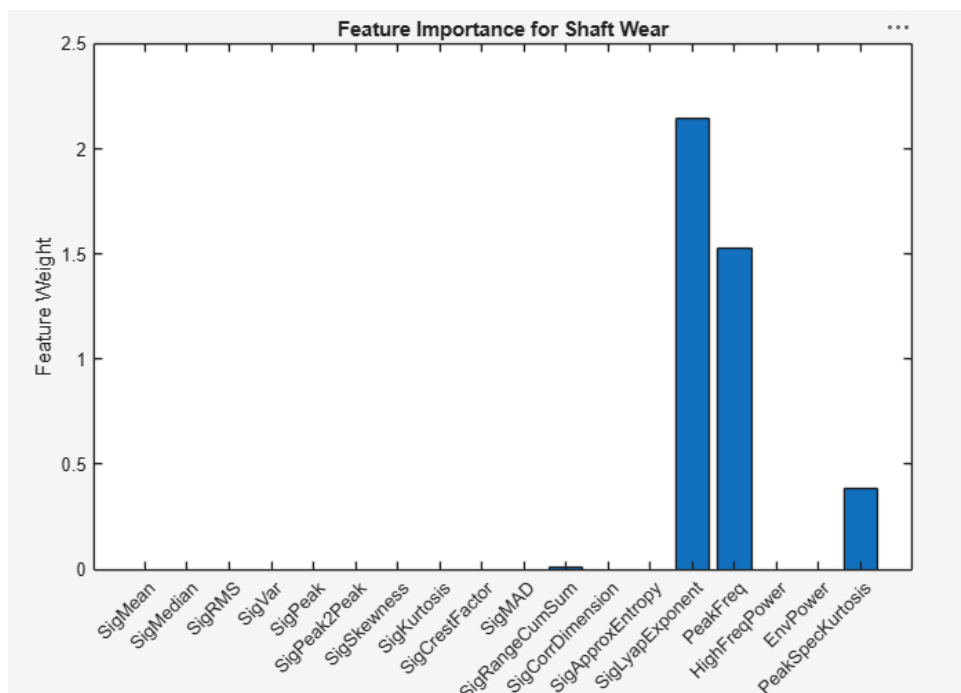


Figure 3 NCA feature importance for shaft wear classification.

Gear-tooth damage was most strongly associated with SigRangeCumSum and PeakSpecKurtosis.

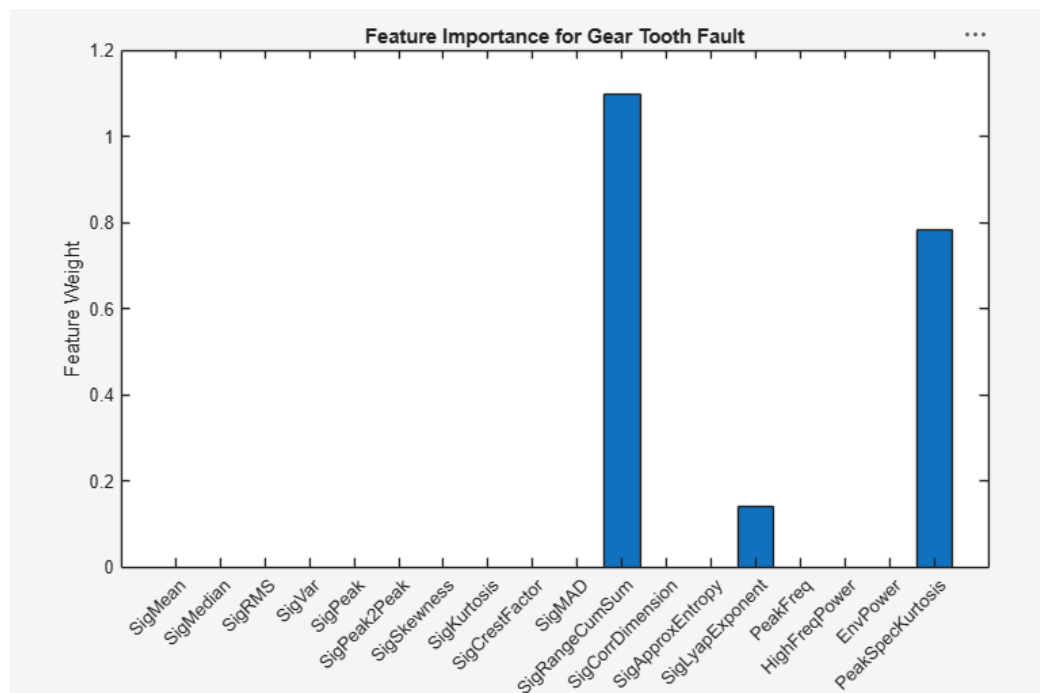


Figure 4 NCA feature importance for gear-tooth fault classification.

However, the strongest individual features showed varying degrees of overlap between healthy and faulty observations, particularly for shaft wear. This suggests that classification using multiple signal characteristics would be preferable to relying on a single feature.

4.3 Neural-Network Configuration

Three separate binary neural networks were developed to classify sensor drift, shaft wear and gear-tooth damage. Each network received the 512 spectral values and contained one hidden layer of 20 ReLU neurons. A shallow architecture was selected because only 208 observations were available, limiting model complexity relative to the size of the dataset. The observations were divided reproducibly into 146 training, 31 validation and 31 held-out test cases. Input standardisation was calculated from the training data only, and subsequently applied validation and test sets to avoid data leakage. Regularisation, validation-based early stopping and class weighting were also used during model development.

Performance was evaluated using the held-out test set and confusion matrices, with five-fold cross-validation providing an additional assessment of generalisation across alternative data partitions. The resulting classification performance is presented and compared with the feature-based SVM in section 5.

5 Comparative Analysis – SVM and Neural Network

5.1 Neural Network Performance

The three neural networks produced markedly different classification performance. On the 31-observation held-out test set, sensor drift achieved 93.55% accuracy – 29/31 correct, shaft wear achieved 48.39% - 15/31 correct and gear-tooth damage achieved 100% - 31/31 correct. The corresponding confusion matrices show that the sensor-drift classifier produced no false positives and two false negatives, while the gear-tooth classifier produced no classification errors. Shaft-wear detection was substantially weaker, producing five false positives and 11 false negatives.

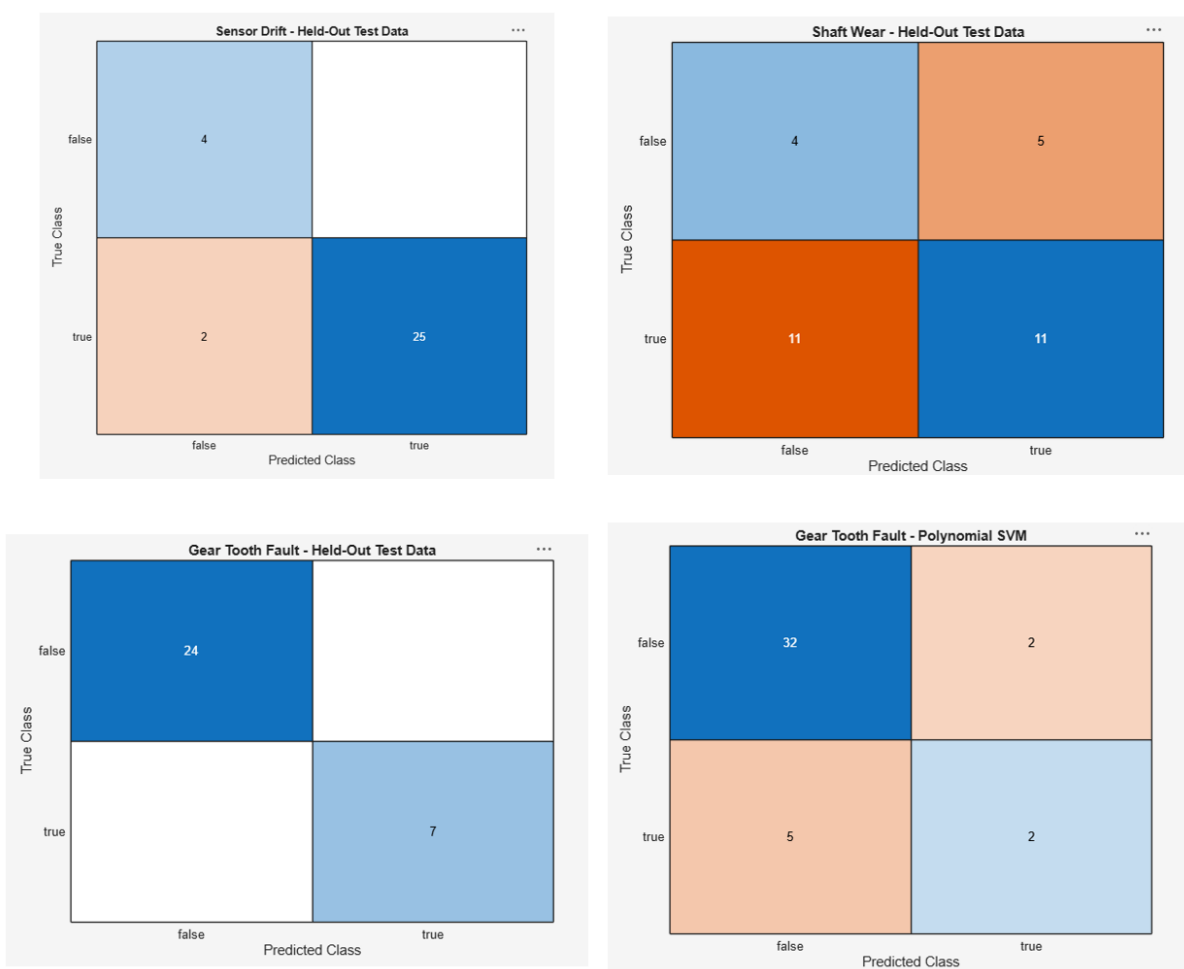


Figure 5 Confusion matrices: sensor drift NN, shaft-wear NN, gear-tooth NN and polynomial SVM (clockwise from the top left).

Five-fold cross-validation was used as an additional check because performance from a single small test partition may not represent behaviour across the complete dataset. Gear-tooth classification remained at 100%, while shaft-wear accuracy remained at 43.27%. Sensor-drift cross-validation

returned as an accuracy of 82.69%, however, all 208 observations were classified as containing drift. The classifier therefore correctly identified all 172 drift cases but incorrectly classified all 36 non-drift cases. This demonstrates why accuracy alone can be misleading when classes are imbalanced.

The cross-validation procedure used stronger regularisation than the initial held-out models and therefore provides evidence of model stability rather than an exact replication of the original model configuration.

5.2 Comparison with the SVM

A polynomial SVM provided a feature-based baseline for gear-tooth classification. Unlike the neural network, which used the 512-bin vibration spectrum, the SVM operated on selected engineered vibration features. The SVM correctly classified 34 of 41 evaluation observations, giving 82.93% accuracy. Its confusion matrix contained 32 true negatives, 2 true positives, 2 false positives and 5 false negatives. In comparison, the raw-spectrum neural network correctly classified all 31 observations in its held-out gear-tooth test set.

Although the neural network achieved the higher measured accuracy, the result should not be treated as a controlled head-to-head comparison. The classifiers used different input representations and were evaluated on different held-out observations. The comparison therefore demonstrates the performance of the two implemented workflows rather than proving that neural networks are inherently superior to feature-based SVMs.

Classifier/fault	Held-out accuracy	5-fold CV accuracy	Key observation
NN – sensor drift	93.55%	82.69%	CV predicted every case as drift
NN – shaft wear	48.39%	43.27%	Weakest separation
NN – gear tooth	100.00%	100.00%	No errors in simulated data
Polynomial SVM – gear tooth	82.93%	Not directly comparable	32 TN, 2 FP, 5 FN, 2 TP

Table 4 Quantitative classification results.

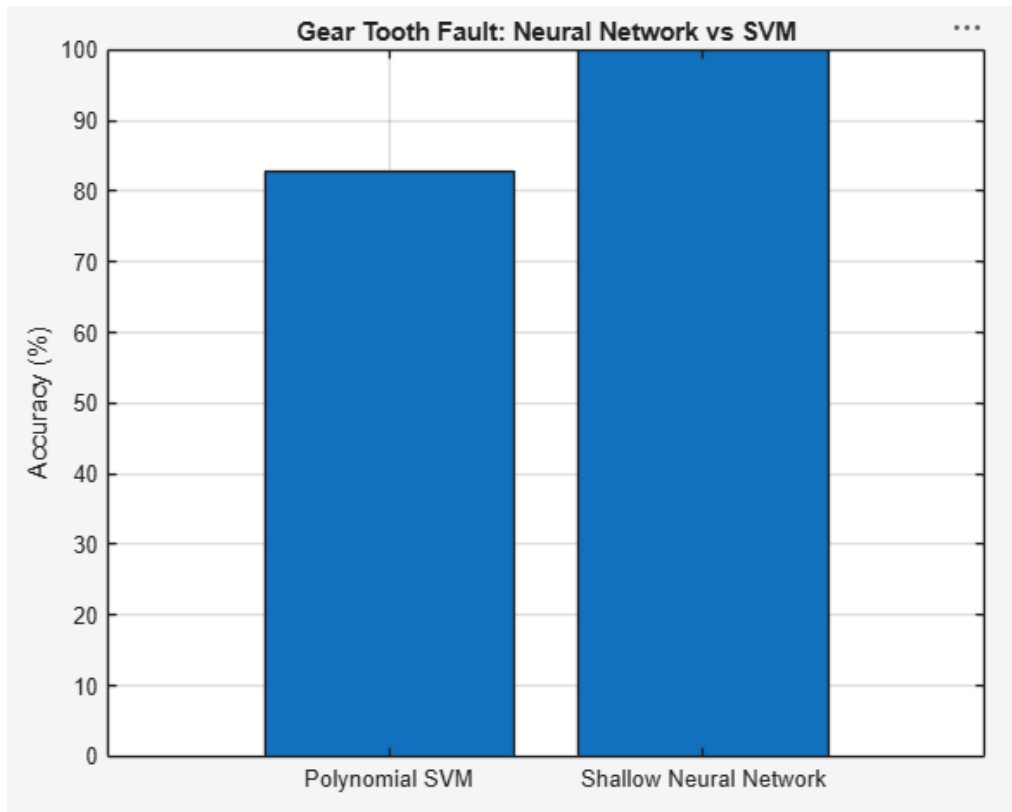


Figure 6 Gear-tooth classification accuracy for the polynomial SVM and shallow neural network.

5.3 Overall Findings

Overall, classification performance was strongly fault-dependent. Gear-tooth damage was consistently distinguishable from the simulated vibration spectra, achieving 100% accuracy in both held-out testing and cross-validation. Sensor drift performed well on the held-out test set, although cross-validation exposed sensitivity to class imbalance. Shaft wear was the most difficult condition, with only 48.39% held-out accuracy and 43.27% cross-validation accuracy. This agrees with the earlier NCA analysis, where the strongest shaft-wear features showed substantial overlap between worn and non-worn observations. The results therefore indicate that the available vibration representation contains much clearer diagnostic information for gear-tooth damage than for shaft wear.

6 Discussion

Shaft wear was the most difficult fault to detect, achieving 48.39% held-out accuracy and 43.27% cross-validation accuracy. This is consistent with the NCA analysis, where the strongest shaft-wear features showed substantial overlap between worn and non-worn observations. In contrast, sensor drift directly alters the measured vibration signal, while the simulated gear-tooth fault produced a more distinctive spectral response. The results therefore demonstrate that classifier effectiveness depends strongly on how clearly each fault is represented within the available vibration data.

The confusion matrices also demonstrate why accuracy alone is insufficient when considering industrial deployment. The shaft-wear network produced five false positives and 11 false negatives, while the SVM missed five of seven actual gear-tooth faults. False negatives could allow degradation to progress towards unplanned failure, whereas excessive false positives could result in unnecessary inspections, maintenance activity and use of spares. Both outcomes reduce the potential availability benefits of predictive maintenance.

For P-2201A, the gear-tooth neural network therefore shows greater diagnostic potential than the shaft-wear classifier, although its 100% performance was obtained using simulated data and should not be assumed to represent field performance. Sensor drift must also be considered because unreliable measurement data could undermine confidence in subsequent condition assessments. Where failure consequences are significant, classifier outputs should therefore support engineering investigation rather than independently trigger maintenance or shutdown decisions.

A combined approach is consequently more appropriate for industrial deployment. Machine-learning classification can supplement conventional vibration analysis and feature trending, while engineering review and additional condition or process measurements provide confirmation. Before deployment, the models should therefore be validated using representative P-2201A data across different operating conditions.

7 Conclusion and Recommendations

PdM can provide a better basis for planning maintenance than reactive or preventive approaches. Conventional vibration analysis remains important because of its physical interpretability, while machine-learning methods can supplement it by automating fault classification from complex vibration data.

The case study demonstrates that classification performance is strongly fault-dependent. The raw-spectrum neural network achieved strong results for simulated gear-tooth damage and sensor drift, whereas shaft-wear detection remained unreliable. The polynomial SVM achieved 82.93% accuracy for gear-tooth detection but missed 5 of 7 actual fault cases. For P-2201A, a combined approach is therefore recommended rather than the reliance on a single classifier. Conventional vibration analysis and feature trending should be supported by machine-learning classification, with gear-tooth and sensor-drift outputs used to prompt further investigation and shaft-wear decisions requiring additional diagnostic evidence.

Before industrial deployment, the models should be validated using representative data across different operating conditions. Further development should investigate additional fault-sensitive measurements and improved features for shaft-wear detection, together with appropriate decision thresholds for balancing missed faults against unnecessary maintenance. Until this validation is completed, the models should remain as decision-support tools.

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