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A Review of Condition Monitoring, Fault Detection, Diagnostic, and Prognostic Approaches for Electropneumatic Point Machines

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Electropneumatic point machines (EPMs) play a critical role in railway signalling systems by enabling the safe routing of trains at junctions and are widely deployed across the London Underground (LU) network. Despite their operational importance, many EPMs on the LU are maintained using periodic inspection regimes, and the literature addressing their condition monitoring and health management remains fragmented. Although fault detection and diagnostic approaches for point machines have been widely studied, existing research predominantly focuses on electromechanical and electrohydraulic systems, with limited consolidation of findings specific to electropneumatic points. This paper presents a structured review of fault detection, diagnostic, condition monitoring, and prognostic approaches relevant to EPM. The review synthesises reported findings from the literature, examining failure mechanisms, monitored parameters, analytical techniques, and their respective strengths and limitations. Reactive and preventive diagnostic methods are compared for their ability to identify abnormal behaviour and incipient degradation, while prognostic approaches are reviewed for their potential to support maintenance planning. Based on insights from the review, a remote condition monitoring framework is proposed that integrates asset prioritization, multi-parameter sensing, diagnostic functions, and prognostic assessment into a coherent monitoring pipeline. The framework emphasises phased deployment, functional parameter selection, and cautious interpretation of analytical outputs. It provides practical guidance for industry practitioners considering the implementation of condition monitoring for EPMs on the LU. The paper concludes by outlining key research gaps and future directions to support the transition towards more condition-based, data-informed maintenance strategies.

Keywords: Electropneumatic Point Machines, Remote Condition Monitoring, Fault Detection and Diagnosis, Predictive Maintenance, Asset Health Management.

1. Introduction

Urban metro systems operate under intense demand, tight headways, and limited access windows for maintenance. In such environments, failures in signaling and switching infrastructure can rapidly propagate into widespread service disruption. The LU, comprising 272 stations across 11 lines, carries millions of passenger journeys daily and relies on high asset availability to maintain service performance. Signaling and point-related failures remain a major contributor to operational disruptions. In the 2023-24 financial year, signaling and point failures on the LU resulted in 3.57 million Lost Customer Hours (Points of Failure 2024).

Point machines are critical components of railway signaling systems, responsible for moving and locking switch rails to route trains safely through junctions. Within the LU network, a substantial proportion of legacy point assets are electropneumatic points, and aging mechanisms and environmental exposure contribute to their gradual degradation. Interactions among pneumatic, mechanical, and electrical subsystems can result in intermittent faults that are difficult to diagnose before functional failure.

A key operational challenge is that approximately 1,000 EPMs in LU are currently not equipped with remote condition monitoring (RCM). As a result, asset interventions are predominantly reactive, following failures or scheduled at fixed intervals. While scheduled inspection regimes are essential for safety assurance, interval-based maintenance may miss incipient fault development. It can also consume resources on inspections that do not accurately reflect the condition of the asset. In contrast, RCM enables remote acquisition of operational parameters, automated identification of abnormal behavior, and improved diagnostic support for the maintenance team. Introducing condition monitoring supports earlier detection of developing failures, reduces unplanned service disruptions, and facilitates a transition towards more predictive, data-driven maintenance strategies.

Although condition monitoring of point machines has been widely studied, much of the existing literature focuses on electromechanical and electrohydraulic systems. In comparison, studies specifically addressing EPMs remain limited and dispersed across different application contexts. As a result, knowledge of failure mechanisms, monitored parameters, and appropriate maintenance strategies for electropneumatic systems remains fragmented.

Consequently, this paper presents a structured review of the literature on EPMs, focusing on system structure, degradation mechanisms, failure modes, fault detection and diagnosis, and monitoring and maintenance strategies. The review synthesizes evidence from academic publications, relevant industry standards, and operational insights.

The paper is structured as follows. Section 2 summarizes EPM subsystems and dominant failure mechanisms. Section 3 describes the review methodology. Section 4 synthesizes fault detection and diagnostic methods and their data requirements. Section 5 reviews prognostic strategies for point machines and their application to maintenance planning. Section 6 presents a remote condition monitoring framework and discusses deployment considerations. Section 7 concludes with the key implications and future research needs.

2. Electropneumatic Point Machines (EPMs)

EPMs use compressed air as the primary working medium, combined with mechanical transmission, locking mechanisms, and electrical detection to reposition and secure switch rails.

Although different point machine designs exhibit structural and operational differences, condition monitoring and fault analysis primarily rely on functional indicators of degradation, allowing common diagnostic logic to be applied with design-specific calibration. A functional abstraction is adopted to support systematic comparison of diagnostic and prognostic approaches across EPMs.

2.1. *Failure-Relevant Subsystems*

EPMs can be decomposed into three interacting subsystems: actuation, locking, and indication (Transport for London 2008c). The actuation subsystem converts pneumatic energy into mechanical motion to move the switch rails. Degradation typically arises from air leakage, contamination, valve malfunction, and increasing friction, which often manifest as increased actuation time or irregular movement rather than immediate failure (Hamadache et al. 2019; Transport for London, 2008d, 2009).

The locking subsystem ensures that the switch rails are securely held in the commanded position once movement is complete. Degradation is commonly associated with mechanical wear, misalignment, and loss of tolerance in locking components (Transport for London 2008b, 2008a, 2009).

The detection and indication subsystem provides electrical confirmation of the correct rail position and locking state. Faults in this subsystem can arise from contact wear, wiring degradation, environmental ingress, and mechanical misalignment. A common consequence is the prevention of route setting despite mechanically successful movement (Transport for London 2008a, 2008b, 2009).

Failures in EPMs frequently result from interactions among subsystems rather than from isolated component degradation. For example, increased mechanical resistance may alter pneumatic demand, movement timing, and detection behaviour (Hamadache et al. 2019; Hu et al. 2023). Such interaction effects contribute to the prevalence of intermittent and incipient faults, where assets continue to operate within tolerance but exhibit inconsistent behaviour. Understanding these interaction characteristics is essential for interpreting monitoring data and underpins the review of fault detection, diagnostic, and prognostic approaches presented in subsequent sections.

3. Literature Review Methodology

The literature review was conducted using established academic databases, focusing on railway point machines, condition monitoring, fault detection and diagnosis, prognostics, and pneumatic systems. The search was restricted to English-language journal and conference publications from 2008 to 2025, reflecting the period during which sensor-based monitoring and data-driven maintenance approaches have become increasingly prominent.

Publications were initially screened based on titles and abstracts to exclude studies unrelated to railway point machines or asset health monitoring. Full-text screening was then applied, and studies were retained if they addressed failure mechanisms and degradation of point machines, fault detection, and diagnostic methods, preventive or prognostic health management approaches, or monitoring parameters relevant to point machine performance. Forward snowballing was applied through reference and citation tracking.

The studies included in this paper were selected to represent the range of diagnostic objectives, monitored parameters, and analytical techniques reported in the literature. Approaches were grouped by diagnostic objective, monitoring parameters, and analytical techniques. This synthesis underpins the literature review and informs the development of the proposed remote condition monitoring framework.

4. Fault Detection and Diagnostic Approaches

Fault detection and diagnosis (FDD) approaches for point machines aim to identify abnormal operating behaviour and inform maintenance decision-making before failures lead to operational disruption. These functions are often considered part of Prognostics and Health Management (PHM) framework in the broader asset health management literature. FDD approaches can be broadly classified by the timing of fault identification into reactive fault detection and diagnosis (RFDD) and preventive fault detection and diagnosis (PFDD). This classification reflects differences in diagnostic objectives, data requirements, and implementation complexity.

Both RFDD and PFDD approaches rely on condition monitoring data from key operational parameters, including electrical, mechanical, and pneumatic indicators. A summary of commonly monitored parameters, their typical performance benchmarks, and indicative fault mechanisms is provided in Table 1, which forms the basis for the diagnostic methods reviewed in this section.

4.1. *Reactive Fault Detection and Diagnosis (RFDD)*

RFDD approaches identify faults during point machine operation, enabling rapid intervention to minimise service disruption (Mendoza & Tsvetkov 2023). RFDD research has focused mainly on current and power signature analysis. Vileiniskis et al. (2016) applied motor current analysis with One-Class Support Vector Machines (OCSVM) and Edit Distance with Real Penalty (ERP) to detect abnormal switching behaviour. While effective for anomaly detection, expert interpretation was required to confirm fault occurrence, as changes in current signatures do not always relate to physical faults.

Wang et al. (2023) addressed the limited availability of fault data by integrating expert knowledge with phase-segmented power signals using a reasoning-diagram-based framework. Using Support Vector Data Description (SVDD), the approach enabled fault detection and localization, outperforming benchmark methods in field deployment. Other RFDD approaches include phase-based feature extraction combined with fuzzy neural networks (Cheng & Zhao 2015) and unsupervised clustering techniques using K-means, Fréchet distance, and fuzzy C-means for automated fault detection and classification without predefined reference curves (Huang et al. 2018).

Although RFDD studies predominantly target electromechanical systems, the underlying diagnostic logic is transferable to EPMs. In such systems, parameters such as pneumatic pressure profiles, actuation force, and movement timing serve as functional equivalents to electric load signals. A comprehensive summary of RFDD approaches is provided in Table 2.

4.2. *Preventive Fault Detection and Diagnosis (PFDD)*

PFDD approaches aim to detect incipient faults and degradation trends while the point machine remains within operational tolerance, enabling proactive maintenance planning (Guida et al. 1997).

Bai (2010) proposed a multi-model preventive diagnostic framework applicable to pneumatic- and electrically driven assets that combines residual analysis with adaptive thresholding across multiple submodels, including state-space and neural networks. Laboratory validation demonstrated effective detection of simulated pneumatic faults, although broader validation across fault modes was recommended.

Indirect monitoring approaches have also been explored. Vehicle-mounted vibration monitoring has been used to detect degradation in turnout components and to optimize inspection scheduling (Zoll 2009), while strain-based monitoring of crossing noses has enabled the detection of subtle geometric degradation under traffic loading (Oßberger et al. 2017). Axle-box acceleration measurements have been applied to assess structural deterioration through dynamic wheel-rail interaction analysis (Kaewunruen 2014). Wright et al. (2016) presented an integrated software platform combining statistical classifiers, neural networks, and phase recognition to support preventive diagnosis using electrical current and hydraulic pressure data. This research demonstrates the effectiveness of detecting developing faults in in-field assets.

More specialised PFDD techniques include ultrasonic guided-wave testing for crack detection in turnout rails (Tian et al. 2025). Collectively, these approaches demonstrate improved early fault detection but remain challenged by environmental sensitivity, data availability, sensor deployment complexity, and threshold calibration. Key PFDD approaches and their characteristics are summarised in Table 3.

4.3. *Implications for Electropneumatic Point Machines*

The reviewed fault detection and diagnostic approaches demonstrate increasing capability for automated identification of abnormal operating behaviour in railway point machines. Reactive approaches provide rapid fault detection during or immediately after switching operations, while preventive methods offer earlier insight into degradation trends that may not yet result in functional failure. However, most published studies focus on electromechanical point machines, with comparatively limited attention given to electropneumatic systems.

For EPMs, diagnostic effectiveness depends strongly on the selection of monitoring parameters that reflect degradation across pneumatic, mechanical, and electrical subsystems. Although the underlying sensing modalities differ, many diagnostic principles reported for electromechanical systems remain applicable when equivalent functional indicators, such as pneumatic pressure behaviour, actuation timing, and force-displacement characteristics, are monitored. At the same time, subsystem interaction and environmental sensitivity introduce additional uncertainty, particularly for intermittent and incipient faults that remain within operational tolerance.

Taken together, the reviewed reactive and preventive fault-detection approaches indicate that no single monitoring parameter or diagnostic method is sufficient to address the interacting, often ambiguous failure mechanisms of EPMs. These findings highlight the need for an integrated monitoring strategy that combines multi-parameter sensing with layered diagnostic functions. Such an approach supports maintenance prioritization and decision-making and provides the basis for the remote condition-monitoring framework introduced in the following section.

5. Failure Prognostic Approaches (FP)

Prognostic strategies aim to assess degradation progression and estimate the future condition of railway assets to support decision-making for preventive maintenance (Babaei & Rashidi-baqhi 2022). In contrast to fault detection and diagnosis, which focus on identifying abnormal behaviour that has already occurred, prognostic approaches attempt to forecast when performance is likely to degrade beyond acceptable limits. Within the context of point machines, this typically involves estimating Remaining Useful Life (RUL) or predicting the timing of functional failure.

Several prognostic approaches for point machines have been reported in the literature, primarily based on degradation modelling and time-series forecasting. Letot et al. (2015) developed a degradation-based prognostic framework using a real-scale test bench under controlled temperature conditions. This framework combines Auto-Regressive Moving Average (ARMA) with Simple State-Based Prognostic (SSBP) to track health status transitions and forecast future behaviour. The study demonstrated that the mean active power during blade displacement was a sensitive indicator of degradation and highlighted the strong influence of environmental conditions on prognostic accuracy.

Other studies have explored residual-based and multivariate approaches for prognostics. Shi et al. (2018) proposed an Auto-Associative Residual (AAR) framework using Auto-Associative Multivariate State Estimation (AAMSET) to diagnose and predict incipient point machine faults based on low-cost onboard sensor data. The approach achieved high diagnostic accuracy under laboratory conditions and reduced reliance on expert feature extraction. However, robustness under operational noise and variable conditions was identified as a key challenge.

Field-oriented prognostic studies have also been reported. Atamuradov et al. (2018) applied force-based degradation indicators combined with k-means clustering and change-point detection to model the wear of the slide chair and estimate RUL for in-service point machines. While k-means clustering can effectively detect significant degradation changes, it is less sensitive to smaller variations, which may delay timely intervention. García et al. (2010) implemented adaptive time-series forecasting using Vector Auto-Regressive Moving Average (VARMA) and harmonic regression to predict expected operational behaviour and generate failure warnings for point machines. Similarly, García Márquez et al. (2007) proposed an Unobserved Component (UC) modelling approach within a state-space framework, using Kalman Filtering (KF) to track hidden wear states under noisy conditions.

Collectively, these studies demonstrate the potential of FP to support predictive maintenance by shifting the focus from fault detection to future-oriented decision-making. The benefits of FP include more accurate RUL estimation, targeted maintenance interventions, and reduced unplanned downtime. Nevertheless, challenges persist in addressing non-linear degradation patterns, ensuring model robustness across diverse environmental conditions, and balancing sensitivity to minor changes with the need to avoid false alarms.

In addition, practical implementation of data-driven diagnostic and prognostic methods presents several operational challenges. AI -based approaches typically require well-labelled training datasets, yet in many railway applications, fault data are limited or inconsistently annotated. Deployment may also be constrained by the cost of installing additional sensors and processing units, as well as the need for a reliable data communication infrastructure to support continuous monitoring.

Table 1 Key operational parameters for point machine condition monitoring and indicative fault conditions (Hu et al. 2023; Letot et al. 2015; Vileiniskis et al. 2016)

Parameter / Component	**Normal behaviour**	**Indicative fault conditions**
Motor electrical signals (current, voltage, power, speed)	Stable profiles during switching	Obstruction, contamination, and increased mechanical resistance
Switch to stock rail gap	Within safety tolerances	Incomplete locking or rail contact risk
Drive rod motion (force, displacement, speed)	Smooth, continuous profile	Friction, wear, obstruction, jamming
Indication rod motion *(displacement, position, speed)*	Consistent with blade movement	Misalignment, mechanical wear
Switch resistance	Within expected operating range	Sticky locks, roller faults, obstruction
Throwing time	Within manufacturer's tolerance	Increased friction or component wear
Acoustic and vibration	Repeatable operating pattern	Mechanical wear, loosened component
Temperature and Humidity	Within operating limits	Motor overload, electrical degradation
Pneumatic pressure	Stable within design range	Air leakage, blockage, valve malfunction
Actuation and drive mechanism condition	Smooth and reliable operation and no visible wear or deformation	Irregular motion, deformation, excessive vibration
Detection and locking subsystem condition	Correct detection and locking	False position indication, delayed or incomplete locking

Table 2 Summary of RFDD Methods for Point Machines

Method	**Monitored Parameter**	**Main Outcome**	**Pros**	**Cons**
OCSVM + ERP	Motor current	Detection of abnormal current patterns	Works with healthy-state data only; automated	Requires expert interpretation; current changes may not indicate faults
Phase segmented reasoning diagram + SVDD	Power signal	Accurate fault detection and localization	Effective with limited fault data; integrates expert knowledge	Sensitive to training data quality and representativeness
Phase-based features + fuzzy neural network	Motor current	Reliable identification of common faults	Robust to uncertainty and imprecision	Computationally intensive; risk of overfitting
K-means + Fréchet distance + fuzzy c-means	Motor current	High accuracy; detection of new fault types	No prior fault labels required; automated reference selection	Sensitive to noise and high-dimensional data

Table 3 Summary of PFDD for Point Machines

Method	**Monitored Parameter**	**Main Outcome**	**Pros**	**Cons**
Multi-model residuals + adaptive threshold	Pneumatic and electrical signals	Detection of incipient faults	Multi-model improves robustness; low false alarms	Limited fault mode coverage; lab validation only
Vehicle-mounted vibration monitoring	Vibration	Early wear detection	Continuous monitoring between inspections	Limited validation against fault ground truth
Strain gauge monitoring	Strain	Detection of geometric degradation	Sensitive to early-stage deterioration	Influenced by environmental conditions
Axle box acceleration + dip angle metric	Wheel–rail dynamic response	Structural deterioration detection	No trackside sensors required; scalable	Sensitive to vehicle and track noise
Ultrasonic guided waves	Ultrasonic response	High-precision crack detection	Sensitive to small defects	Requires specialised sensors

6. Remote Condition Monitoring Framework for Electropneumatic Point Machines (EPMs)

This section presents a remote condition monitoring (RCM) framework that integrates the fault detection, diagnostic, and prognostic concepts reviewed in Sections 4 and 5 for EPMs. A schematic overview is provided in Figure 1.

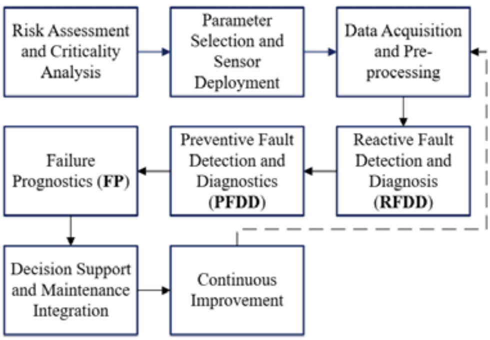

Figure 1 RCM pipeline for EPMs.

The framework begins with a detailed risk assessment to guide the prioritization of assets for RCM deployment. Historical failure records, operational experience, and expert judgement are used to identify high-risk components and failure modes. Following prioritization, failure modes are mapped to a limited set of monitoring parameters that provide functional visibility of degradation across pneumatic, mechanical, and electrical subsystems. Parameter selection prioritises sensitivity to asset condition changes over exhaustive instrumentation. Monitoring data are acquired either continuously or during switching operations and consolidated within a centralized data environment.

Diagnostic functionality is implemented in a layered manner. Reactive fault detection supports rapid identification of abnormal behaviour, while preventive diagnostics track gradual changes indicative of emerging degradation. Where sufficient data are available, prognostic analysis is applied to assess degradation trends and estimate RUL for selected components.

Outputs from diagnostic and prognostic modules are consolidated into decision-support views summarising asset condition, fault history, and degradation trends. These outputs inform condition-based maintenance actions and resource allocation.

7. Conclusions and Future Research

This paper presented a structured review of fault detection, diagnostic, condition monitoring, and prognostic approaches applicable to EPMs. The review highlighted that, despite extensive research on point machine condition monitoring, existing studies predominantly focus on electromechanical and electrohydraulic systems, with knowledge specific to electropneumatic assets remaining fragmented.

The synthesis of reactive and preventive diagnostic approaches indicated that effective monitoring relies on functionally meaningful parameters that capture degradation across interacting pneumatic, mechanical, and electrical subsystems. Reactive approaches support the timely identification of abnormal behaviour, while preventive methods support earlier detection of incipient degradation. Prognostic techniques offer additional potential to support maintenance planning, but their practical application to point machines remains constrained by data availability, the scope of validation, and sensitivity to operating conditions. Consequently, prognostic outputs should be interpreted as indicative decision-support information rather than precise failure predictions.

To address these challenges, a remote condition monitoring framework was proposed that integrates asset prioritization, multi-parameter sensing, diagnostic functions, and prognostic assessment into a coherent monitoring pipeline. The framework provides practical guidance for the systematic deployment of condition monitoring for EPMs.

Future research should prioritize long-term, in-field validation of diagnostic and prognostic methods for EPMs, with particular attention to environmental variability and intermittent fault behaviour. Further work is also required to evaluate the impact of integrated monitoring frameworks on maintenance effectiveness, resource allocation, and service reliability in operational railway networks.

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