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Review

Fault Detection for Point Machines: A Review, Challenges, and Perspectives

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Abstract: Point machines are the actuators for railway switching and crossing systems that guide trains from one track to another. Hence, the safe and reliable behavior of point machines are pivotal for rail transportation. Recently, scholars and researchers have attempted to deploy various kinds of sensors on point machines for anomaly detection and/or incipient fault detection using date-driven algorithms. However, challenges arise when deploying condition monitoring and fault detection to trackside point machines in practical applications. This article begins by reviewing studies on fault and anomaly detection in point machines, encompassing employed methods and evaluation metrics. It subsequently conducts an in-depth analysis of point machines and outlines the envisioned intelligent fault detection system. Finally, it presents eight challenges and promising research directions along with a blueprint for intelligent point machine fault detection.

Keywords: point machines; fault detection; anomaly detection; condition monitoring

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1. Introduction

Many countries and regions favor railway transportation because of its advantages of large volume, fast speed, low price, punctuality, low energy consumption, and small occupation of land [1]. Although there are many kinds of rail transportation systems, covering high-speed rail networks, urban rail transit systems, mag-lev (magnetic levitation) lines, heavy haul railways, and existing railroads, all of them require turnouts to connect multiple lines. More precisely, point machines (known as railway switch machines) are designed to push and pull the switch rails to allow a train on one track to cross over to another.

Clearly, the safe and reliable operation of point machines contributes enormously to the safety and efficiency of rail transportation. Unfortunately, point machines naturally undergo a degradation process as operational wear takes hold. Mechanical transmission components and electrical units in point machines inevitably fail. Furthermore, point machines work alongside railway lines, where the environment is ordinarily harsh. Diverse faults, including common, intermittent, or even unexpected ones, can occasionally occur, and may cause incidents or even accidents. Poor maintenance and missed faults tend to cause system delays or even heavy casualties, e.g., the Potters Bar accident in 2002, which resulted in seven deaths and 76 injuries) [2]. Consequently, railway operators have to confront complicated fault detection during regular inspections. Maintenance and repair staff are required to detect faults over time with a missed detection rate of zero. Hence, scholars and engineers have put forth considerable effort to capture the relevant behavioral characteristics by means of different sensors installed on point machines for fault detection, thereby forming a matter of rising concern as well as a research focus.

Scholars engaged in railway signaling have been taking up the related research directions for more than twenty years, and a number of review articles concerning condition monitoring and fault detection have been published. For example, Márquez et al. [3] summarized the different kinds of sensors and fault detection methods used in three typical types of point machines for the actuators of turnout systems, i.e., electro-mechanical, electro-hydraulic, and electro-pneumatic point machines, up to 2009. Hamadache et al. [2] described the fundamentals of point machines and presented a review of existing techniques according to model-based and data-driven methods up to 2019. In addition, they discussed potential opportunities for future studies.

As studies have become more abundant, a comprehensive review of condition monitoring and fault detection of point machines is highly desirable. Consequently, we have decided to complete this review. The key contributions of the present review article are as follows:

1. We provide a review of fault detection in point machines for research and development personnel, scholars, and engineers, covering the latest data-driven algorithms with comments as well as evaluation metrics.
2. We conduct a comprehensive analysis of point machines, including their requirements, inherent features, and external influences.
3. We describe the anticipated requirements for an intelligent point machine fault detection system.
4. We propose eight urgent issues and possible solutions for future point machine fault detection research which can be of genuine use to infrastructure maintainers and owners, and present a blueprint for intelligent point machine fault detection.

In brief, we try to answer the following questions in this review:

1. Which types of data-driven algorithms are employed for point machine fault detection, what are their pros and cons, and what are their specific application scenarios?
2. What metrics are appropriate for evaluating the task of fault detection in point machines?
3. What are the requirements for an intelligent point machine condition monitoring and fault detection system?
4. What future directions can be identified for the advancement of intelligent point machine fault detection?

The rest of this paper is organized as follows. Section 2 introduces the fundamentals of turnouts and point machines. Section 3 summarizes common faults associated with point machines, describes the current condition monitoring parameters, and discusses data-driven algorithms and evaluation metrics for point machine fault detection. In Section 4, we conduct a comprehensive analysis of point machines in terms of their requirements, inherent features, and external influences, then discuss the anticipated requirements for an intelligent point machine fault detection system. Combining the previously described current research progress and system requirements, Section 5 highlights urgent challenges and future directions along with with potential solutions. Section 6 outlines a blueprint for intelligent point machine fault detection. Finally, Section 7 concludes the paper.

2. Fundamentals of Turnouts and Point Machines

Turnouts (sometimes known as switches and crossings [4]) connect different tracks into a multi-line network, allowing a train to switch from one line to another. A simple turnout structure diagram is shown in Figure 1. It comprises two switch rails, two stock rails, one point frog, two wing rails, and two guard rails. A point machine pushes or pulls the moving parts in its closed position, which is simultaneously locked adjacent to its stock rail, while the other switch rail is locked in the open position to allow the wheel to pass over the rail on the open side [2]. Train wheels move along the rails guided only by the small area of the wheel that sits on the rail head. The wheel rim or flange does not usually touch the rail; the flanges are only a last resort to prevent the wheels from becoming derailed (wheel–rail interaction, shown in Figure 2). Thus, trains can run in different directions, either to the normal position (called "normal" movement or the normal route) or to the opposite "reverse" lie (termed "reverse" movement or the reverse route) via wheel–rail interaction [5,6]. Additionally, wing rails and guard rails ensure safe passage for rolling stock, and the stretcher bars connecting two switch rails are used to maintain the distance between the blades for free wheel passage.

Various types of point machines have been developed and invented, most of which are grouped into three categories (electro-mechanical, electro-hydraulic, and electro-pneumatic). Figure 3 shows a general structural diagram of a point machine installed on a simple turnout, and exhibits several examples from manufacturers around the world. These examples vary in terms of their transmission mechanism components and specific principles; nevertheless, on the whole, a point machine works as shown below.

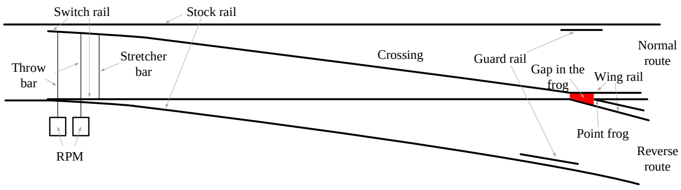

Figure 1. The schematic diagram for a simple turnout layout.

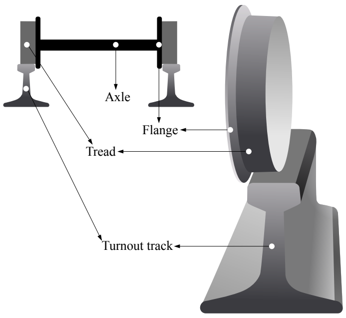

Figure 2. The schematic diagram for wheel–rail interaction.

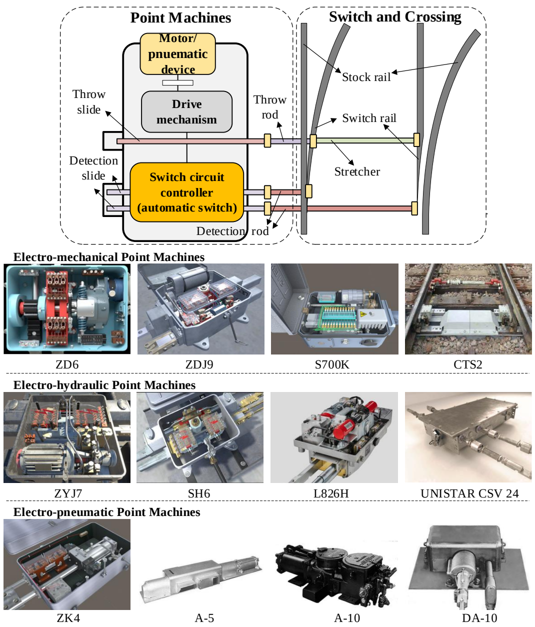

Figure 3. Above, the general point machine structure installed on a simple turnout; below, examples of different types of point machines.

The motive power (i.e., electrical and mechanical energy) is transmitted to the longitudinal motion of the operating bar via the transmission mechanisms (e.g., the gearbox, hydraulic cylinder, and pneumatic cylinder), thereby moving the switch rails or even movable point frogs and movable wing frogs (point frogs and wing frogs may be movable in certain situations involving high speed requirements). The detection rods linked to the switch rails via detection slides indicate whether the switch rails have reached the end position. The switch circuit controller monitors the position of rail switch points and provides corresponding electrical signals. The contacts of the switch circuit controller indicate positional information, including whether the switch rail is in the closed position and whether the moving parts are being moved.

Although a wide portfolio of point machines is offered by many railway signaling suppliers for compatibility with high-speed lines, conventional lines, heavy haul lines, mass transit railways, light-rail, rapid transit lines, suburban (metro/suburban), and tramway ballasted lines, the general technical characteristics of point machines are summarized in Table 1.

Table 1. Technical characteristics of point machines.

Designation	Description
Power supply	DC and AC electric motor, hand (rarely), etc.
Transmission mechanism	Mechanical, hydraulic, and pneumatic drives.
Throwing/reversing force	A broad range, typically up to 9 kN.
Retaining force	A wide variety.
Throwing time	Slow action: over 6 s; medium: 3 s to 6 s; fast action: not more than 0.8 s.
Stroke	Approximately ranging from 30 mm to 300 mm.
Product lifetime	Normally over one million throwing movements.
Locking system	External lock, internal lock.
Installation configuration	Track center and beside the tracks (right-hand or left-hand layouts); stock rail fixation and sleeper fixation (in-tie or on-tie).
Trailability	Trailable and non-trailable.
Environmental conditions	Operating temperature: −40 °C to +80 °C; humidity: up to 95%.
Degree of protection	Resistance to sand, dust, dirt, snow, meltwater, humidity, and flood water.
Weight & profile	Diversity.
Electrical interface	Various interlocking systems, e.g., single-drive (four wires, five wires) and multi-drive technology.
Turnout interface	No limitation on the types of turnouts.

Table 1 shows a number of technical characteristics of point machines, which need to meet the requirements of different turnout specifications, line standards, and locations. It is important to note that components such as the motor, retarder, throw slide, and detection slide need to be configured with specific parameters in order to meet the switching requirements and reliability demands of different turnouts. More accurately, the throwing force is affected by the turnout weight and the number of drives, the stroke of the switching point determines the length of the throw slide and detection slide, the selection of protection performance depends on the working environment, and the reliability requirements influence on the locking mode. Moreover, high-speed lines requiring more than one machine per turnout (“multiple drive” solutions) are common.

3. Condition Monitoring and Fault Detection

3.1. Common Failure Modes

The common failure modes along with their effects, and safety impacts are summarized in Table 2. Specifically, the table lists various parts, including the actuator, drive mechanism, switch circuit controller, throw slide, detection or locking slide, and housing. Each part is associated with potential failure modes such as short circuits, aging, wear and tear, mechanical fracture, deformation, and jams. The table describes the effects of these failure modes on the railway system, including reduced operational efficiency, inability to move the turnout, and potential train derailment. Safety impacts are evaluated for each failure mode, with ratings such as "No" (indicating no significant safety impact), "Possible" (suggesting a potential safety impact that needs monitoring), "Hardly" (implying minimal safety impact), and "Yes" (indicating a significant safety impact).

Table 2. Common failure modes of point machines and their effects.

No.	Part	Failure Mode	Effect	Safety Impact
1	Actuator	Short circuit or open circuit	Unable to move the turnout	No
		Aging	Reducing operational efficiency	No
2	Drive mechanism	Wear and tear, slight deformation & jam (increased resistance)	Reducing operational efficiency	No
		Mechanical fracture, significant deformation & complete jam	Unable to move the turnout	No
3	Switch circuit controller	Wear and tear, slight deformation & jam (increased resistance)	Reducing operational efficiency	No
		Mechanical fracture, significant deformation & complete jam	Unable to move the turnout/train derailment	Possible
		Short circuit or open circuit	Unable to move the turnout	Hardly
4	Throw slide	Wear and tear, slight deformation & jam (increased resistance)	Reducing operational efficiency	No
		Mechanical fracture, significant deformation & complete jam	Unable to move the turnout/train derailment	Possible
5	Detection or locking slide	Wear and tear, slight deformation & jam (increased resistance)	Reducing operational efficiency	No
		Mechanical fracture, significant deformation & complete jam	Train derailment	Yes
6	Housing	housing damage	Reducing operational efficiency/unable to move/train derailment	Low

It is crucial to detect all types of faults, as fault detection is instrumental in improving the level of intelligence of railway operations and optimizing their efficiency. However, in practical railway operations, different railway companies may adopt varying maintenance strategies based on their financial resources, tolerance for fault-related risks, and the potential risks associated with specific faults. For instance, on busy urban transit lines, faults that impact operational efficiency may require immediate attention, while those with minimal operational impact may be addressed based on established maintenance schedules. On less busy rail lines, even faults with operational impact may not necessarily require immediate action, and can be managed based on the prevailing circumstances.

3.2. Monitored Parameters

Parameters monitoring is a foremost requisite for fault detection in point machines. Over the years, railway signaling scholars and engineers have identified a set of signals to inspect their condition [7]. Table 3 summarizes the vast majority of these monitored devices and parameters. The highest-priority variables are the electric motor, the gap, and the parameters relating to the whole machine. Other monitoring devices can be added depending on extra needs. Oil pressure and level and pneumatic pressure need to be measured on electro-hydraulic and electro-pneumatic point machines.

Table 3. Currently popular parameters for condition monitoring of point machines and their components.

Monitored Devices	Monitored Parameters	Type of Point Machines
Motor	Current, voltage, power, speed, torque	All motor-driven point machines
Gap	size	All
Throw rod	Throwing force, displacement, position, speed	All
Indication/detection rod	Displacement, position, speed	All
Locking rod	Gap size, locking depth, locking force	point machines equipped with internal locking devices
External locking devices	Gap size, locking force	point machines armed with external locking devices
The whole machine	Switching resistance, sound, vibration, temperature humidity, throwing time, change of movement direction	All
Switch circuit controller	Contact depth, rotation angle, contact pressure, contact resistance, opening thickness of stationary contact, thickness of movable contact ring, angular displacement/real-time angle/ angular velocity of movable contact	Most of point machines made and used in China (ZD6, ZD(J)9, ZYJ7, ZK4)
Hydraulic device	Oil pressure, oil level, electro valve	Hydraulic transmission type point machines
Pneumatic device	Pneumatic pressure, electro valve	Pneumatic transmission type point machines

1. **Motor-related parameters.** Studies have revealed that the switching resistance best reflects the condition of the point machine [2,3,8]. However, real-time and reliable switching resistance measurement is not easy to achieve; motor-related parameters are an alternative, as the energy provided by the motor overcomes the resistance between movable parts and the track bed during the switching process. In other words, whether the motor operating parameters are normal or not when there are no faults with the motor is consistent with whether the switching resistance is normal or not. Therefore, the motor current, voltage, and power are extensively monitored in actual condition monitoring. In contrast, the motor output speed and torque are rarely employed in actual railway operation due to the difficulties involved in sensor installation.
2. **Gap-related parameters.** The gap between the lock/detection slide notch and the edge of the lock/detection hammer notch in a point machine is considered an indirect measurement of the gap between a switch point and its adjacent stock rail in the closed position, which is a crucial safety parameter for monitoring the condition of a turnout.

Too large a gap may cause disastrous consequences, such as train derailment, human injury, and severe damage to both infrastructure and the environment [9,10]. Because the sensor is installed beside the rails at a point where the train wheel sets often pass through, the direct measurement method results in low reliability. At present, alarms based on a threshold gap are widely used in the railway field [11].

3. **Whole-machine-related parameters.** Recently, sound and vibration signals during point machine operation have gained attention for fault detection [12,13]. While the throwing time and in-machine temperature have been monitored traditionally, they are less commonly considered for fault detection.
4. **Other parameters.** Fault detection based on other parameters is largely absent, as it is not easy to deploy real-time online monitoring sensors, particularly the switch circuit controller. Nonetheless, these parameters can be beneficial for on-site operations and maintenance.

3.3. Fault Detection in Point Machines

Fault detection is synonymous with anomaly or outlier detection in data science. It serves as the initial step in determining the occurrence of a fault, leading to further fault diagnosis and analysis. Broadly, fault detection for point machines involves identifying abnormal behaviors, including functional failures and parameter deviations. Unlike fault diagnosis, which aims to identify specific fault modes, fault detection focuses on detecting unpredictable or uncertain events and distinguishing between normal and abnormal conditions. Fault detection is crucial in compensating for the limitations of fault diagnosis, particularly in data-driven methods during the training phase. This is because new and unexpected events can occur as operating and environmental conditions change. In railway scenarios, normal data are predominant, while abnormal data are scarce and diverse. Early attempts to monitor point machine conditions using simple threshold techniques were limited by false alarms and missed failures [3].

Therefore, fault detection plays a pivotal role in the intelligent operation and maintenance of point machines, especially considering the scarcity of model-based fault detection studies [14,15] in this field. Thus, in this section we primarily review the data-driven methodologies.

3.3.1. Statistical Analysis-Based Methods

Fault detection methods based on statistical analysis for point machines involve creating Probability Density Functions (PDFs) for normal samples or their characteristics. By applying a defined confidence interval, it identifies samples falling outside this population as anomalies using the established PDF. These methods can be categorized into parametric and nonparametric approaches.

Parametric approaches typically select a distribution model or create a statistical variable based on experience. They then estimate unknown parameters of the PDF or the statistic variable using randomly selected samples from the population [16]. For example, Adachi et al. [17] employed a t-test and normal distribution for point machine fault detection based on the power parameter. However, this method depends on distribution assumptions, limiting its generalization.

Nonparametric methods, on the other hand, conduct statistical tests and judgment analysis directly based on known category samples without assuming a specific distribution or parameters. This allows the data to determine the shape of unknown functions [18]. For instance, Finket et al. [19] used Multivariate Kernel Density Estimation (MKDE) to assess the PDF of resistance characteristics. While this approach is suitable for cases with no information about the data distribution, it can be complex to optimize hyperparameters and kernel functions, potentially impacting detection performance. Nonparametric tests may require larger sample sizes for similar confidence levels compared to parametric tests.

Overall, statistical analysis-based methods offer a strong theoretical foundation and simplicity, although they may have limited generalization performance, as thresholds may require adjustment in different operational environments.

3.3.2. Proximity-Based Methods

Proximity, often referred to as similarity, measures the closeness between a test sample $\boldsymbol{x} = (x^1, \ldots, x^i, \ldots, x^n)^{\mathrm{T}}$ and several examples of the normal condition $\mathbb{T}$. Figure 4 illustrates how proximity-based approaches to point machine fault detection function. By computing the proximity S_t between $\boldsymbol{x}$ and $\boldsymbol{T}_t$ $(t = 1, \ldots, N)$, with N being the number of normal templates, the sample $\boldsymbol{x}$ is classified as normal if the lowest S_t (represented by S_{t^*}) surpasses a predefined threshold.

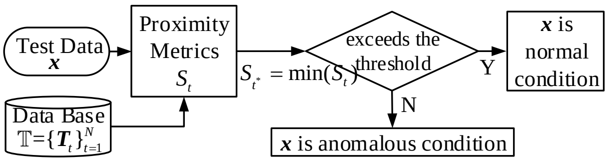

Figure 4. Process of proximity-based methods of point machine fault detection.

For parameters with unequal lengths, such as throwing force, current curves, and power profiles, Dynamic Time Warping (DTW) [20] and its variants [21,22] are the go-to metrics for aligning time series data. Additionally, distribution similarity methods are gaining popularity, including the Mahalanobis distance, mutual information, cross-entropy, Kullback–Leibler divergence, Hellinger distance, and earth mover's distance (Wasserstein distance), as they can model monitored signals as PDFs.

García et al. [23] and Pedregalet et al. [24] used harmonic regression to predict the next movement current curve of an M63 type point machine, then compared it with the actual sensor data to identify anomalies. Mistry et al. [25] applied the fast Fourier transform to extract frequency domain features from current signals and detect anomalies based on linear correlations. Li et al. [26] introduced a density-based approach using the Local Outlier Factor (LOF) to quantify abnormality degrees, while the iForest technique [27] considers anomalies as sparse points far from dense clusters. Guzman et al. [27] created a temperature-based anomaly detection binary tree forest, identifying points with shorter path lengths as outliers, which is suitable for small datasets. Li et al. [26] explored angle-based outlier detection, which is suitable for high-latitude data.

In summary, proximity-based methods in point machine fault detection do not necessitate a plethora of fault samples or complex feature extraction from raw data. However, they require manual threshold adjustments and can be computationally intensive as data dimensionality increases. Furthermore, their accuracy and robustness are somewhat limited due to their reliance on predefined thresholds.

3.3.3. Supervised Learning-Based Methods

Supervised learning approaches for point machine fault detection involve training a detector or classifier based on available data and using it for inference. These methodologies can be categorized into One-Class Classification (OCC) and Binary Classification (BC).

OCC addresses scenarios where negative class (abnormality) data are absent, poorly sampled, or poorly defined [28]. OCC algorithms aim to classify positive cases without well-characterized negative cases [29]. Common models include Support Vector Data Description (SVDD) and One-Class Support Vector Machine (OCSVM). For instance, SVDD creates a hyper-sphere around normal samples in pattern space to distinguish normal and abnormal observations [30,31]. SVDD-based fault detection for point machines has a good effect on the unbalanced data set of normality and abnormality; however, the hyperparameters and the nonlinear mapping function must be determined manually. OCSVM seeks a hyperplane farthest from the origin (or points close to the origin) in the feature space, treating the origin (or points close to the origin) as abnormal [32]. These studies have proven that OCC methods are superior to alarm threshold-based techniques, particularly on unbalanced datasets.

BC involves training a classifier to predict the class label (fault or fault-free) based on the provided dataset. Support Vector Machine (SVM) [33–36], Gaussian Naive Bayes (GNB) [37], and Convolutional Neural Networks (CNNs) [37,38] are among the models used for BC-based fault detection in point machines. SVMs create hyperplanes to separate data classes, while GNB and CNNs leverage various features such as current curves and audio signals to classify normal and abnormal conditions.

While BC models can perform fault detection in point machines, they often underperform compared to OCC approaches due to the heterogeneity of fault patterns and imbalanced data sets. Effective BC models require ample fault data for training, which can be time-consuming to acquire. Additionally, these models may lack interpretability.

3.3.4. Unsupervised Learning-Based Methods

Railway operators have collected vast amounts of data from point machines over the years. While supervised learning has been useful, it has limitations when dealing with large amounts of unlabeled data. Unsupervised learning methods such as Generative Adversarial Networks (GANs) and Autoencoders (AEs) have emerged as powerful tools for anomaly detection [39,40] in such scenarios.

GAN-based approaches create two models, a generator and a discriminator; the generator produces realistic normal examples, while the discriminator distinguishes real from fake data. These models achieve equilibrium through a competitive training process, with the generator creating plausible examples and the discriminator verifying whether or not a sample is normal. For example, Xue and Gao [41] used a 1D-CNN GAN model to detect point machine faults even with limited abnormal data.

An AE is a neural network that learns efficient representations of data. It consists of an encoder and a decoder along with a bottleneck layer that compresses data. AEs minimize the reconstruction error between the input and output, thereby serving as an anomaly score. In point machine fault detection, AEs are typically trained solely on normal observations; they excel at reconstructing normal data, while they struggle with anomalies. Fault detection hinges on measurement of the reconstruction error, which acts as an indicator for spotting anomalies or failures [42]. For instance, Guo et al. [43] proposed an AE-based scheme for point machine fault detection, achieving better performance than other methods. Subsequently, Guo et al. [44] introduced a Deep AE (DAE) algorithm that combines normal and faulty data to improve detection. Zhuang et al. [45] used Deep Denoising AE (DDAE) for feature extraction and DBSCAN for clustering. This approach achieved an accuracy of 98.67% with 0% missed alarms and a low false detection rate (1.33%) on a dataset with 300 test samples.

Guo et al. [46] proposed a multi-stage anomaly detection approach to address the three challenges of large amounts of labeled data, multiple unknown modes of normal current curves due to the individual difference, and the small number of samples available for certain modes. Their approach involved clustering, threshold estimation, and transfer learning, and demonstrated superior fault detection accuracy. An experiment conducted on a test set containing 350 normal three-phase curves and 150 faulty three-phase curves indicated a 0% missed detection rate and false alarm only rate of 2.37% on the part of the proposed model.

In addition to GANs and AEs, other methods have been explored for fault detection, including Growing Neural Gas (GNG) and combinations of AE, Self-Organizing Maps (SOMs), and K-means clustering [19,47].

In brief, these unsupervised learning methods are particularly suitable for scenarios where abnormal data are scarce, making them valuable tools in the railway industry. However, their performance may not match supervised learning methods with ample anomalous observations.

3.3.5. Semi-Supervised Learning-Based Methods

In the context of point machine fault detection, both supervised and unsupervised learning methods have limitations. Supervised learning relies on labeled data, which can be expensive and time-consuming to acquire. Unsupervised learning methods might not perform optimally in certain situations. Semi-supervised learning [48] is a solution that combines the strengths of both approaches by utilizing both labeled and unlabeled data. Semi-supervised learning allows all available data to be leveraged, including cases with abundant unlabeled samples and a small amount of labeled data, without the need for extensive manual annotation or sacrificing accuracy. The key idea is to treat samples differently based on whether or not they have labels. Labeled data are used for traditional supervised learning and to update the model weights. Unlabeled data, on the other hand, help to minimize prediction differences between similar training examples.

For example, Ham and Han [49] applied a semi-supervised SVM to enhance point machine fault detection. Their S3VM model leverages both both labeled and unlabeled samples, resulting in higher accuracy. Shi et al. [50] introduced Positive and Unlabeled (PU) learning, a subfield of semi-supervised learning, to improve point machine fault detection based on current signals. They developed a novel biased SVM detector that uses the Chebyshev distance to minimize the farthest distance between the samples and the hyperplane.

Semi-supervised learning methods blend labeled and unlabeled data to enhance fault detection performance. However, their effectiveness relies on certain assumptions about the data distribution, and they may not perform well if the labeled samples do not adequately represent the entire distribution. Additionally, they lack reliable ways to choose the hyperparameters.

3.3.6. Evaluation Metrics

Evaluation metrics are designed to assess the performance of a fault detection model on the test set, and include the Accuracy (Acc), Precision (P), Recall (R)/True Positive Rate (TPR), $F_\beta - score$, False Alarm Rate (FAR)/False Positive Rate (FPR), Missed Detection Rate (MDR)/False Negative Rate (FNR), Precision–Recall (PR) curve, Receiver Operating Characteristic (ROC) curve, and Area Under the ROC Curve (AUC) [51,52].

(a) The Acc is generally not the most efficient metric for point machine fault detection due to the presence imbalanced data where normal instances greatly outnumber faulty instances. High Acc can be achieved by simply predicting the majority class (normal instances) without effectively detecting faults.

(b) P is quite important for point machine fault detection. It ensures that when the model predicts a fault, it is more likely to be correct. In the context of railway operation and maintenance, high P helps to reduce unnecessary interventions and maintenance.

(c) R is crucial for point machine fault detection. It indicates the ability of the model to capture actual faults among all the true faulty instances. In railway systems, high R means that the model is effective at identifying faults, thereby minimizing the risk of missing genuine problems that could impact railway safety. The R value should ideally verge on or even reach 100%.

(d) The F_β metric balances P and R, making it particularly useful when the class distribution is imbalanced. In point machine fault detection, maintaining a balance between correctly identifying faults and minimizing false alarms is essential; F_β helps to achieve this balance. β ($\beta > 0$) measures the relative importance of R to P. When $\beta = 1$, then F_β degenerates into the harmonic mean F_1. If $\beta > 1$, then R has a larger influence. If $\beta < 1$, then P dominates. In the field of point machine fault detection, it is typical to pay more attention to R.

(e) FAR reflects the rate of false alarms among all predictions. It is important to keep FAR low in order to avoid unnecessary maintenance actions and ensure efficient railway operations. In point machine fault detection, the value of FAR should ideally be kept very low and controlled within an acceptable range.

(f) MDR represents the rate of missed detections. Reducing MDR helps to ensure that real faults are not overlooked, thereby minimizing safety risks. In point machine fault detection, MDR should be low within an acceptable value or even reach zero; to achieve the latter case, the model has to detect all the abnormal conditions, particularly those fault modes with harmful repercussions.

(g) The PR and ROC curves both provide insight into the performance of a model across different operating points. They can help to find the optimal balance between between P and R. In point machine fault detection, if a detector's PR curve wholly covers another PR curve, then the enclosed one is inferior. If two PR curves intersect, the F_{β} index could be an alternative. It should be noted that the PR curve is more likely to fit balanced observations between each class and that ROC curves are sensitive to balanced datasets.

(h) The AUC reflects the model's ability to distinguish between faulty and non-faulty instances. In point machine fault detection, a higher AUC indicates better overall performance in identifying true faults while maintaining a low false alarm rate.

In point machine fault detection, F_{β}, FAR, MDR, PR curves, ROC curves, and AUC are efficient metrics to focus on. Overall, the relationships among these metrics helps in making informed decisions to ensure the safety and efficiency of point machines. It should be noted that these evaluation metrics indicate the performance on the test set, meaning that they cannot be used to verify the performance of models in actual industrial applications unless the distribution of the test samples is consistent with that of observations from the real application scenario.

4. Analysis of Point Machines and Monitoring Systems

While there is a considerable body of research on point machine fault detection, the majority of previous studies focused solely on implementing data-driven models on collected data and have often neglected to consider the requirements of condition monitoring and fault detection system of point machines, particularly data-driven algorithms.

In order to describe the requirements for a point machine fault detection system, we start with the requirements, inherent features, and external impacts of point machines.

4.1. Requirements for Point Machines

1. **High safety and reliability** . Because point machines drive the turnout, which is the crucial section of railway track, they involves the operational safety of trains. Any hardware device or software installed in point machines should be reliable and trustworthy, including the sensors, supporting signal processing, and monitoring procedures.
2. **Long service life**. Point machines are designed and manufactured with a focus on a lengthy service life, as replacing the entire machine that works along the trackside requires time and money. Therefore, providers can guarantee high quality, with suppliers typically claiming more than one million throwing movements before machine overhaul.

4.2. Inherent Features for Point Machines

1. **Electro-mechanical**. A point machine is a typical mechanical or electro-mechanical device; it is often driven by an AC or DC motor, and outputs the displacement of the throw slide with the aid of mechanical drive mechanisms. In addition, its structure is non-redundant, that is to say, each component is indispensable to realization of the point machine's required functions.
2. **Limited space**. The majority of point machines are tailored products. Limited space is a basic attribute, as they need to be convenient for transportation and maintenance. This advantage, however, means that there is limited remaining space inside the point machine, making it challenging to fix and to a certain extent relying on sensing units to determine maintenance needs.
3. **Complexity**. The electro-mechanical components make a point machine's structure complex, comprising many mechanical, electrical and even hydraulic or pneumatic

items that can potentially cause diverse fault modes. The include single faults, compound faults, intermittent faults, and NFF (no fault found) failures. Furthermore, the constituent parts can vary quite considerably in terms of their failure probability, and these failure probabilities are normally very low. As a result, gathering all possible fault data is extremely difficult.

4. **Variety**. Point machines come in three main types: electro-mechanical, electro-hydraulic, and electro-pneumatic [53,54]. Each type has unique parameters. For example, electro-mechanical point machines focus on throwing force and motor power, while electro-hydraulic ones mainly consider the hydraulic system pressure. Second, these three types have different failure mode distributions. Electro-mechanical point machines commonly experience wear and transmission component fractures, electro-hydraulic ones are prone to oil leakage, and electro-pneumatic ones often face pneumatic subsystem-related issues.
   Furthermore, various subtypes exist within each type to meet specific turnout requirements. These subtypes can vary in their motor type, output force, length and displacement distance of the throw slide detection slide, locking mode, etc. For instance, the China Railway Signal and Communication Corporation produces over forty specific subtypes of the ZDJ9 electro-mechanical point machine; among these, the throwing force range is between 2.5 kN and 4.5 kN, the displacement distance of the throw slide ranges from 80 mm to 220 mm, and the same figure for the detection slide varies from 75 mm to 170 mm. It should be noted that these slight discrepancies need to be taken very seriously.
5. **Individual differences**. Even within a subclass, there may be non-negligible differences in point machines due to production errors. More significantly, differences may result from external factors such as action frequency, ambient temperature and humidity, electromagnetic interference, and train impacts with varying speeds. As a result, the switching resistance between individual machines can very. This variation in the duration of point machine movements exists within a specific range. It is important to recognize that every individual point machine has its own unique behavior due to slight individual differences and diverse external impacts.

4.3. External Impacts for Point Machines

1. **Rolling stock and operational planning**. The complete structure and compliant dimensional parameters of the turnout determine the safe and reliable passage of trains. Deviation of the geometry or component damage of a turnout may make the point machine unable to work normally, e.g., rail creeping, alignment of switch rails, and rail wear. Train passage through turnouts can generate significant impact loads, especially during wheel–rail transitions in the switch and crossing zones, resulting in high vertical and horizontal loads [55]. In [56], a numerical investigation reported maximum lateral displacements of up to 5 mm and variations of up to 8 mm in high-speed rail. Table 4 shows the vertical displacement of CRH2 EMU after passing through the turnout at a speed of 250 km/h. In fact, the extent of displacement depends on the condition of the point machine, track, and traffic characteristics such as the speed, axle load, and train formation. Operation plans, including train passing frequencies, influence geometric parameters and turnout frame integrity. Train-related events, encompassing rolling stock and operation plans, provide essential insights into the mechanical system's stability.
2. **Service environment**. Point machines operate in diverse service environments influenced by geographical factors such as location, latitude, longitude, and ocean currents. These environments can range from extreme heat during the day to sharp temperature drops at night. For instance, Chinese railway regulations require point machines to function in temperatures ranging from −40 °C to +70 °C. A prime example are the CTS2 point machines installed on the Qinghai–Tibet Railway, which operate in cold high-altitude areas.

In certain cases, railways traverse challenging environments, such as the Saudi Arabian Railway across desert terrain known for its harsh climate and abrasive sand and wind. Polar regions with heavy snowfall pose challenges for point machines as well. Despite implementing protective measures, extreme climates can accelerate performance degradation. Additionally, point machine adjustments made at night may become inaccurate during the day due to changing conditions.

Table 4. Vertical displacement after CRH2 EMU passing through the turnout at a speed of 250 km/h [57].

China Technical Turnout in Wuhan-Guangzhou Test Section		German Technical Turnout in Wuhan-Guangzhou Test Section		French Technical Turnout in Hefei-Nanjing Railway	
Sleeper No.	**Vertical Displacement**	**Sleeper No.**	**Vertical Displacement**	**Sleeper No.**	**Vertical Displacement**
10	0.62 mm	−3	0.84 mm	−3	0.33 mm
28	0.76 mm	10	0.46 mm	13	0.37 mm
37	0.65 mm	27	0.99 mm	27	0.1 mm
47	0.44 mm	44	0.96 mm	50	0.56 mm

4.4. Requirements for Point Machines Condition Monitoring & Fault Detection System

Considering the Requirements (Req.), Inherent Features (IF), and External Impacts (EI) of point machines and the characteristics of data-driven algorithms, we have identified eight requirements for point machine fault detection algorithms. These requirements are essential for the development of an intelligent point machine fault detection system as outlined in Table 5.

1. **Req. 1: Trustworthiness.** Any software and hardware equipped with point machines should be trustworthy. Data-driven models, while achieving impressive results, pose difficulties in terms of understanding their internal mechanisms, as most data-driven models function as "black box" models. However, commercialization necessitates clear explanations about how the models learn, what knowledge they acquire, their decision-making rationale, and the level of trustworthiness they offer. Hence, it is highly recommended that point machine fault detection systems be built on a trustworthy foundation, including both software and hardware. The most important thing is to ensure the interpretability of AI models and the trustworthiness of their outcomes.
2. **Req. 2: Handling multi-source data.** Because a single modality provides incomplete insights into the overall condition of point machines [7], even though the force and the current and power signals can best reflect the point machine's states [2,3], it is highly suggested that point machine fault detection systems effectively integrate data from various sensors in order to comprehensively monitor the state of point machines in terms of Req. 1 and IF 1 of point machines. In addition, certain special scenarios such as sensor failure and parameter offset need to be considered.
3. **Req. 3: Designing and deploying sensors.** Due to the Req. 1, IF 2, and EI 2, reliable, high-accuracy, compact, and interference-free sensors should be favored in point machines, particularly non-intrusive and "plug and play" (easily and quickly interchangeable) types. Thus, it is highly recommended to design suitable sensors and to use a reasonable layout.
4. **Req. 4: Handling imbalanced data.** In light of IFs 3 and 4, practical point machine fault detection problems face extremely imbalanced datasets (i.e., with over 99% normal samples and less than 1% abnormal). Furthermore, abnormal data contain a variety of fault types. Because imbalanced datasets are detrimental to model training for data-driven methods [58,59], leading to bad performance on fault detection, this is an urgent and critical requirement.

5. **Req. 5: Handling unseen and complex fault modes.** Rethinking IFs 3 and 4 of point machines, there are theoretically a number of different fault types for point machines. It is almost impossible to gather all the fault data, as not all faults occur during real operations, especially for new railway lines without historical data. Despite this, unrecorded or unseen faults can affect the determination of the classification boundary between normal and abnormal data. As a result, it is suggested that the system be able to handle both unseen and complex fault modes, even though this is a difficult task.
6. **Req. 6: Handling part-level fault modes**. Considering IF 4 of point machines in combination with the literature survey, electro-pneumatic point machines, which are commonly used in turnout areas and marshaling yards, have received limited attention from researchers. Moreover, scholars have overlooked fault detection for specific parts, such as the retarder, throw rod, and switch circuit controller [60]. However, every part within a point machine is crucial, as all lack redundancy. Previously, researchers have mistakenly taken the current, power, or other condition monitoring parameters as an overall performance indicator for point machines. To enhance precision, there is a need to shift focus towards detecting faults at the part level, such as hydraulic cylinders [61] and bearings [62] under daily loads.
7. **Req. 7: Universality, generalization, and robustness**. Based on IFs 4 and 5 and EIs 1 and 2, developing a model with high universality, generalization, and robustness is recommended. More precisely, a highly universal model can operate on different types and models of point machines without the need for individual model training in each case, which reduces the costs of system deployment and maintenance while allowing the model to be used across a wider railway network. Strong generalization capabilities imply that the model performs well even when facing new and previously unseen fault patterns or environmental conditions. In addition, a robust model maintains stable performance when dealing with noise, interference, sensor failures, and changes in environmental conditions. This means that the model can reliably perform fault detection even in complex real-world operating environments, thereby reducing the FAR and MDR.
8. **Req. 8: Maintaining fault detection performance over time.** Considering Req. 2, IFs 4 and 5, and EIs 1 and 2, more and more observations (e.g., unanticipated fault modes, numerical accumulations) need to be collected throughout the whole life cycle of a point machine while accounting for the changing service environment and imposed time-dependent operation plans. Hence, it is of great importance to ensure that the fault detection model remains effective over time until it can be replaced with a new one.

Table 5. Requirements for condition monitoring and fault detection systems.

Point Machines			Condition Monitoring & Fault Detection System		
Req.	**IF**	**EI**	**Req.**	**Difficulty**	**Suggested Priority Level**
1			Trustworthy	Hard	High
1	1		Handling multi-source data	Easy	High
1	2	2	Designing and deploying sensors	Moderate	High
	3, 4		Handling imbalanced data	Moderate	Critical
	3, 4		Handling unseen and complex fault modes	Hard	Medium
	4		Handling part-level fault modes	Moderate	Medium
	4, 5	1, 2	Universality & generalization and robustness	Moderate	Medium
2	5	1, 2	Maintaining fault detection performance over time	Hard	Medium

5. Urgent Problems and Challenges

The introduction of sensor and computer technologies has undeniably propelled the field of point machine fault detection forward. However, it is noteworthy that the majority of research efforts have primarily fixated on enhancing accuracy by employing increasingly complex models. To achieve a trustworthy and robust point machine fault detection system with high generalization and transferability, it is imperative to delve deeper into key performance metrics such as F_β, FAR, and MDR, along with the detailed requirements outlined for intelligent point machine condition monitoring and fault detection systems in Section 4.4.

In essence, the goal is to develop an intelligent and dependable fault detection algorithm for point machines that possesses the capacity to identify faults across diverse point machine types throughout their entire life cycle and under various operational conditions. It is important to acknowledge that significant strides are required before these advancements can find practical applications within the railway industry. To this end, we present a set of urgent problems and challenges for consideration.

Challenge One: Ensuring Trustworthiness of Point Machine Fault Detection Algorithms. Considering Req. 1, in most cases it is necessary to evaluate the reliability of data-driven point machine fault detection algorithms, as most data-driven models function as "black box" models. In certain specific railway signaling control systems, point machine fault detection algorithms must be independently certified to a SIL2∼4 safety integrity level by a third-party safety assessment of globally renowned organizations, such as TüV Rheinland and CRCC, because the status of the point machine requires feedback to the control system, thereby affecting the release of train routes. Therefore, the issue becomes more pronounced when transitioning from research into practical applications. Consequently, an exciting and rapidly changing research direction called trustworthy artificial intelligence [63–65] has sprung up. Keeping abreast of the latest developments [66,67] in this field is paramount in endeavoring to enhance the trustworthiness of point machine fault detection algorithms.

Challenge Two: Integrating Diverse Sensor Data for Point Machine Fault Detection. Regarding Req. 2, an array of sensors including current, force, voltage, power, motor speed, motor torque, temperature, resistance of contacts, displacement of the operating rod and indication rod, vibration, strain, audio, tension and 2D/3D measurement sensors has been contemplated [2,52,68,69]. Obviously, reasonably deploying these transducers and fusing the mass signals becomes a problem. Moreover, point machine fault detection research based on multi-source data fusion has not yet provided solutions, especially in cases of incomplete data (i.e., sensor failures). Hence, there exists a promising path for researchers to explore multisensor data fusion technology [70,71] for more reliable and precise fault detection.

Challenge Three: Designing and Deploying Sensors for Point Machine Monitoring. Considering Req. 3, it is not easy to ensure continuous and online monitoring of specific parameters (e.g., throwing force, operating resistance, contact resistance and contact wear) in a narrow space in various environments (NF EN 50125-3). Thus, measurement sensing and instrumentation scientists need to design and develop customized sensors for safe and reliable point machine online condition monitoring via new technologies and materials. The layout of the sensing units presents another challenge. This challenge can be effectively tackled by utilizing optimization algorithms that consider trade-offs among cost, fault detection accuracy, and fault detection performance.

Challenge Four: Building Precise Point Machine Fault Detection Models under Imbalanced Datasets. In light of Req. 4, the issue of data imbalance urgently needs to be addressed. The following solutions can be considered. (1) Data Expansion: expanding data is the most effective; however, it is not simple, as fault occurrences are not frequent. It is recommended that railway operators build a cloud platform for data sharing, with a leader collecting comprehensive data and providing members with pretrained models [72,73]. In this way, robust and precise fault detection for point machines be achievable after finetuning the pretrained models. If the data need to be kept secret, then Federal Learning (FL) [74,75] is one way to handle the issue. FL allows all the participants (i.e., railway operators) to jointly train a federal model without sharing data, which represents a good choice under the data privacy mechanism. (2) Data Augmentation: a possible solution is to adopt data augmentation techniques [76] such as undersampling, the Synthetic Minority Over-sampling Technique (SMOTE), GANs, and meta-learning [77] to increase the number of abnormal datasets or optimize neural networks to conduct neural augmentation [78,79]. (3) Weight Adjustment: reasonably adjusting the weights of rare samples is a prevalent approach when using traditional deep learning approaches.

Challenge Five: Enhancing Fault Detection Models for Unseen and Complex Fault Modes. With regard to Req. 5, in order to fulfill this difficult requirement, three possible solutions are put forward: (1) Lab tests and computer simulations offer onee solution, though they may not perfectly mimic real-world conditions, while Transfer Learning (TL) techniques [80,81] can aid in adapting models from lab settings to real service environments; (2) Zero-Shot Learning (ZSL) [82] can help to identify previously unseen cases; and (3) combining prior knowledge and mechanism models can significantly enhance fault detection, particularly for compound faults, intermittent faults, and NFF failures, which are extensively common during practical operation.

Challenge Six: Achieving Part-Level Point Machines Fault Detection. In view of Req. 6, inspecting these parts of a point machine is not an easy task, as discussed in the Challenge Three above. If Challenge Three can be resolved, this related challenge will be easily overcome via learning.

Challenge Seven: Enhancing Universality, Generalization, and Robustness in Point Machine Fault Detection Models. Considering Req. 7, to address this challenge, a fault detection model for point machines can be trained on an extensive dataset encompassing various types of point machines operating in different environmental conditions. Another method is to use TL techniques for building transferable models. Furthermore, developing algorithms that dynamically adjust fault detection thresholds based on external factors is essential for practical operational success.

Challenge Eight: Maintaining Fault Detection Performance Over Time. With regard to Req. 8, the model should learn newly accumulating data in order to update and renovate itself over time. One seemingly feasible way to achieve this is to retrain the model on a combination of historical datasets and a newly acquired dataset whenever model updating is required. This demands a large amount of hard disk space to store all historical data, and can encounter the "catastrophic forgetting" problem, in which a retrained model forgets knowledge learned from older data and its performance on old data is greatly reduced. To handle this, it is possible to consider strategies such as Incremental Learning (IL), Continuous Learning (CL), and Lifelong Learning (LL) [83,84], which allow models to adapt to new data without forgetting valuable insights from the past.

6. Blueprint

The eight critical issues and challenges highlighted above are likely to shape future research into intelligent point machine fault detection for railway applications. Addressing these problems is essential for the successful implementation of this technology in the railway industry. We urge scholars to share their datasets openly, and encourage railway industry leaders to collect comprehensive observations and make them accessible to the research community.

Below, we propose a blueprint for intelligent point machine fault detection, shown in Figure 5. This architecture, referred to as "center–edge–terminal," leverages cloud computing, edge computing, and advanced AI algorithms [85] to create a distributed fault detection system for point machines. This blueprint is versatile and suitable for various railway scenarios, whether covering extensive regions or smaller areas. More precisely, a good plan for China is to set up a cloud center under the China State Railway Group Co., Ltd. and edge clouds under its subsidiaries. Alternatively, the subsidiary could constructs the cloud center and its affiliated stations and sections could be equipped with edge cloud servers. Similarly, the railway systems of EU countries can refer to this architecture to develop a smart point machine fault detection system.

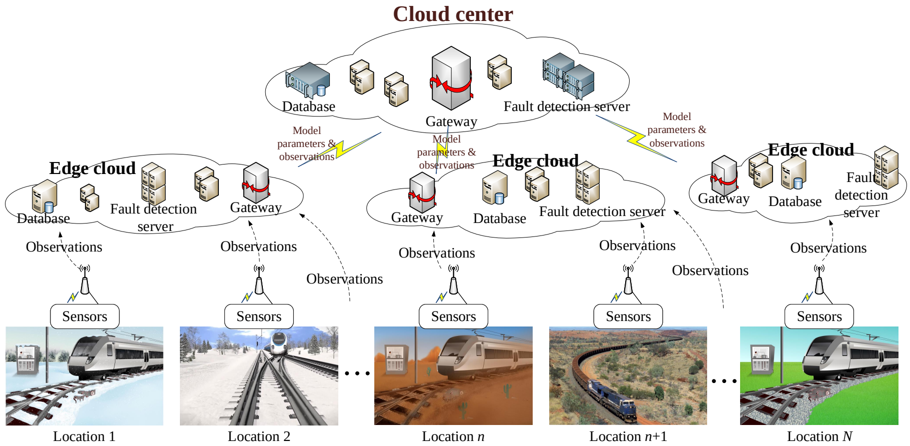

Figure 5. A blueprint for intelligent point machine fault detection.

In the terminal layer, multiple sensors and data fusion techniques are employed to enhance system robustness even in cases of sensor malfunction. Ensemble learning and group decision-making algorithms are utilized to boost performance. In situations where data is scarce, prior knowledge is combined and TL is employed for newly-developed point machines or newly-constructed railway lines. Meanwhile, IL, CL, and LL methodologies can be used to update the models.

The cloud center serves as a hub for aggregating data from monitored point machines. It facilitates the exchange of fault detection model parameters with edge clouds located across different companies, regions, or countries. Data sharing is tailored to suit privacy requirements, with condition monitoring data being transmitted explicitly or model parameters being shared. The regional or global fault detection model undergoes training in the edge clouds or the central cloud center. When the local or global model parameters have been shared and transmitted among terminals and edge clouds, the model can then be customized and updated based on the data it has accumulated. This collaborative pattern solves the problem of data islands and sample scarcity (unbalanced, small, and zero samples) [86] and ensures precise and generalized model performance.

In addition, it is imperative that both the algorithms and hardware within this framework are trustworthy and reliable and that communication channels are secured through encryption. This distributed framework is not limited to point machine fault detection, and can be applied to fault diagnosis for various types of rail transit equipment with similar distributed characteristics.

7. Conclusions

In this article, we have provided a comprehensive review of existing data-driven approaches and evaluation metrics for point machine fault detection. In addition, we have outlined the challenges faced by the intelligent point machine condition monitoring and fault detection system based on a thorough system requirement analysis, and have presented a blueprint for intelligent point machine fault detection.

Several key insights can be concluded from this review:

1. Compared to traditional machine learning, deep learning-based algorithms exhibit the capability to autonomously learn features from massive datasets and efficiently detect faults. Notably, they have demonstrated remarkable potential for point machine fault detection. There is considerable room for further exploration of deep learning in point machine fault detection direction. Moreover, the diverse nature of the relevant datasets mandates flexibility in selecting appropriate fault detection

algorithms. While supervised learning methods excel when abundant labeled data are available, scenarios involving data scarcity or incompleteness can benefit from the utilization of semi-supervised and weakly supervised learning approaches. These techniques make efficient use of limited labeled data and abundant unlabeled data, thereby enhancing model performance. This flexibility empowers practitioners to choose the most suitable method based on the characteristics of the available data, ultimately achieving enhanced fault detection outcomes.

2. Concerning evaluation metrics, the traditional accuracy metric is unsuitable for the imbalanced datasets inherent to the point machine fault detection task. Instead, emphasis is placed on other vital metrics such as the precision, recall, F_1 score, false alarm rate, and missed detection rate. These metrics provide a more accurate assessment of model performance, ensuring precise and reliable fault detection in practical railway applications.
3. In the context of developing an intelligent point machine condition monitoring and fault detection system, it is imperative that the system exhibit trustworthiness, robustness, and a high degree of generalization and transferability. While there are eight essential requirements that need to be addressed, they come with varying degrees of priority. The core essence of most of these requirements is to effectively address the challenges posed by limited training data in diverse and complex operational scenarios.
4. In terms of future directions, the field of point machine fault detection confronts several urgent challenges and opportunities. These encompass the application of trustworthy artificial intelligence methodologies to enhance model safety and reliability as well as the exploration of multi-sensor data fusion techniques to elevate detection precision. Moreover, imbalanced datasets, the presence of unseen and complex fault modes, and the need for fault detection at the device level remain critical challenges that researchers must tackle. Techniques such as data augmentation, transfer learning, and zero-shot learning hold promise for addressing these challenges and building robust models that can effectively detect various fault scenarios. In addition, building fault detection models with high generalization ability is necessary. Models must be capable of adapting to changing environments, accumulating data over time, and maintaining their performance throughout the long service life of point machines.

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