

Article

A Multi-Criteria Decision Framework for Railway Switch Maintenance Prioritization in Urban Rail Systems

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Abstract

This study proposes a multi-criteria decision-making (MCDM) framework for the prioritization of railway switch maintenance in urban rail systems. Railway switches are critical infrastructure components subject to complex operational and structural conditions, making maintenance planning a challenging task. To address this problem, the proposed approach integrates the Analytic Hierarchy Process (AHP) for criteria weighting with TOPSIS and PROMETHEE methods for ranking alternatives. The methodology is applied to real-world data obtained from the urban rail system of Istanbul, Türkiye, including maintenance and failure records of railway switches over the period 2018–2023. Failure frequency is used as a performance indicator to evaluate the consistency of model-based rankings. The results indicate a high level of consistency between model-based and failure-based rankings, with most switches exhibiting only minor ranking deviations across methods. The proposed framework successfully identifies high-priority switches that correspond to those with the highest observed failure frequencies. Observed discrepancies are limited and can be attributed to external operational factors and data limitations. The findings demonstrate that the proposed framework provides a structured and data-informed approach for maintenance prioritization. By integrating multiple criteria with real operational data, the approach offers a practical alternative to conventional time-based maintenance strategies and supports more efficient resource allocation in urban rail systems.

Keywords: railway switch; maintenance prioritization; MCDM; AHP; TOPSIS; PROMETHEE



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1. Introduction

Urban rail systems play a crucial role in providing high-capacity, reliable, and sustainable transportation in large metropolitan areas. With the continuous expansion of these systems, ensuring operational reliability and infrastructure safety has become increasingly important. In this context, maintenance management is a key component of railway system performance, as inadequate maintenance may lead to service disruptions, increased costs, and safety risks [1,2].

Among railway infrastructure elements, switches and crossings (S&C), also known as railway turnouts, are critical components due to their function of enabling trains to change tracks. However, their complex geometry, movable parts, and exposure to high dynamic loads make them more susceptible to wear and failure compared to plain track sections. Previous studies have shown that turnout-related failures significantly affect railway reliability and maintenance costs [3,4].

In practice, railway switches operate under varying conditions depending on factors such as traffic load, operational speed, geometric characteristics, and superstructure type. Therefore, applying uniform maintenance intervals to all switches may not be efficient. Instead, maintenance planning should consider the relative importance and condition of each switch. Recent studies emphasize the need for systematic and data-driven approaches for maintenance prioritization in railway systems [5,6].

Recent developments in railway infrastructure management increasingly focus on predictive maintenance, digital twins, and data-driven decision-support systems to improve system reliability and reduce operational costs [7]. In particular, switches and crossings have been identified as one of the most maintenance-intensive and cost-critical components in railway networks [8]. While advanced analytical and machine learning approaches are gaining attention, many railway operators still require transparent and interpretable decision-support tools for maintenance prioritization.

Multi-criteria decision-making (MCDM) methods provide an effective framework for addressing such complex problems involving multiple and often conflicting criteria. These methods allow the integration of both quantitative and qualitative factors into a structured decision-making process. Among them, the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), and the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) are widely used in engineering and transportation applications [9,10].

Although MCDM methods have been applied in various transportation-related decision problems, studies focusing specifically on railway switch maintenance prioritization in urban rail systems remain limited. Existing studies generally focus on maintenance strategy selection, condition assessment, or predictive maintenance applications, whereas practical decision-support frameworks for prioritizing individual railway switches using real operational data are relatively scarce. Furthermore, comparative applications of different MCDM methods under the same criteria structure and validated against observed failure records are rarely reported in the literature. This gap highlights the need for practical, transparent, and data-informed maintenance prioritization frameworks that can support resource allocation decisions in urban rail systems.

This study aims to develop a multi-criteria decision-making framework for prioritizing the maintenance of railway switches in urban rail systems. In the proposed approach, AHP is used to determine the weights of the evaluation criteria, while TOPSIS and PROMETHEE methods are applied to rank switches according to their maintenance priority. The methodology is implemented using real data from two major urban rail lines in Istanbul, namely the M1 and M2 lines.

The main contributions of this study are as follows:

- Unlike many previous MCDM-based maintenance studies that focus on general railway infrastructure or maintenance strategy selection, this study specifically addresses railway switch maintenance prioritization in an urban rail context.
- The proposed framework incorporates urban rail-specific operational and structural criteria, including traffic load, operating speed, switch geometry, frog material, blade type, and superstructure type.
- The study applies the AHP–TOPSIS–PROMETHEE framework to real-world maintenance and failure records obtained from Istanbul’s urban rail network, thereby enhancing the practical relevance of the approach.
- The model-based rankings are compared with observed failure-frequency rankings, providing a retrospective validation of the proposed prioritization framework.

- The remainder of the paper is organized as follows: Section 2 presents the literature review. Section 3 describes the methodology. Section 4 introduces the case study. Section 5 presents the results and discussion. Finally, Section 6 concludes the study.

2. Literature Review

This section reviews the relevant literature on railway infrastructure maintenance, railway switches, maintenance prioritization, and MCDM applications. The review first discusses the maintenance characteristics of railway switches and then positions the present study within the existing decision-support literature.

2.1. Railway Infrastructure Maintenance and Switches

Railway infrastructure maintenance has been widely studied due to its role in ensuring safety, reliability, and cost efficiency in rail transport systems. Traditional maintenance strategies have evolved from corrective and preventive approaches toward more advanced condition-based and predictive maintenance frameworks [11–18].

Several studies and standards emphasize that railway maintenance should consider both deterioration mechanisms and structured maintenance procedures. Profillidis [11] distinguished between geometric and mechanical deterioration, noting that geometric parameters may deteriorate faster but can often be restored through maintenance, whereas mechanical degradation generally requires component replacement. Maintenance guidelines such as DB Netz AG procedures and DIN 31051 define preventive maintenance around routine maintenance, inspection, and planned interventions [12,13], while Wang [14] classified track maintenance activities into cyclical maintenance, repetitive maintenance, and emergency repair.

Among railway infrastructure elements, switches and crossings are recognized as highly maintenance-intensive and failure-prone components. Hamarat et al. [15] emphasized that switch maintenance strategies are primarily oriented toward failure prevention and are influenced by inspection intervals, track category, resource availability, and infrastructure managers' experience. Due to their structural complexity and exposure to dynamic loads, switches are also susceptible to rolling contact fatigue, plastic deformation, and material degradation [3,19,20]. Previous studies have shown that turnout-related failures can significantly affect railway reliability, maintenance costs, and service continuity [4,21,22].

Recent research has increasingly focused on data-driven and condition-based strategies for switch maintenance. Studies have examined fault diagnosis with machine learning [23], failure mode and effects analysis for urban rail turnouts [24], data-driven monitoring of fixed-turnout frogs [25], accelerometer-based condition monitoring [26], sensor-based monitoring of fixed crossings [27], and deep learning-based visual inspection [28]. These studies show the potential of predictive and condition-based approaches, but many of them focus mainly on fault detection or condition diagnosis rather than practical maintenance prioritization.

2.2. Maintenance Prioritization in Railway Systems

Maintenance prioritization is a key challenge in railway infrastructure management, especially in systems with a large number of assets and limited maintenance resources. Decision-makers must consider safety, operational importance, traffic intensity, failure risk, and cost implications when allocating maintenance resources [29–34].

Several studies have proposed risk-based, performance-based, and condition-index approaches for infrastructure prioritization. These methods typically rely on condition indices, failure probabilities, degradation models, and cost-based analyses to support maintenance decisions [35–38]. For railway switches specifically, Rahmani and Seyed-

hosseini [35] proposed a structural condition index, Patlasov et al. [36] emphasized the need for systematic maintenance decision frameworks, and Wang et al. [37] developed a multi-source data-based turnout service state indicator to support maintenance decisions. However, these studies do not fully address comparative MCDM-based prioritization using real urban rail switch data.

In urban rail systems, where service continuity and operational efficiency are critical, there is a need for decision-support frameworks that are both robust and easy to interpret. Approaches that combine expert knowledge with measurable operational and technical criteria are particularly valuable for maintenance planning, especially when data availability is limited or uncertain [34].

2.3. Application of MCDM Methods in Transportation and Railway Engineering

Multi-criteria decision-making methods have been extensively used in transportation engineering to support complex decision-making processes involving multiple and often conflicting criteria. These methods enable the integration of quantitative and qualitative factors into a structured analytical framework [39,40].

The Analytic Hierarchy Process, developed by Saaty [9], is one of the most widely used methods for determining criteria weights through pairwise comparisons. AHP has been applied in various transportation-related problems, including infrastructure evaluation, maintenance planning, and asset management [40]. The TOPSIS method, introduced by Hwang and Yoon [41], ranks alternatives according to their relative distance from ideal and negative-ideal solutions and is widely recognized for its simplicity and computational efficiency [42].

The PROMETHEE method, developed by Brans and Vincke [10], is based on outranking relationships and allows decision-makers to incorporate different preference functions into the evaluation process. PROMETHEE provides both partial and complete rankings and offers graphical analysis tools such as the GAIA plane, which improves the interpretability of results [43,44].

Recent review studies have highlighted the increasing use of MCDM methods in transportation and infrastructure management applications [45,46]. In railway engineering, MCDM approaches have been applied to component selection, maintenance strategy evaluation, and performance assessment; however, most studies focus on general infrastructure evaluation rather than the specific problem of maintenance prioritization for railway switches.

2.4. Research Gap and Contribution of the Study

Although significant progress has been made in railway maintenance and decision-support methodologies, several important gaps remain in the literature. First, recent studies predominantly focus on predictive maintenance and fault detection using sensor-based, machine learning, or computer-vision approaches, while comparatively less attention is given to practical prioritization of existing assets for maintenance planning and resource allocation in operational environments [23,28,47].

Second, studies specifically addressing railway switch maintenance prioritization through transparent multi-criteria frameworks remain limited. Given the critical role of switches in railway operations and their high maintenance requirements, this represents an important research gap [15,35,37].

Third, comparative analyses of different MCDM methods applied to the same railway switch maintenance problem using identical datasets and criteria weights are relatively scarce. Such comparisons are essential for understanding the strengths and limitations of different decision-making approaches in practical applications.

To address these gaps, this study proposes a comprehensive MCDM-based framework for railway switch maintenance prioritization. The proposed approach integrates AHP for determining criteria weights and applies both TOPSIS and PROMETHEE methods for ranking switches. The use of real-world data from an urban rail system further enhances the practical relevance and applicability of the proposed methodology.

In addition, the study contributes to the literature by focusing specifically on railway switches in urban rail systems, which represent one of the most maintenance-intensive infrastructure components but remain relatively underrepresented in maintenance prioritization studies. Unlike many previous studies that emphasize condition monitoring, fault detection, or maintenance strategy selection, the proposed framework provides a practical decision-support tool for ranking individual switch assets based on multiple operational and structural criteria. Furthermore, the framework is retrospectively validated using observed failure records, allowing the consistency of model-based rankings with actual operational performance to be evaluated.

3. Methodology

This section presents the methodology developed to prioritize railway switches for maintenance. The proposed approach is based on a multi-criteria decision-making framework integrating AHP, TOPSIS, and PROMETHEE methods.

The overall framework of the proposed methodology is illustrated in Figure 1.

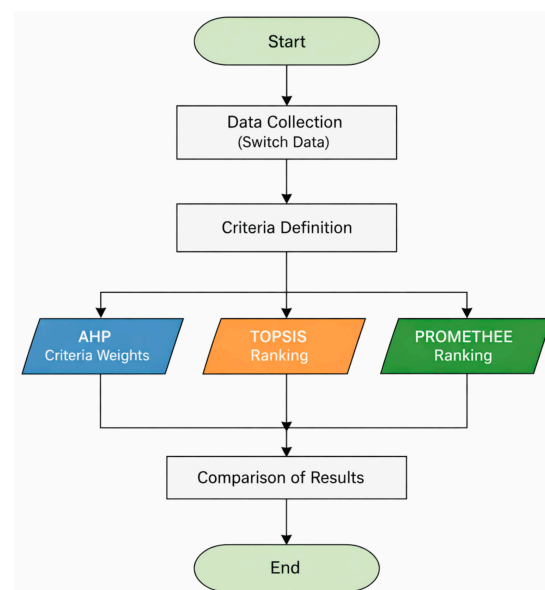


Figure 1. Flowchart of the proposed methodology for railway switch maintenance prioritization.

3.1. Problem Definition and Framework

This study aims to prioritize railway switches for maintenance in an urban rail system. Due to limited maintenance resources and varying operational conditions, uniform maintenance strategies are not efficient. Therefore, a structured decision-making framework is required.

The proposed framework is based on multi-criteria decision-making (MCDM) methods and consists of three main steps:

Determination of criteria and alternatives;

Calculation of criteria weights using the Analytic Hierarchy Process (AHP) [9];

Ranking of alternatives using TOPSIS [41] and PROMETHEE [10] methods.

3.2. Criteria and Alternatives

The alternatives consist of railway switches located on selected urban rail lines. The evaluation criteria were determined based on expert opinions and technical considerations affecting maintenance requirements.

The evaluation criteria were identified through a combination of literature review, expert consultation, and operational practices used in railway infrastructure management. Previous studies on railway turnout performance, maintenance planning, and asset management were reviewed to identify factors influencing switch deterioration and maintenance requirements. In addition, discussions with railway maintenance professionals were conducted to ensure that the selected criteria reflect real operational conditions encountered in urban rail systems.

The criteria include switch type, traffic load, operating speed, geometric characteristics, superstructure type, and material properties. Qualitative criteria were quantified using expert-based scoring on a numerical evaluation scale.

The selected criteria represent both structural characteristics (e.g., switch radius, frog material, blade type, and superstructure type) and operational factors (e.g., traffic load, operating speed, and switch location) that may influence deterioration mechanisms, maintenance needs, and failure occurrence.

3.3. Criteria Weights Using AHP

The Analytic Hierarchy Process (AHP) [9] was used to determine the relative importance of criteria through pairwise comparisons.

The pairwise comparison matrix was developed based on the judgments of five experts, including three railway maintenance engineers from Metro Istanbul and two academics from Istanbul Technical University specializing in railway engineering and transportation systems. The experts had substantial experience in railway infrastructure maintenance, turnout systems, and urban rail operations. Individual pairwise comparison matrices were aggregated using the geometric mean method to obtain a single group decision matrix, which was subsequently used in the AHP analysis.

A pairwise comparison matrix $A = [a_{ij}]$ is constructed, where

$$a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1$$

The criteria weights are obtained by normalizing the matrix and calculating the average of each row. Consistency of the comparisons was evaluated using the consistency ratio (CR), where values below 0.10 are generally considered acceptable. The calculated consistency ratio for the final group comparison matrix was 0.0855, which is below the acceptable threshold and indicates a satisfactory level of consistency among expert judgments.

Based on expert evaluations, pairwise comparison matrices were constructed using Saaty's 1–9 scale. Individual expert judgments were aggregated through the geometric mean method to generate a single comparison matrix. The resulting criteria weights obtained from the AHP analysis are presented in Table 1. The consistency ratio (CR) of the final comparison matrix was calculated as 0.0855, which is below the acceptable threshold of 0.10, indicating a satisfactory level of consistency and reliability in the weighting process.

Table 1. Criteria weights obtained from the AHP analysis based on expert evaluations.

Variable	Description
Switch type	0.04
Wheel–rail interaction type	0.02

Table 1. *Cont.*

Variable	Description
Switch radius	0.14
Vertical geometry	0.03
Horizontal geometry	0.09
Switch location	0.01
Frog material	0.09
Traffic load	0.21
Operating speed	0.14
Blade type	0.03
Superstructure type	0.21

Note: The consistency ratio (CR) of the final AHP comparison matrix was calculated as 0.0855.

3.4. Ranking with TOPSIS

The TOPSIS method [41] ranks alternatives based on their distance to ideal and negative-ideal solutions.

The normalized decision matrix is calculated using Equation (1):

$$r_{ij} = \frac{x_{ij}}{\sqrt{x_{ij}^2}} \quad (1)$$

The weighted matrix is calculated, and the relative closeness to the ideal solution is given in Equation (2):

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (2)$$

Alternatives are ranked according to C_i values.

3.5. Ranking with PROMETHEE

The PROMETHEE method [10] is based on pairwise comparisons using preference functions.

The aggregated preference index is defined in Equation (3):

$$\pi(a, b) = \sum w_j P_j(a, b) \quad (3)$$

The final ranking is obtained based on Equation (4):

$$\phi(a) = \phi^+(a) - \phi^-(a) \quad (4)$$

Alternatives are ranked according to net flow values.

3.6. Implementation

The methodology was applied in three steps. First, criteria weights were determined using AHP. Second, switch rankings were obtained using TOPSIS. Third, the same data and weights were used in PROMETHEE, and the results were compared.

4. Case Study

4.1. Study Area and Selected Rail Lines

This study is based on data obtained from the urban rail system of Istanbul, which is a large and complex rail network in Europe. The system consists of metro, light metro, and tramway lines with diverse operational and infrastructural characteristics.

Two representative rail lines were selected for the analysis: the M1 light metro line and the M2 metro line. These lines were chosen due to their high passenger demand,

operational importance, and structural differences, which provide a suitable basis for evaluating railway switches under varying conditions.

The M1 line is the only light metro line in Istanbul and consists of two operational branches (M1A and M1B). It includes both ballasted and ballastless track sections and operates under varying environmental and loading conditions. The M2 line, on the other hand, is a fully grade-separated metro line with predominantly underground sections and relatively homogeneous infrastructure characteristics.

The locations of the selected rail lines are shown in Figure 2. The M1 and M2 lines are highlighted in red and green, respectively. The intersection point of the two lines at Yenikapı represents a critical transfer hub within the network.



Figure 2. Schematic representation of the selected urban rail lines (M1 and M2) in Istanbul.

4.2. Railway Switch Characteristics

Railway switches (turnouts) are critical components of rail infrastructure that enable trains to transfer between tracks. Due to their structural complexity and exposure to dynamic loads, switches are more susceptible to wear, degradation, and failure compared to standard track sections.

An example of a typical railway switch is shown in Figure 3. As illustrated in Figure 3, a switch consists of several key components, including switch blades, stock rails, frogs, and guard rails, which work together to ensure safe and continuous train movements.

The structural configuration of these components, as shown in Figure 3, plays a significant role in determining the mechanical behavior and maintenance requirements of switches. Variations in geometry, material properties, and operational conditions directly influence the deterioration process and failure likelihood.

In this study, the characteristics of railway switches were evaluated based on a set of criteria determined through expert judgment and operational experience. These criteria were selected to represent both structural and operational factors affecting switch performance.

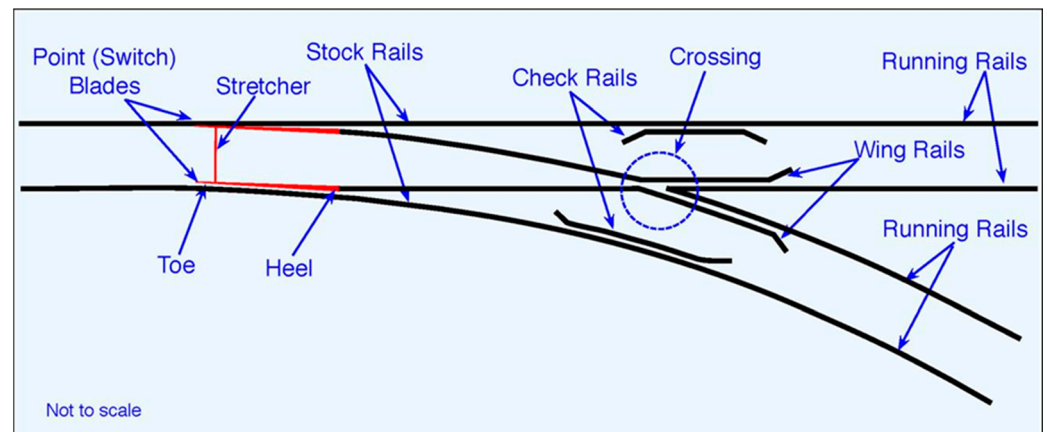


Figure 3. Schematic representation of a railway switch (turnout) and its main components.

The main criteria considered in the analysis include:

- Switch type;
- Wheel–rail interaction type;
- Switch radius;
- Vertical geometry;
- Horizontal geometry;
- Switch location (main line, depot, etc.);
- Frog material;
- Traffic load;
- Operating speed;
- Blade type;
- Superstructure type.

These criteria form the basis of the decision matrix and are used in the application of the AHP, TOPSIS, and PROMETHEE methods presented in the previous section.

The analyzed railway switches consist of 17 turnouts located on the M1 and M2 urban rail lines in Istanbul. These switches were selected to represent different operational and infrastructural conditions within the network. The selected switches differ in terms of switch geometry, radius, traffic intensity, operating speed, superstructure type, and operational location, such as mainline and depot areas. In addition, different frog materials, wheel–rail interaction characteristics, and blade configurations are included in the dataset. This diversity is important for evaluating the applicability of the proposed maintenance prioritization framework under heterogeneous urban rail operating conditions.

4.3. Data Description

The dataset used in this study consists of real maintenance and failure records obtained from the selected urban rail lines in Istanbul. These data were collected from operational maintenance systems used in the rail network.

The selected switches do not represent identical infrastructure elements; instead, they reflect a range of structural and operational conditions observed in the urban rail network. Therefore, the prioritization process considers not only historical failure frequency but also the physical and operational characteristics of the switches.

Since 2018, maintenance and failure records have been systematically recorded using the SAP ERP system. Prior to this period, different data management systems were used, resulting in inconsistencies in format and content. Therefore, to ensure data reliability and consistency, the analysis was limited to the period between 2018 and 2023.

A summary of the dataset used in the analysis is presented in Table 2. The dataset includes two urban rail lines (M1 and M2) and a total of 17 railway switches evaluated as alternatives in the decision-making framework.

Table 2. Summary of the dataset used in the analysis.

Variable	Description
Number of rail lines	2 (M1 and M2)
Number of switches	17
Analysis period	2018–2023
Data source	SAP ERP system
Type of data	Failure records
Number of criteria	11

For confidentiality reasons, the actual switch identifiers used by the railway operator were anonymized and represented as S1–S17 throughout the analysis.

The dataset includes information on failure occurrences for each railway switch. Since maintenance activities are generally performed at fixed time intervals regardless of switch characteristics, maintenance frequency was not considered a reliable indicator for prioritization. Instead, failure records were used as the primary performance indicator.

The failure counts of the railway switches during the analysis period are presented in Table 3. For each switch, the total number of recorded failures was calculated and used as a proxy for maintenance priority.

Table 3. Failure counts of railway switches (2018–2023).

Switch ID	Line	Failure Count
S1	M1	42
S2	M1	38
S3	M1	35
S4	M1	31
S5	M1	28
S6	M1	25
S7	M1	22
S8	M1	19
S9	M2	47
S10	M2	44
S11	M2	39
S12	M2	33
S13	M2	30
S14	M2	27
S15	M2	23
S16	M2	21
S17	M2	18

To facilitate comparison with the results obtained from the MCDM methods, the switches were ranked based on failure frequency, as shown in Table 4. This ranking represents the actual operational performance of the switches.

The results indicate that failure frequencies vary significantly across switches, suggesting differences in operational conditions, structural characteristics, and exposure to traffic loads. Switches with higher failure counts can be considered as requiring higher maintenance priority.

Table 4. Ranking of switches based on failure frequency.

Rank	Switch ID	Failure Count
1	S9	47
2	S10	44
3	S1	42
4	S11	39
5	S2	38
6	S3	35
7	S12	33
8	S4	31
9	S13	30
10	S5	28
11	S14	27
12	S6	25
13	S15	23
14	S7	22
15	S16	21
16	S8	19
17	S17	18

It should be noted that some inconsistencies and missing values were observed in the dataset due to differences in historical data recording practices and system transitions. Although efforts were made to clean and standardize the data, certain limitations remain.

Despite these limitations, the dataset provides a reliable basis for comparing model-based rankings obtained from AHP, TOPSIS, and PROMETHEE methods with actual operational performance.

5. Results and Discussion

In this study, railway switches were ranked using TOPSIS and PROMETHEE methods based on criteria weights obtained from AHP analysis and expert evaluations, and the obtained results were compared with actual failure data derived from operational records.

A comparison of the rankings obtained from the MCDM methods and the failure-based ranking is presented in Table 5.

Table 5. Comparison of rankings obtained from MCDM methods and failure data.

Switch ID	TOPSIS Rank	PROMETHEE Rank	Failure Rank
S1	3	2	3
S2	5	4	5
S3	6	6	6
S4	8	7	8
S5	10	9	10
S6	12	11	12
S7	14	13	14
S8	16	15	16
S9	1	1	1
S10	2	3	2
S11	4	5	4
S12	7	8	7
S13	9	10	9
S14	11	12	11
S15	13	14	13
S16	15	16	15
S17	17	17	17

While Table 5 provides a numerical comparison of the rankings, a visual representation is presented in Figure 4.

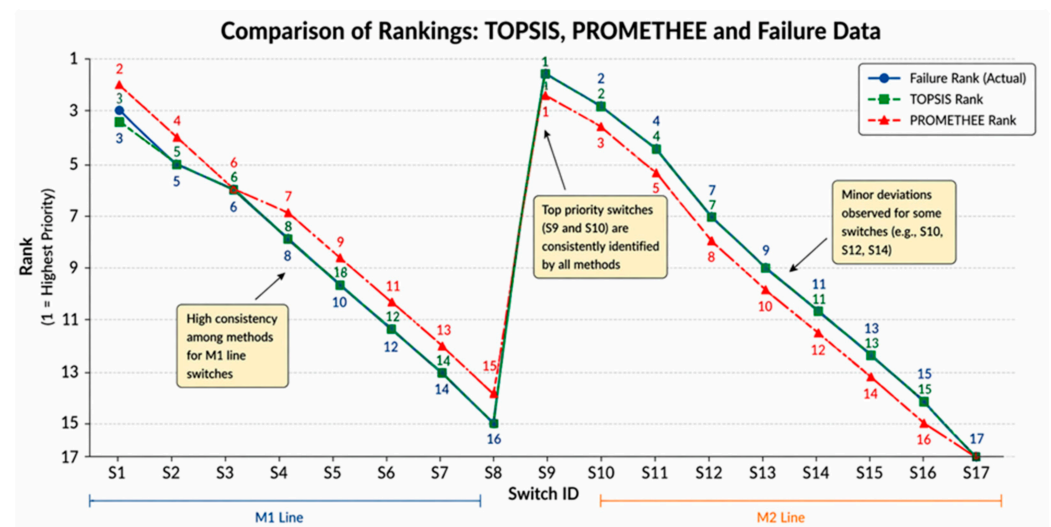


Figure 4. Comparison of rankings obtained from TOPSIS, PROMETHEE, and failure data (2018–2023).

To quantitatively evaluate the consistency between the model-based rankings and the observed failure-based ranking, additional statistical validation metrics were calculated. As shown in Table 6, both TOPSIS and PROMETHEE rankings exhibit very strong agreement with the failure-based ranking. The Spearman and Kendall correlation coefficients indicate a near-identical ranking structure, while the average rank deviations remain relatively small. These findings provide quantitative evidence that the proposed framework is capable of identifying maintenance priorities that are highly consistent with actual operational performance.

Table 6. Statistical validation of model-based rankings against failure-based rankings.

Metric	TOPSIS vs. Failure Rank	PROMETHEE vs. Failure Rank
Spearman Rank Correlation (ρ)	0.998	0.993
Kendall Tau (τ)	0.985	0.971
Average Rank Deviation	0.12	0.71
Maximum Rank Deviation	0	1

As shown in Table 5 and Figure 4, there is a high level of agreement between the rankings produced by the MCDM methods and the failure-based ranking. In particular, the top-priority switches, such as S9 and S10, are consistently identified by all methods. This indicates that the proposed evaluation framework successfully captures the key factors influencing switch performance.

The statistical validation results presented in Table 6 support these observations. The high correlation values indicate that the ranking patterns obtained from the MCDM methods are strongly aligned with actual failure occurrences. This finding suggests that the selected evaluation criteria and weighting structure provide a reasonable representation of the factors affecting switch maintenance priority.

In particular, traffic load and superstructure type were identified as the most influential criteria in the AHP analysis.

These findings are consistent with previous studies emphasizing the importance of operational and structural characteristics in railway turnout maintenance. Rahmani and Seyedhosseini [35] highlighted the significance of infrastructure condition indicators for

maintenance decision-making, while Wang et al. [37] demonstrated that operational and technical parameters can effectively support turnout maintenance evaluation. Similarly, the results of the present study indicate that traffic load and superstructure type are among the most influential factors affecting maintenance priority. The strong agreement between model-based rankings and observed failure records further supports the practical relevance of these criteria in urban rail maintenance planning.

The close alignment of the ranking curves in Figure 4 further demonstrates the consistency between the methods. In most cases, the difference between the rankings is limited to one or two positions, indicating that both TOPSIS and PROMETHEE produce stable and reliable results.

However, minor deviations can be observed for certain switches. For example, switches such as S10, S12, and S14 show slight differences in ranking positions between the methods. These variations can be attributed to the inherent differences in the aggregation mechanisms of TOPSIS and PROMETHEE, as well as the influence of criteria weighting.

Furthermore, discrepancies between model-based rankings and failure-based rankings highlight the influence of external factors that are not explicitly included in the model. These factors may include variations in maintenance practices, localized operational stresses, and inconsistencies in historical data recording.

Despite these limitations, the overall consistency between the rankings demonstrates that the proposed MCDM framework provides a robust and practical decision-support tool for maintenance prioritization in urban rail systems.

From an operational perspective, the results suggest that transitioning from traditional time-based maintenance strategies to criteria-based prioritization can significantly improve maintenance planning efficiency and resource allocation.

For railway operators, the proposed framework may be used as a decision-support tool during periodic maintenance planning cycles. By updating the decision matrix with current inspection results and operational data, maintenance managers can identify high-priority switches and allocate limited maintenance resources more effectively. This approach may contribute to improved infrastructure reliability and more efficient maintenance scheduling.

6. Conclusions

This study proposed a multi-criteria decision-making (MCDM) framework for the prioritization of railway switch maintenance in urban rail systems by integrating AHP, TOPSIS, and PROMETHEE methods. Railway switches, as critical and failure-prone components of railway infrastructure, require systematic and data-informed approaches for effective maintenance planning.

The application of the proposed framework to real-world data obtained from Istanbul's urban rail network demonstrated its practical applicability and robustness. The results revealed a high level of consistency between model-based rankings and failure-based rankings, indicating that the selected criteria and weighting structure successfully capture the key factors affecting switch performance. In particular, switches identified as high-priority alternatives by the MCDM methods correspond closely to those with higher observed failure frequencies.

Although minor discrepancies were observed, these differences highlight the influence of external factors not explicitly included in the model, such as variations in maintenance practices, localized operational stresses, and limitations in historical data quality. These findings emphasize that model-based approaches should be interpreted as decision-support tools rather than exact representations of real-world behavior. Accordingly, the proposed framework should be regarded as a maintenance prioritization and resource allocation support tool rather than a predictive maintenance or degradation prediction model.

A comparison of TOPSIS and PROMETHEE results further indicates that both methods produce stable and consistent ranking patterns, with only slight variations due to their different aggregation mechanisms. This consistency strengthens the reliability of the proposed framework and demonstrates its applicability under different decision-making perspectives.

From a practical standpoint, the results suggest that adopting a criteria-based maintenance prioritization approach can significantly enhance decision-making processes in railway infrastructure management. Compared to conventional time-based maintenance strategies, the proposed framework enables more efficient allocation of maintenance resources by focusing on the relative importance and condition of infrastructure components.

Despite its contributions, the study has several limitations. First, the analysis is based on historical failure records and therefore reflects past operational conditions rather than future deterioration processes. Second, the proposed framework relies on expert-defined criteria and weights, which may introduce a degree of subjectivity into the decision-making process. Third, the study is based on a relatively limited dataset consisting of 17 railway switches from two urban rail lines in Istanbul. Consequently, the findings should be interpreted with caution and should not be directly generalized to other railway networks without additional validation. Furthermore, data inconsistencies and missing values in historical maintenance records may have influenced the obtained rankings.

Future research may focus on integrating real-time condition monitoring data, inspection measurements, and sensor-based indicators into the proposed framework. In addition, the methodology could be combined with degradation modeling, failure prediction techniques, and machine learning-based condition assessment approaches to support predictive maintenance applications. Further validation using larger datasets from different railway networks would also improve the generalizability and robustness of the proposed framework.

Despite these limitations, the proposed framework provides a transparent, practical, and easy-to-implement decision-support approach for maintenance prioritization in urban rail systems. The integration of expert knowledge with operational data enables infrastructure managers to systematically identify critical assets and support more efficient allocation of maintenance resources.

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References

- Ben-Daya, M.; Duffuaa, S.O.; Raouf, A.; Knezevic, J.; Ait-Kadi, D. (Eds.) *Handbook of Maintenance Management and Engineering*; Springer: London, UK, 2009. [\[CrossRef\]](#)
- Higgins, A.; Ferreira, L.; Lake, M. Scheduling rail track maintenance to minimize overall delays. In Proceedings of the 14th International Symposium on Transportation and Traffic Theory, Jerusalem, Israel, 20–23 July 1999.
- Esveld, C. *Modern Railway Track*, 2nd ed.; MRT-Productions: Delft, The Netherlands, 2001.
- Grossoni, I.; Hughes, P.; Bezin, Y.; Bevan, A.; Jaiswal, J. Observed failures at railway turnouts: Failure analysis, possible causes and links to current and future research. *Eng. Fail. Anal.* **2021**, *119*, 104987. [\[CrossRef\]](#)
- Lidén, T. Railway infrastructure maintenance—A survey of planning problems and conducted research. *Transp. Res. Procedia* **2015**, *10*, 574–583. [\[CrossRef\]](#)
- Macchi, M.; Garetti, M.; Centrone, D.; Fumagalli, L.; Pavirani, G.P. Maintenance management of railway infrastructures based on reliability analysis. *Reliab. Eng. Syst. Saf.* **2012**, *104*, 71–83. [\[CrossRef\]](#)
- Jamshidi, A.; Hajizadeh, S.; Su, Z.; Naeimi, M.; Núñez, A.; Dollevoet, R.; Li, Z. A decision support approach for condition-based maintenance of rails based on big data analysis. *Transp. Res. Part C Emerg. Technol.* **2018**, *95*, 185–206. [\[CrossRef\]](#)
- Liu, X.; Markine, V.L.; Wang, H.; Shevtsov, I.Y. Experimental tools for railway crossing condition monitoring. *Measurement* **2018**, *129*, 424–435. [\[CrossRef\]](#)
- Saaty, T.L. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **2008**, *1*, 83–98. [\[CrossRef\]](#)
- Brans, J.P.; Vincke, P. A preference ranking organisation method: The PROMETHEE method for multiple criteria decision-making. *Manag. Sci.* **1985**, *31*, 647–656. [\[CrossRef\]](#)
- Profillidis, V.A. *Railway Management and Engineering*; Ashgate Publishing: Farnham, UK, 2013.
- Lothar, M.; Dietmar, M.; Hermann, K. *Work Procedures for Maintenance of the Permanent Way of the DB Netz AG*; The Railway Publishing Company: Heidelberg, Germany; Mainz, Germany, 2003.
- DIN 31051; Fundamentals of Maintenance. Deutsches Institut für Normung; Berlin, Germany, 2012.
- Wang, P. *Design of High-Speed Railway Turnouts: Theory and Applications*; Academic Press: Cambridge, MA, USA, 2015. [\[CrossRef\]](#)
- Hamarat, M.Z.; Silvast, M.; Kaewunruen, S. Railway turnouts and inspection technologies. In *Rail Infrastructure Resilience: A Best-Practices Handbook*; Calçada, R., Kaewunruen, S., Eds.; Woodhead Publishing: Cambridge, UK, 2022; pp. 319–340. [\[CrossRef\]](#)
- Vale, C.; Lurdes, S.M. Stochastic model for the geometrical rail track degradation process in the Portuguese railway Northern Line. *Reliab. Eng. Syst. Saf.* **2013**, *116*, 91–98. [\[CrossRef\]](#)
- Andrews, J.; Prescott, D.; De Rozières, F. A stochastic model for railway track asset management. *Reliab. Eng. Syst. Saf.* **2014**, *130*, 76–84. [\[CrossRef\]](#)
- Mobley, R.K. *An Introduction to Predictive Maintenance*, 2nd ed.; Butterworth-Heinemann: Oxford, UK, 2002.
- Grassie, S.L. Rolling contact fatigue on the British railway system: Treatment. *Wear* **2005**, *258*, 1310–1318. [\[CrossRef\]](#)
- Cannon, D.F.; Edel, K.O.; Grassie, S.L.; Sawley, K. Rail defects: An overview. *Fatigue Fract. Eng. Mater. Struct.* **2003**, *26*, 865–886. [\[CrossRef\]](#)
- Zwanenburg, W.J. A model for the life expectancy of railway switches and crossings for maintenance and renewal planning in asset management systems. *WIT Trans. Built Environ.* **2008**, *103*, 765–773. [\[CrossRef\]](#)
- Sadeghi, J.; Askarinejad, H. Development of railway track maintenance management models. *Struct. Infrastruct. Eng.* **2010**, *6*, 675–684. [\[CrossRef\]](#)
- Zhang, Y.; Xu, T.; Chen, C.; Wang, G.; Zhang, Z.; Xiao, T. A hierarchical method based on improved deep forest and case-based reasoning for railway turnout fault diagnosis. *Eng. Fail. Anal.* **2021**, *127*, 105446. [\[CrossRef\]](#)
- Choi, J.Y.; Kim, S.H.; Han, K.S.; Oh, S.M. Application of failure mode effects analysis for maintenance of turnout system on serviced urban rapid transit. *Appl. Sci.* **2023**, *13*, 2978. [\[CrossRef\]](#)
- Loidolt, M.; Egger, J.; Korenjak, A.K. Data-driven condition monitoring of fixed-turnout frogs using standard track recording car measurements. *Appl. Sci.* **2025**, *15*, 11122. [\[CrossRef\]](#)
- Krč, R.; Ambur, R.; Hadaš, Z.; Věchet, S. Condition monitoring and trend analysis of railway turnouts based on in-situ accelerometer measurements. In Proceedings of the 5th International Conference on Railway Technology, Montpellier, France, 22–25 August 2022.
- Oßberger, U.; Kollment, W.; Eck, S. Insights towards condition monitoring of fixed railway crossings. *Procedia Struct. Integr.* **2017**, *4*, 106–114. [\[CrossRef\]](#)
- Hovad, E.; Wix, T.; Khomiakov, M.; Carstensen, J.M.; Harder, S.; Galeazzi, R. Deep learning for automatic railway maintenance. In *Intelligent Quality Assessment of Railway Switches and Crossings*; Galeazzi, R., Danielsen, H.K.D., Ersbøll, B.K., Eds.; Springer: Cham, Switzerland, 2021; pp. 207–228.
- Dekker, R. Applications of maintenance optimization models: A review and analysis. *Reliab. Eng. Syst. Saf.* **1996**, *51*, 229–240. [\[CrossRef\]](#)
- Al-Turki, U. A framework for strategic planning in maintenance. *J. Qual. Maint. Eng.* **2011**, *17*, 150–162. [\[CrossRef\]](#)

31. Jardine, A.K.S.; Lin, D.; Banjevic, D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mech. Syst. Signal Process.* **2006**, *20*, 1483–1510. [\[CrossRef\]](#)
32. Wang, H. A survey of maintenance policies of deteriorating systems. *Eur. J. Oper. Res.* **2002**, *139*, 469–489. [\[CrossRef\]](#)
33. Bertolini, M.; Bevilacqua, M. A combined goal programming—AHP approach to maintenance selection problem. *Reliab. Eng. Syst. Saf.* **2006**, *91*, 839–848. [\[CrossRef\]](#)
34. Wang, W.; Christer, A.H. Towards a general condition-based maintenance model for a stochastic dynamic system. *Int. J. Prod. Econ.* **2000**, *51*, 145–155. [\[CrossRef\]](#)
35. Rahmani, A.; Seyedhosseini, S.M. Development of railway turnout structural condition index. *Iran. J. Sci. Technol. Trans. Civ. Eng.* **2020**, *45*, 219–226. [\[CrossRef\]](#)
36. Patlasov, O.M.; Fedorenko, Y.; Shulha, D. Development of methods to increase the efficiency of railway maintenance. *ScienceRise* **2021**, *2*, 11–22. [\[CrossRef\]](#)
37. Wang, P.; Yang, L.; Wang, S.; Ma, X. Evaluation and maintenance method for general speed railway turnouts based on multi-source data. *Constr. Build. Mater.* **2024**, *451*, 138896. [\[CrossRef\]](#)
38. Swier, J. Ways to improve the performance (and cost) of switches. In *Intelligent Quality Assessment of Railway Switches and Crossings*; Galeazzi, R., Danielsen, H.K.D., Ersbøll, B.K., Eds.; Springer: Cham, Switzerland, 2021; pp. 261–274.
39. Triantaphyllou, E. *Multi-Criteria Decision Making Methods: A Comparative Study*; Kluwer Academic Publishers: Dordrecht, The Netherlands, 2000. [\[CrossRef\]](#)
40. Vaidya, O.S.; Kumar, S. Analytic hierarchy process: An overview of applications. *Eur. J. Oper. Res.* **2006**, *169*, 1–29. [\[CrossRef\]](#)
41. Hwang, C.L.; Yoon, K. *Multiple Attribute Decision Making: Methods and Applications*; Springer: New York, NY, USA, 1981.
42. Behzadian, M.; Otaghsara, S.K.; Yazdani, M.; Ignatius, J. A state-of-the-art survey of TOPSIS applications. *Expert Syst. Appl.* **2012**, *39*, 13051–13069. [\[CrossRef\]](#)
43. Brans, J.P.; Mareschal, B. PROMETHEE methods. In *Multiple Criteria Decision Analysis: State of the Art Surveys*; Figueira, J., Greco, S., Ehrgott, M., Eds.; Springer: New York, NY, USA, 2005; pp. 163–186. [\[CrossRef\]](#) [\[PubMed\]](#)
44. Behzadian, M.; Kazemzadeh, R.B.; Albadvi, A.; Aghdasi, M. PROMETHEE: A comprehensive literature review on methodologies and applications. *Eur. J. Oper. Res.* **2010**, *200*, 198–215. [\[CrossRef\]](#)
45. Ho, W. Integrated analytic hierarchy process and its applications—A literature review. *Eur. J. Oper. Res.* **2008**, *186*, 211–228. [\[CrossRef\]](#)
46. Mardani, A.; Jusoh, A.; Zavadskas, E.K.; Khalifah, Z.; Nor, K.M. Multiple criteria decision-making techniques in transportation systems: A systematic review of the state of the art literature. *Transport* **2016**, *31*, 359–385. [\[CrossRef\]](#)
47. Carvalho, T.P.; Soares, F.A.A.M.N.; Vita, R.; Francisco, R.P.; Basto, J.P.; Alcalá, S.G.S. A systematic literature review of machine learning methods applied to predictive maintenance. *Comput. Ind. Eng.* **2019**, *137*, 106024. [\[CrossRef\]](#)

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