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A review and research trends

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A taxonomy of railway track maintenance planning and scheduling: A review and research trends

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ABSTRACT

Railway track maintenance and renewal are vital for railway safety, train punctuality, and travel comfort. Therefore, having cost-effective maintenance is critical in managing railway infrastructure assets. There has been a considerable amount of research performed on mathematical and decision support models for improving the application of railway track maintenance planning and scheduling. This article reviews the literature in decision support models for railway track maintenance planning and scheduling and transforms the results into a problem taxonomy. Furthermore, the article discusses current approaches in optimising maintenance planning and scheduling, research trends, and possible gaps in the related decision-making models.

1. Introduction

Railway track is a crucial civil infrastructure. A reliable railway track is vital for safety, train punctuality, travel comfort, and cost-effectiveness of maintenance and renewal activities. Railways require maintenance to ensure an acceptable level of operating conditions. In 2018, railway maintenance expenditure in the European Union (EU27) was estimated at 20,6 billion Euros, accounting for more than half of the total rail infrastructure expenditure [1]. Furthermore, railways are amongst the longest-lasting and most capital-intensive assets, and even minor improvements in maintenance cost and efficiency can have significant effects on the total life cycle costs [2]. Therefore, a maintenance management system is necessary to ensure the infrastructure system's availability [3]. Planning and scheduling processes are at the core of improving maintenance management performance [4]. Railway infrastructure owners and maintenance contractors need decision-making tools and models to plan resources efficiently and maintain the track by effective scheduling.

The growth in rail traffic, increasing maintenance needs, and technological development have generated growing interest from researchers and practitioners to develop decision support models for railway track maintenance planning and scheduling (RTMP&S). For example, the increased availability of low-cost sensors with high sampling frequency has increased the possibility of monitoring vital railway infrastructure assets [5]. Opportunities arising from extensive data collection and analytics have recently attracted research interest. Proposed methods serve varying purposes for research and practice. While the new methodology is useful for advancing knowledge for a wide range of applications, the great variety of approaches also presents new challenges, particularly for comparative studies.

The primary purpose of this article is to develop a taxonomy, that is a hierarchical classification, for the RTMP&S problems, provide an overview of relevant literature, and highlight current research trends. The field of maintenance planning and scheduling has been the scope of several research articles, and this article aims to build on these results by highlighting new research trends. Lidén [6] provided an overview of RTMP&S problems and classified them using three levels based on the length of planning periods: strategic, tactical, and operational. We aim to expand on the review by Lidén [6] by covering articles from 2015 to 2020. Furthermore, we propose a taxonomy for RTMP&S decision support models, separating the planning and scheduling decision areas in railway, discussing the optimisation frameworks, and analysing the research trends and gaps. The differences in the planning and scheduling processes have been established in the production and maintenance management literature [4,7]. However, railway maintenance literature has not discussed differences in scheduling and planning definitions.

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Table 1
Review protocol.

Item	Description	
Keywords	First round	'Decision making AND Railway AND Track AND Maintenance AND Planning AND scheduling '.
	Second round	'Railway AND Track AND Maintenance AND (Planning OR Scheduling).
Databases	ISI Web of Science, Google Scholar.	
Search fields	Title; Abstract; Keywords.	
Exclusion criteria	Papers covering maintenance planning and scheduling outside railway track; Papers not written in English.	
Language	English.	
Publication type	Journal and conference proceeding articles.	
Time window	1998 to 2020.	

Therefore, planning and scheduling have been used inconsistently, as discussed in Section 4.5. Additionally, the proposed taxonomy discusses the structural configuration of the railway track affecting decision-making models. We believe that the taxonomy offers researchers and practitioners an overview of the railway track structure configuration and associated modelling complexities.

Section 2 of this article discusses the literature review method, provides a bibliometric analysis and proposes our novel taxonomy to classify different attributes of the RTMP&S decision support models based on system structural characteristics, maintenance management decisions and the decision-making framework. This taxonomy is then applied in Sections 3, 4 and 5 to review the literature. In Section 6, we discuss trends and research gaps in RTMP&S based on this review. Finally, Section 7 provides a conclusion of the presented work.

2. Method

The literature review method aims to provide historical and in-depth perspectives on the research area and identify gaps in the literature for future research. We used a systematic review process to cover the RTMP&S literature in three steps: (1) planning the review protocol and search strategy, (2) bibliometric analysis, and (3) thematic analysis.

2.1. Review protocol and search strategy

The first step in our review was on identifying the need for a literature review on the maintenance planning and scheduling (MP&S) decision-making models in railway track and defining a literature review protocol (Table 1). We used the ISI Web of Science as the primary database and Google Scholar to broaden the domain in the next step. Together, these sources were deemed sufficient to capture the most relevant articles. In the first search round, we used the ISI Web of Science to search the main keywords (Table 1). This search resulted in 24 articles. To reduce the probability of missing relevant literature, we used more general search strings in the second round (Table 1). Combinations of these primary keywords guided the identification of the relevant literature (Table 1). The search fields included the title, abstract, and keywords, and we limited the search to include hits related to railway track MP&S written in English.

2.2. Bibliometric analysis

A bibliometric analysis is a method for mapping the research topic by analysing relationships among the articles [8]. There are different bibliometric methods. Zupic and Čater [8] discusses the five methods: citation, co-citation, bibliographic coupling, co-author, and co-word. In this article, we first used *co-word*, which connects keywords appearing in the same title, abstract, or keyword list. The VOSviewer software (version 1.6.16, 2020, https://www.vosviewer.com) was used to create a density map of the most important keywords for the reviewed articles (Fig. 1). According to Van Eck and Waltman [9], each keyword's density depends on the number of neighbouring keywords and the weights. In other words, more neighbouring keywords and smaller distances between them and the point of interest will result in higher density and a more intense colour [9]. From Fig. 1, we can, for example, conclude that *maintenance, optimisation* and *track maintenance* are important keywords connecting the reviewed articles since they have the most intense colour.

We then continued with *bibliographic coupling* to find countries and universities most frequently associated with the reviewed articles. A bibliographic coupling connects documents based on the number of shared references. We applied a limit of at least three publications to

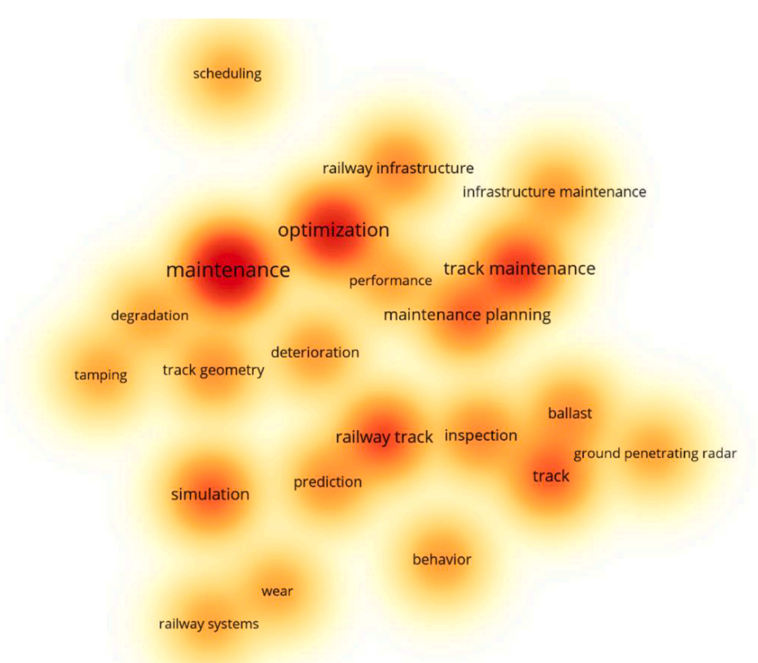

Fig. 1. Density map of co-words in the reviewed articles created in VOSviewer.

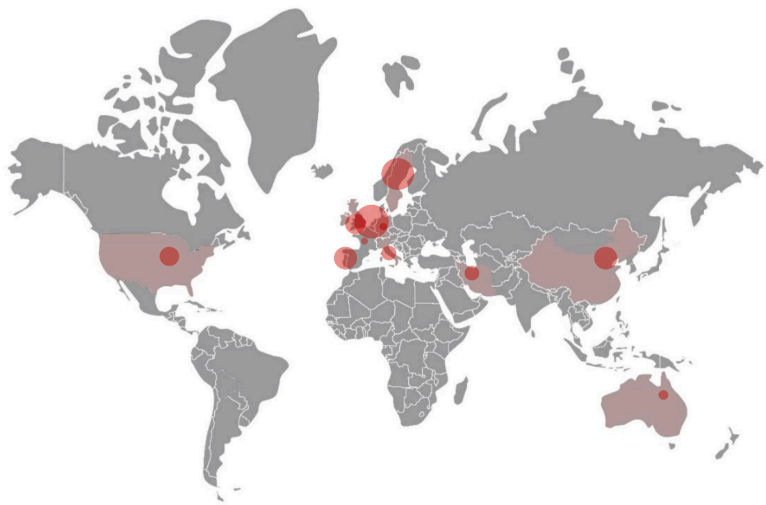

Fig. 2. The origin of the articles in our review. At least three contributions are required to appear on this World map. Further details are given in Table 2.

Table 2
Countries and related universities with at least three publications.

Countries	Publications	Universities
Netherlands	15	Delft University of Technology, Erasmus University Rotterdam, University of Twente, Eindhoven University of Technology.
Sweden	14	Luleå University of Technology, Linköping University, Chalmers University of Technology.
Portugal	10	University of Lisbon, University of Porto.
China	10	Beijing Jiaotong University, Wuhan University of Technology, National University of Defence Technology, University of Finance and Economics.
UK	9	University of Nottingham, University of Birmingham, University of Newcastle.
USA	7	University of Illinois, University of Florida.
Italy	6	University of Genoa, Politecnico di Torino, Technical University of Bari, Roma Tre University.
Iran	4	Iran University of Science and Technology.
Australia	4	Queensland University of Technology, University of South Australia.
France	3	University of Paris-Est Marne-la-Vallée, Université de Toulouse, Université de Technologie de Troyes.
Germany	3	Technische Universität Braunschweig

Table 3
Journal names sorted according to the number of articles selected in our review.

	Journal name	Number of publications	Citations
1	Proceedings of The Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit	11	131
2	Transportation Research, Part C: Emerging Technologies	10	151
3	Journal of Transportation Engineering	8	101
4	Structure and Infrastructure Engineering	6	73
5	Reliability Engineering & System Safety	5	190
6	Journal of Infrastructure Systems	4	14
7	Journal of Transportation Engineering, Part A: Systems	4	15
8	European Journal of Operational Research	3	64
9	Journal of The Operational Research Society	3	213
10	Computers & Industrial Engineering	3	66
11	Euro Journal on Transportation And Logistics	3	34
12	Computer-Aided Civil and Infrastructure Engineering	2	77

Table 4
The ten most cited articles among the ones selected in our review.

Reference		Journal name	Publication year	Citations
1	Budai et al. [10]	Journal of The Operational Research Society	2006	105
2	Podofillini et al. [11]	Reliability Engineering & System Safety	2006	79
3	Higgins [12]	Journal of The Operational Research Society	1998	77
4	Li et al. [13]	Transportation Research Part C-Emerging Technologies	2014	59
5	Peng et al. [14]	Computer-Aided Civil and Infrastructure Engineering	2011	56
6	Liden [6]	18th Euro Working Group on Transportation, Ewgt 2015	2015	56
7	Peng and Ouyang [15]	Computer-Aided Civil and Infrastructure Engineering	2014	45
8	Vale et al. [16]	Journal of Transportation Engineering	2012	44
9	Gustavsson et al. [17]	Computers & Industrial Engineering	2014	42
10	Quiroga and Schnieder [18]	Proceedings of The Institution of Mechanical Engineers Part O-Journal of Risk and Reliability	2012	41

qualify for the world map overview in Fig. 2. We can conclude that European researchers author many articles in our review. Frequent contributions to the topic also come from China, the US, Iran, and Australia. Table 2 provides more details on the number of publications from each country and the associated universities.

In our bibliometric analysis, we looked at the journals with the most publications featured in the reviewed articles (Table 3) and the highly cited articles (Table 4). Based on the results in Table 3, which presents journals with at least two articles in our review, we argue that the body of RTMP&S research seems to be distributed between multiple journals focusing on areas such as transportation, reliability and maintenance engineering, operations research, and industrial engineering. We can also see that the five articles in Reliability Engineering & System Safety (RESS) together have the second most citations among the journals in Table 3. The three most cited articles in Table 4, of which one appeared in RESS, were all published before 2010, which suggests that they may be viewed as seminal articles in RTMP&S.

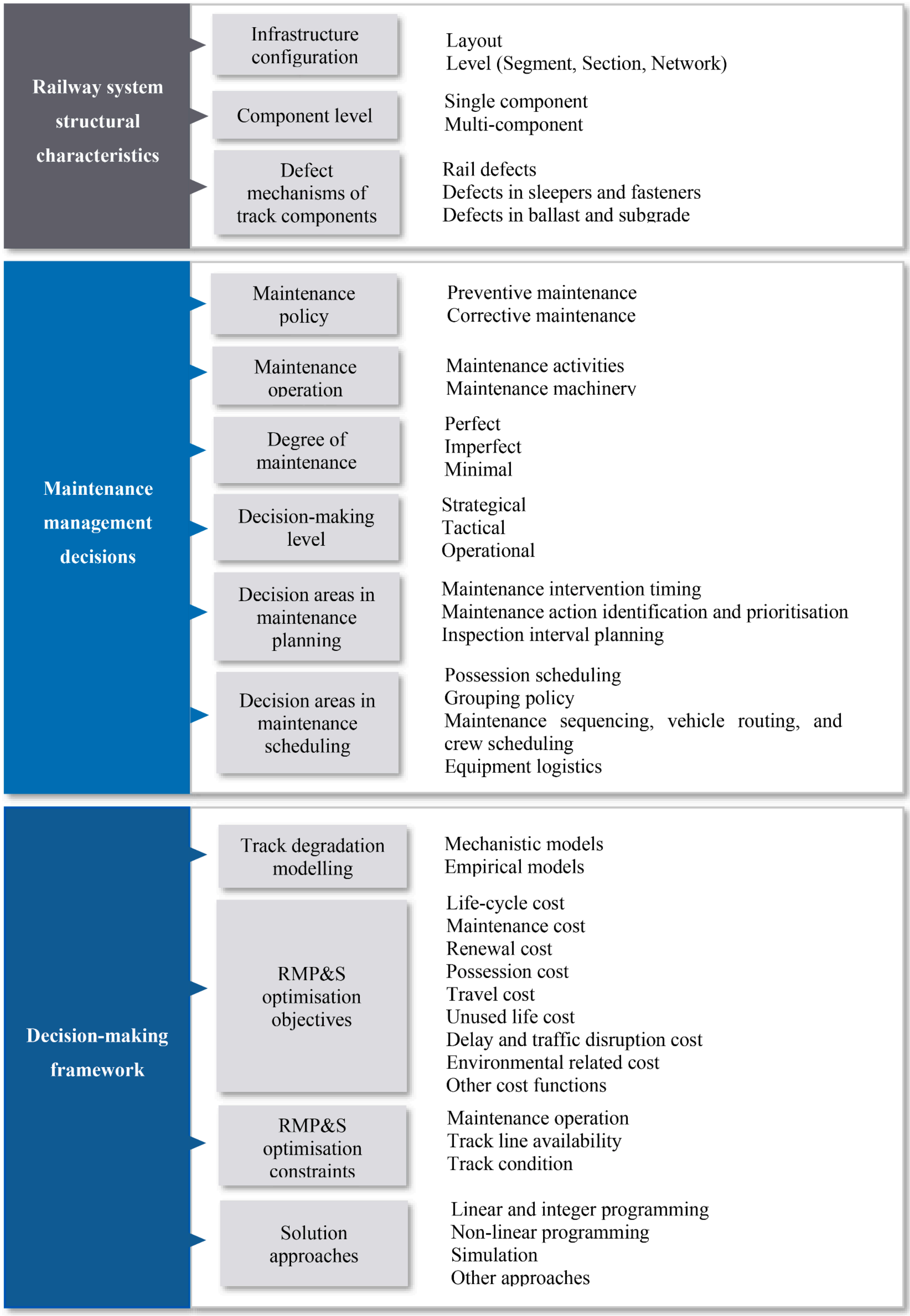

Fig. 3. Our proposed taxonomy for RTMP&S problems.

2.3. *Thematic analysis*

We analysed the collected data through the first and second steps of the review process based on a thematic analysis. We developed the main classification themes based on two classification frameworks [19,20]. Three main themes and subthemes emerged to address the attributes of the MP&S problem:

a) Railway system structural characteristics (infrastructure configuration, component level, defect mechanisms of track components)
b) Maintenance management decisions (maintenance policy, maintenance operation, degree of maintenance, decision-making level, decision areas in maintenance planning, and decision areas in maintenance scheduling)

c) Decision-making framework (track degradation modelling, RMP&S optimisation objectives, RMP&S optimisation constraints, and solution approaches).

The thematic analysis and bibliometric analysis of the keywords in the selected papers aided the development of a taxonomy for RTMP&S (Fig. 3). We developed a taxonomy to provide a classification scheme of RTMP&S decision-making problems and provide a foundation for future research. The taxonomy guided the classification of the details of the most relevant articles. The results of the classified literature were analysed to determine trends and gaps.

The first category of the taxonomy in Fig. 3 describes the structural characteristics of the railway track affecting MP&S. Two attributes of infrastructure configuration and component level indicate how scholars regularly characterise the railway track corridor.

The second category describes the management decisions of RTMP&S and includes six attributes, shown in Fig. 3. These attributes define the essential characteristics of the RTMP&S operation addressed in the identified articles. The decision areas in the RTMP&S category are modified versions of the RTMP&S problem classification scheme used by Lidén [6]. Lidén classified RTMP&S into three levels: strategic, tactical, and operational problems based on the planning horizon's domain and duration. Herein, we separated the planning and scheduling classifications compared to Lidén [6]. Furthermore, we found an inconsistency between the planning time horizon for RTMP&S problems generally found in the literature and the defined planning horizon range in the Lidén [6] classification. Therefore, we chose to separate the two planning strategy attributes: the level of decision making and the decision area. In the third category, we adopted the classification of mathematical models from Bouajaja and Dridi [19] to summarise the applied objective function and solution methods.

If we compare the taxonomy (Fig. 3) to the density map presented in Fig. 1, we can compare "Railway system structural characteristics" with the cluster at the bottom Fig. 1, "Maintenance management decisions" with the top right cluster, and "Decision-making framework" with the top left cluster. In the following sections, our taxonomy will be used to classify and analyse the selected articles.

3. Railway track structural characteristics

3.1. Infrastructure configuration

3.1.1. Infrastructure layout

The layout of the railway track corridor has specific characteristics that affect the RTMP&S problem. The railway track is a series system in which each part of the track is critical for system performance. In this context, the defective point assets (e.g., switches and crossings) or components (e.g., rail, ballast, sleeper, or fastening) can affect system performance through track shutdown, speed restriction, or occasionally cause accidents such as derailments.

Corman and Meng [21] classified the track corridor characteristics into five groups: single track, double-track, single direction, double direction, and crossing. In the single-track configuration, only one track is available, and the track line will thus need to be closed for traffic during any maintenance activity. Planning and scheduling of maintenance activities are therefore more critical in a single-track layout [10,12]. For a double-track layout, trains can pass using parallel tracks. The single and double directions indicate whether trains can pass in one or both directions. At crossings, trains from two different directions and tracks cross each other, for instance, at stations. The defined track layout in the RTMP&S decision models can affect the complexity of the proposed models. Most papers have discussed single-track maintenance due to the challenges this layout poses; maintaining single-track forces traffic to stop during maintenance (e.g. [22–25]).

In a double-track layout, maintenance or renewal is possible on one of the tracks, while dispatchers reroute the train traffic to the other. Zhang et al. [26] and Sadeghi et al. [27] provide examples of RTMP&S on a double-track line. In some studies, the defined track corridors include single and double track links that make the problem description more realistic [10,12,28].

3.1.2. Infrastructure level (segment, section, and network)

The railway track is a linear asset. A common approach is to split the asset, such as a railway line, into different segments or sections. Researchers often define segments as the smallest segmentation of the track of a fixed length, for example 200 m, or where similar characteristics such as a particular curve radius constitute the segmentation base. Authors often define a section as a length of track containing multiple segments. A ubiquitous approach to defining a section splits the track between two railway network nodes such as stations. However, a section can also be defined based on factors affecting track degradation behaviour. For instance, Peralta et al. [29] proposed a two-level segmentation to first divide the track line into sections based on curvature, age and track type, maintenance history, and the existence of bridges, tunnels, or switches. At the second level they split each section into fixed-length segments.

A network-level definition of the asset is also possible. The network level includes the whole or a large proportion of a country's railway infrastructure network. Recent studies have investigated RTMP&S decision-support models at the network level to develop more realistic and comprehensive models [22,26,28,30]. However, defining the problem at the network level likely increases the computational complexities of the proposed solutions.

3.2. Component level

The railway track is a heterogeneous system comprising interdependent components, i.e., steel rail, sleepers, joints and fasteners, ballast, and subgrade [31]. A categorisation of the multi-component system dependence is as economic, stochastic, structural, and resource dependence [32,33]. Economic dependence indicates the increase or decrease in maintenance cost when multiple components are maintained simultaneously [32]. Structural dependence refers to the maintenance connection between structural parts. For example, to maintain a component, structurally dependent parts may also need maintenance or replacement. Stochastic dependence describes one deteriorating component's interaction effect, for example, failing to fulfil its designated function, thereby transferring load and increasing the deterioration rates of other parts of the system [32]. Olde Keizer et al. [33] split the stochastic dependence into three categories: failure-induced damage, load sharing, and common-mode deterioration. Resource dependence corresponds to restrictions on shared tools, budget, maintenance crew, spare, and transport when performing maintenance on components [33].

3.2.1. Single-component perspective

The primary purpose of research using a single component perspective is to monitor, assess, and predict one component's condition and analyse its degradation and irregularities. The single-component perspective, which isolates linked system effects, simplifies the modelling. This simplification is likely the reason why approaches with a single-component perspective dominate the literature (e.g. [24,26,29,34]). A limitation of this approach is that the single-component perspective may be over-simplified, leading to faulty system-level conclusions.

3.2.2. Multi-component perspective

Descriptions of the dynamic interaction between rolling stock and track components are the most common multi-component perspective found in the reviewed literature. The multi-component perspective is less common in studies on track infrastructure components than in studies of the interaction between the track and the rolling stock.

Table 5
Literature classification based on maintenance policy and single- or multi-component perspectives.

Policy	References	
	Single-component	Multi-component
Predetermined maintenance	Higgins [12], Cheung et al. [63], Lake et al. [64], Lake & Ferreira [65], Huisman [66], Van Zante-De Fokkert et al. [67], Gorman & Kanet [68], Nemani et al. [69], Peng et al. [14], Peng & Ouyang [70], Heinicke et al. [71], Boland et al. [72], Forsgren et al. [73], Lannez et al. [74], Santos et al. [75], Famurewa et al. [76], Luan et al. [77], Lidén & Joborn [78], Lidén et al. [79], Su & Schutter [80], Kidd et al. [81], Li et al. [82], D'Ariano et al. [28], Zhang et al. [83], Lidén [22], Zhang et al. [26].	Budai & Dekker [84], Budai et al. [10], Zhao et al. [35], Pouryousef et al. [85], Peng & Ouyang [15], Letot et al. [86], Khalouli et al. [87], Pargar et al. [36], Dao et al. [25], Dao et al. [88].
Predictive condition-based maintenance	Oyama & Miwa [89], Meier-Hirmer et al. [90], Podofillini et al. [11], Oh et al. [91], Vale et al [16], Caetano & Teixeira [92], Zhang et al. [93], Lovett et al. [94], Vale & Ribeiro [95], Palo et al. [49], Consilvio et al. [96], Famurewa et al. [97], Caetano & Teixeira [98], Wen & Salling [99], Villarejo et al. [100], Daddow et al. [101], Peralta et al. [29], Faris et al. [102], Miwa & Oyama [103], Khajehei et al. [104], Consilvio et al. [105], Gerum et al. [106], Rahimikelarijani et al. [107], Consilvio et al. [23], Daddow et al. [108], Bressi et al. [109].	Simson et al. [110], Dell'Orco et al. [111], Gustavsson et al. [17], Gustavsson [112], Caetano & Teixeira [37], Caetano & Teixeira [113] Su et al. [114], Su et al. [115], Khajehei et al. [116].
Non-predictive condition-based maintenance	Zhao et al. [117], Santos & Teixeira [118], Camci [119], Su et al [120], Consilvio et al. [121], Phanyakit & Satiennam [122], Sasidharan et al. [123].	Verbert et al. [38], Bakhtiary et al. [124].

A few studies considered the economic dependencies between track components in the RTMP&S problem. Zhao et al. [35] proposed two scenarios to combine different renewal activities, and they grouped nearby segments to acknowledge the economic dependence in renewal operations. Gustavsson et al. [17] applied a multi-component model to rail grinding using an opportunistic replacement strategy. Pargar et al. [36] addressed the multi-component perspective, considering the joint setup and preparation cost for combining the renewal and maintenance operations at the available track possession times. Caetano and Teixeira [37] investigated the economic dependence between the integrated maintenance of the ballast, rail, and sleeper. Verbert et al. [38] proposed two optimisation models for maintenance planning at the single component level and one at the multi-component system level. They concluded that results based on the simultaneous consideration of the multi-component arrangement differ from separate optimal plans for each component. Table 5 in the following sections presents the complete list of articles with single- and multi-component perspectives.

Nicolai and Dekker [32] discussed how rail track components' degradation level could affect other track components' degradation behaviour. Therefore, structural and stochastic dependence should be considered essential for defining a proper maintenance strategy [39]. However, we found no article considering the structural or stochastic dependence between track components.

3.3. Defect mechanisms of track components

The track components experience vertical, horizontal, and longitudinal forces resulting in deterioration of the track over time, impacting ride quality and system reliability. The interaction between the vehicles and track components creates a complex degradation process for both the rail and wheels. The dynamic rail–track contact degrades both rail and wheel profiles, and the properties of this contact can affect degradation rates [40]. Researchers have developed a range of models that consider contact forces between the rail and the wheel to aid in the reliability analysis of rail defects [40–48,50,51]. Rail defects correspond to abrasive wear, plastic flow or deformation, rail corrugation, rail fatigue cracking, and rail creep [52].

Degradation of sleepers and fasteners is influenced by traffic and operational factors, e.g., axle loads, train speed, accumulative tonnage and performed maintenance [52]. Ferdous and Manalo [53] reviewed timber, concrete, and steel sleeper failures. Examples of concrete sleeper defects are: cracking due to dynamic loads, centre binding, environmental or chemical degradation, wear or fatigue of the fastening system, and abrasion of the soffit [53,54].

The ballast bed has a vital role in railway track settlement. Deformation speed of the ballast likely increases with higher axle load and train speed [55]. Ballast degradation is caused by particles breakage and changes in their sizes [55]. Dirty and fouled ballast can degrade the track and affect the track geometry [52]. Tzanakakis [52] provide further information on ballast, sub-ballast, and subgrades degradation and failure modes.

4. Maintenance management decisions

4.1. Maintenance policy

A maintenance policy refers to the managerial decision or course of action suggested by maintenance models to ensure that the system performs its required functions [56–58]. The international standard of maintenance terminology, EN 13306:2017 [59], defines three types of maintenance policies, the preventive, the corrective, and the improvement policy. The preventive maintenance policy aims to inspect, repair, and replace the asset to mitigate its degradation and reduce failure probabilities [20,60]. The EN 13306:2017 [59] defines corrective maintenance as the reactive action to manage the consequences of failure. The improvement policy refers to actions performed to enhance an asset's inherent reliability, maintainability, or safety without changing the original function [59]. Selecting the appropriate maintenance type, such as corrective or preventive maintenance, is a core maintenance policy decision [60].

4.1.1. Preventive maintenance

Preventive maintenance can be split into two groups: predetermined and condition-based [59]. Pre-established time intervals or the monitored asset's use governs predetermined maintenance actions without considering the asset condition [59]. Scholars, however, usually define predetermined maintenance as time-based maintenance [60]. In the condition-based maintenance policy, the measured conditions steer actions [59]. Therefore, asset condition observations are the foundation of the maintenance intervention plan. Condition-based maintenance is either predictive or non-predictive, depending on whether or not the maintenance decision includes degradation prognoses.

4.1.2. Corrective maintenance

The EN 13306:2017 [59] standard considers preventive maintenance activities schedulable, whereas corrective maintenance activities are not. However, there are studies on scheduling corrective maintenance [61]. Thus, planned or unplanned maintenance is another terminology that scholars use to avoid corrective maintenance scheduling confusions [62].

4.2. Maintenance operation

The purpose of performing maintenance and renewal on the railway track is to ensure safety and meet quality standards [125]. Track maintenance corresponds to rail geometry, track geometry, track structures, ballast bed, level crossing, and miscellaneous [125]. Restoring track geometry can be performed as local (spot) maintenance carried out manually or by small machines or as systematic (mechanical) maintenance performed by heavy machinery [125]. Typical examples of systematic maintenance activities are tamping, ballast regulating, ballast stabilising, rail grinding, joint straightening, and ballast cleaning. These activities use heavy, often highly specialised and expensive, machinery such as tamping machines, ballast regulators and stabilisers, rail grinding machines, STRAIT (Straightening of Rail Welds by Automated Iteration Techniques) for straightening welds, and ballast cleaners. Rail grinding machines remedy the track irregularities (e.g., rolling defects and corrugations) by grinding the rail surface [17,30,120,125]. STRAIT is utilised to rectify the structural changes that occurred during rail welding [125]. Tamping machines are used to correct track geometry level, cant, and alignment. The tamping machine lifts the track and then squeezes the ballast under the sleepers [125]. Tamping studies dominate the reviewed literature [18,86,89,91,95,98,118,124,126–128]. The ballast regulators reshape the ballast bed and are often used in connection with tamping. A ballast stabiliser is installed between the ballast and sub-ballast layer to improve the track grid's anchoring. Finally, the ballast cleaner digs away the ballast below the sleepers and filter out materials smaller than 35 mm [125]. The reader is referred to Esveld [125] for more detailed information on features of small and heavy maintenance.

4.3. Degree of maintenance

The purpose of preventive or corrective maintenance is to restore a characteristic, such as the track quality, to the desired operational level. Maintenance actions range from perfect repair to minimal repair [129,130]. Perfect maintenance restores the track components' condition to 'as good as new' while minimal repair restores them to 'as bad as old' or the condition just prior to failure. Researchers have defined perfect maintenance differently: replacing all components of one segment or a section of a railway track with new components or replacing only one track component.

Imperfect maintenance has drawn more attention because of its similarity to real-life scenarios. Major imperfect maintenance activities on various railway track components include ballast tamping, rail grinding, ballast cleaning, and small routine maintenance work [52,107].

Minimal maintenance is a corrective action invoked when there is a failure, and it does not improve the condition beyond the asset's condition before the failure [129]. Some maintenance actions even result in worsened conditions [129]. An example is excessive tamping, which causes ballast particles to break, thereby worsening the track substructure condition [131].

4.4. Decision-making level

Maintenance management requires an organisational structure to plan and organise tasks and resources, implement and control maintenance activities at different levels [132]. Lidén [6] classified maintenance planning according to three levels: strategic, tactical, and operational, according to the domain and duration of the planning horizon. The strategic level problems have time horizons of one to several years, and they include service life and maintenance frequency determination, network design considering maintenance, and renewal scheduling and project planning. Tactical level problems have a time horizon from weeks to years, and they cover timetabling and possession scheduling, deterioration-based maintenance scheduling, maintenance vehicle routing, and workforce scheduling. Finally, the operational level problems have a time horizon from hours to a month, and they include work timing and resource scheduling.

Researchers mainly consider the strategic, tactical, and operational levels separately. Few studies have considered the interaction between these three levels of the decision-making process. Su et al. [114] proposed a multi-level planning approach considering three decision-making levels of long-term strategic planning, tactical allocation of time slots, and operational clustering of work. Su et al. [115] extended the model presented in Su et al. [114] for large-scale railway networks. Further, Sharma et al. [56] used a multi-level approach to track defect prediction and maintenance planning optimisation. Sharma et al. [56] selected segments based on predictions from three data mining approaches at the tactical level. Sharma et al. [56] then used a Markov decision process to optimise maintenance intervention times at the operational level.

4.5. RTMP&S decision-making areas

The planning process aims to make critical decisions about the maintenance interval time on track segments and the necessary maintenance operation resources. In maintenance management literature, Campbell et al. [133] defined the purpose of planning as: "ensuring that all the known resources necessary to do a job are accounted for and available". The planning determines needed actions, sequence, and skills [133]. Palmer [4] defined the planner tasks as determining maintenance job scope, required craft and skill level, estimating the time, and specifying predicted parts and tools. According to Duffuaa and Al-Sultan [134], the planning function includes work identification, determining complexity on the composition of works, estimating required workforce, spare part identification and material requirements, and identifying if specific tools are required. The planning process aims to make critical decisions concerning the time of the maintenance interval time on track segments and the required maintenance resources.

In the railway maintenance literature, planning and scheduling problems are mainly distinguished based on the decision-making model time horizon. However, based on the above definitions, the time horizon is an inferior metric to determine if the problem belongs to planning or scheduling. Therefore, a precise classification of decision-making areas in planning and scheduling can help consistent use of terminology. Budai-Balke [135] distinguished several decision phases in structuring the maintenance planning and scheduling process and described the entire RMP&S process as the planning process. However, we have grouped the decision phases in Budai-Balke [135] into two areas of planning and scheduling decisions. We have considered budget determination, long-term quality prediction, project identification, and definition (diagnosis) in our classification planning process. The scheduling process covers project prioritisation and selection, possession allocation and timetabling of track possession, project combination, short-term maintenance, project scheduling, evaluation of maintenance work performance, and performance feedback. The Budai-Balke [135] structure of the planning decision phases is a thorough representation of the entire planning and scheduling process. Therefore, the structure of

Budai-Balke [135] inspired the planning and scheduling decision-making areas in this article.

4.5.1. Planning decision-making areas

4.5.1.1. Maintenance intervention timing. In the condition-based maintenance policy, the track condition prediction helps determine each track segment's maintenance cycle [16,101,112,136]. Infrastructure managers need to make decisions to allocate resources and ensure railway track safety [137]. Therefore, the track condition prediction accuracy plays a vital role in maintenance activity planning and scheduling. The key track quality indicators are the track geometry index and the track structure index [138]. Researchers use various track geometry parameters such as gauge, longitudinal level, cant, alignment, and twist to integrate the planning decisions with track condition predictions. Maintenance planners can use track geometry parameters individually or use different track quality indices based on parameter combinations. Researchers apply such track condition indicators by combining various track geometry parameters into one index [27,34,137,139].

However, as discussed earlier, the degradation process of the railway track is complicated. The degradation and the dynamic interaction between the track and rolling stock depend, among other things, on the substructure's non-linear stress-strain behaviour [27]. Therefore, using track geometry variables as the only track quality indicators may lead to poor condition predictions [27]. For instance, Sadeghi et al. [27] proposed identifying maintenance actions based on ballast geometry degradation and ballast fouling. Herein, we only discuss the articles that use track quality prediction as a basis for maintenance planning. Thereby, we exclude articles that solely focused on predicting track quality. Soleimanmeigouni et al. [138] and Higgins and Liu [140] provided comprehensive reviews of track geometry degradation models.

Meier-Hirmer et al. [90] proposed a decision support system for condition-based maintenance planning using a stochastic degradation model. Vale et al. [16] used the track degradation rate and the recovery of track quality after tamping to develop a model to optimise the number of tamping interventions. Gustavsson [112] improved the Vale et al. [16] model and let the cost function consider setup cost for tamping equipment.

4.5.1.2. Maintenance action identification and prioritisation. The maintenance interval in railway infrastructure management is either predetermined or condition-based. The EN 13848-5:2017 [141] standard is primarily used in Europe to identify maintenance action based on track geometry inspection data. The standard defines three action limits (immediate, alert, and intervention) for many track geometry variables but does not consider their interaction. Furthermore, the maintenance limit defined in the EN 13848-5:2017 [141] standard can affect maintenance action identification efficiency.

Andrade and Teixeira [142] explored the effect of modifying the defined maintenance limit for both the longitudinal level and the alignment on maintenance costs. For each train speed group, Andrade and Teixeira [142] found the optimal interval of maintenance limits of the track quality indicators based on the quantified preventive and corrective maintenance cost besides the penalty cost for the planned train delays. Khajehei et al. [104] studied the optimal region for the standard deviation of the longitudinal level and the extreme value of the isolated defects to minimise the inspection, preventive, and corrective maintenance costs.

Another critical aspect of maintenance identification is determining the proper maintenance action based on condition monitoring data. Zhao et al. [117] proposed an optimisation model to decide whether the sleepers must be immediately maintained or if the maintenance could be deferred. The Zhao et al. [117] model minimises the total number of corrective maintenance activities based on the sleeper's reliability function. Lovett et al. [94] proposed the case-based reasoning approach to select the most appropriate maintenance action type. The case-based reasoning could be the basis for a library containing maintenance action circumstances and related costs for each action. For instance, if the rail wear and fatigue crack values are significant, it might be more cost-effective to replace the rail rather than grind it. Kovačević et al. [143] used multi-attribute utility theory as a decision support framework to select and prioritise maintenance actions. The maintenance history, visual inspection data, ground-penetrating radar data, depth of ballast layer, ballast fouling indicating the quality of ballast, and irregularities in sub-ballast helped calculate the overall condition. The estimated condition then governed the maintenance action prioritisation. Phanyakit and Satiennam [122] developed a fuzzy multi-attribute decision-making model to plan the maintenance or replacement action based on the observed defects.

4.5.1.3. Inspection interval planning. Inspection intervals aim to ensure the railway track's safety and reliability and effectively manage the maintenance and inspection costs. Inspection intervals are intertwined with maintenance scheduling. Therefore, the scheduling of inspection intervals is briefly discussed to draw attention to the importance of inspection scheduling in RTMP&S. Podofillini et al. [11] proposed a multi-objective model to optimise the inspection interval based on maintenance cost and safety risks. Lannez et al. [74], Bin Osman et al. [144], and Bin Osman et al. [145] proposed optimisation models for scheduling the inspection time. Bin Osman et al. [146] explored the disruption of inspection scheduling, and they proposed an optimisation-based decision support model for rescheduling inspection intervals.

4.5.2. Scheduling decision-making areas

4.5.2.1. Possession scheduling. In railway transportation, all non-train activities on the railway infrastructure need to obtain a track possession time in the train timetable [78]. A possession schedule specifies the start times, duration, and sequence of segments defining possession timetabling for infrastructure maintenance and train operation [147]. The increasing demand for rail transportation during the past decade has accelerated both train traffic density and the required maintenance of railway infrastructure [78]. Therefore, the efficient scheduling of maintenance possession time plays a critical role in the RTMP&S decision-making process [78,147,148]. Armstrong and Preston [148] discussed the opportunities of improving infrastructure design, using predictive maintenance, and improving the efficiency of maintenance planning in finding the optimal trade-off between the possession times of maintenance and the traffic.

Arenas et al. [149] classified the interaction between scheduling the train timetable and maintenance possession in three categories. The first category is a fixed train timetable and variable maintenance possession time. In this category, the maintenance possession time is scheduled without modifying the train timetable [10,12,14,84,85,87]. In practice, this is the most common approach to estimate and plan for maintenance work when timetabling. Later, the primary allocated maintenance windows steer the operational maintenance scheduling.

The second category uses fixed maintenance possession times, and train timetabling uses slots not filled by maintenance work [149,150]. Compared to the first and third categories, this category is less prevalent in RTMP&S literature and practice. The train timetable can also be adjusted based on changes in the maintenance possession plan [151].

The third category, which has seen increased interest in recent years, involves the simultaneous scheduling of the maintenance possession time and the train timetabling [22,24,26,28,73,77–79,83,152]. However, simultaneous scheduling requires a large-scale optimisation model to capture both train timetabling and maintenance planning characteristics.

4.5.2.2. Grouping policy. The grouping policy considers the multi-component characteristic of railway track infrastructure in RTMP&S decision support models. Dekker et al. [153] defined two main grouping policy categories: stationary and dynamic. The stationary category corresponds to a stable scenario where uncertainty in component deterioration does not need to be considered [153]. Dynamic grouping is a short-term planning model that considers the unexpected opportunities and varying deterioration of components [153]. The stationary grouping models include corrective, preventive, and opportunistic maintenance. Preventive or corrective maintenance actions on one component can create opportunities for maintaining other components, which is opportunistic maintenance [153]. Another simple grouping policy classification is to combine different maintenance and renewal activities on the same track segment or the same activity on adjacent segments [35]. In this article, we classified the grouping policies based on the two possible scenarios discussed by Zhao et al. [35], and we added a mixed approach category.

4.5.2.2.1. Grouping policy: combining activities. Budai and Dekker [84] studied the advantages of combining maintenance activities in RTMP&S. They considered grouping of routine work, including inspections and minor repairs with projects such as rail grinding and tamping, in their first-step planning model. Using a numerical example, they showed that grouping maintenance could reduce track possession time and cost by 33% [84]. In another study, Budai et al. [10] developed a model for scheduling and grouping routine and project works. Further, Pouryousef et al. [85] and Khalouli et al. [87] used the Budai et al. [10] models for the RTMP&S problem.

Caetano and Teixeira [92,113] proposed an optimisation model for grouping renewal intervention on railway components, for example, ballast, rails, and sleepers. Their results suggested significant savings by combining renewal actions on different components, especially in possession cost. By combining the maintenance and renewal activities in long-term planning, Pargar et al. [36] demonstrated that costs could be reduced by up to 14% compared to the regular maintenance planning operation addressing renewal and maintenance activities separately. Further, Dao et al. [88] considered the economy-of-scale effects in integrating the renewal intervention of the multiple railway infrastructure components such as track components (rails, ballast, and sleepers), switches, and level crossings. Dao et al. [88] indicated that applying their model in the Northern Netherlands reduced costs by 13%. Kidd et al. [81] proposed a model to perform maintenance projects simultaneously to decrease the inconvenience caused by maintenance.

4.5.2.2.2. Grouping policy: grouping segments. Opportunistic maintenance also involves grouping adjacent track segments for a particular maintenance activity. When a line is closed for traffic and the maintenance crew has brought machinery and staff to a particular asset, the extra effort to maintain another nearby asset (in time or space) is often small. Literature examples include adaptive opportunistic maintenance policy for segments with tamping actions close in time [86] or tamping of geographically close segments [116,124]. Khajehei et al. [116] proposed an optimisation model for grouping nearby segments in six maintenance windows over three years. The adaptive maintenance policy is a terminology used in the literature to describe the grouping policy [86]. Gustavsson et al. [17] used a dynamic grouping strategy that employs the deterioration cost for a preventive rail grinding intervention schedule. Peng and Ouyang [15] used vehicle routing to schedule maintenance crew and cluster maintenance jobs as projects. Each maintenance job was defined as a customer and each project as a vehicle. Dell'Orco et al. [111] used a fuzzy clustering approach to group maintenance interventions in both space and time.

4.5.2.2.3. Grouping policy: mixed approaches. Zhao et al. [35] considered combining maintenance activities for different components on the same segment or to group adjacent segments for the same activity. The model results presented in Zhao et al. [35] showed that the grouping policy could result in cost savings. Zhao et al. [35] noted that an accurate estimation of combined renewals might be challenging where various contractors are involved.

4.5.2.3. Maintenance sequencing, vehicle routing, and crew scheduling. Finding the sequence of maintaining track segments in the defined period is one of the primary purposes of the maintenance-scheduling problem. Vehicle routing and crew scheduling are two distinct problems in maintenance scheduling with many similarities. Stenström et al. [154] studied the preventive and corrective maintenance costs in practice and estimated that logistics and travel costs account for around 15 to 20% of the maintenance costs. Therefore, finding the optimal vehicle and crew transportation route can result in significant cost savings [68,80].

Two modelling approaches are the basis for how scholars have formulated the vehicle routing and, sometimes, crew scheduling problems: vehicle routing problem (VRP) and time-space network (TSN). The VRP is a well-known transportation network problem; it aims to design optimal delivery routes to fulfil customer demands in a defined network [155]. In RTMP&S, the VRP is used to formulate the dispatching and travelling of equipment for fulfilling the maintenance operation [71,80]. Heinicke et al. [71] formulated the maintenance schedule as a multi-depot VRP with customer costs. Su and Schutter [80] used a capacitated arc routing problem with a fixed cost to find the optimal schedule of maintenance interventions and optimal routes for maintenance equipment from a depot to a maintenance site and back without exceeding the vehicle capacity.

Researchers have formulated the crew scheduling problem as a VRP with time windows wherein the crew plays the vehicles' role [15,68]. Scheduling maintenance crew to projects with multiple constraints regarding work hours, availability, competence, and travelling to the maintenance spot and on the track is complicated [12,68]. Higgins [12] presented a model for scheduling multi-maintenance projects and crew to minimise disruption to train traffic. This model included availability, minimum travel time for the crew to travel from one track link to another, and each maintenance crew's cost for crew scheduling.

The TSN approximates the VRP model in which the starting time of the activities transforms from continuous to discrete. Gorman and Kanet [68], Nemani et al. [69], and Peng et al. [14] have formulated the crew scheduling problem as a TSN with side constraints to minimise the different cost functions; for example, the workforce and equipment travel and use cost. Vehicle routing and crew scheduling for maintenance intervention are involved, especially at the multi-section or network level [68,80].

Researchers have also used other approaches to solve the vehicle and crew transportation problems. Zhang et al. [93] used a genetic algorithm to schedule maintenance interventions for different maintenance crew teams. Santos et al. [75] used a decision rule model to find sequences of tamping interventions based on optimal transportation cost. Huisman [66] defined a crew rescheduling model if train timetables change due to significant maintenance works. Li et al. [82] proposed a joint optimisation approach to determine the time of maintenance intervention based on maximum network flow, assign maintenance task to available teams, and find the optimal route for each team.

4.5.2.4. Equipment logistics. Some maintenance activities on the railway track, such as tamping, require track transports of heavy machinery and equipment to reach the maintenance location. Despite its importance, only a few studies have addressed the logistics of the maintenance equipment and heavy machinery. Santos and Teixeira [118] analysed maintenance scheduling through tamping machine capacity and operational limitations. They assumed a maximum number of segments that the tamping machine can maintain per period as the machine capacity. Further, Santos and Teixeira [118] considered the maintenance depot location. Oyama and Miwa [89] proposed an optimisation model to select the tamping machine's depot locations based on a ten-day tamping schedule.

5. Decision-making framework

5.1. Track degradation modelling

Track degradation modelling is the basis of estimating the appropriate time for condition-based maintenance interventions in railway track maintenance. The railway track degrades continuously, and proper maintenance actions must restore the track quality to a reliable and safe level. Track degradation behaviour is affected by uncertainties about heterogeneous influencing factors such as weather conditions, train axle loads, the track-bed settlements, and the construction materials [109]. Researchers classify degradation models into mechanistic or physics-based, empirical or data-driven, and hybrid models considering both physics-based and data-driven models [156]. Soleimanmeigouni et al. [138], Elkhoury et al. [157], and Higgins and Liu [140] review railway track degradation models.

5.1.1. Mechanistic (physics-based) models

Mechanistic degradation models estimate the track degradation based on the physics of failure and mechanical properties of the track components [138]. One advantage of the mechanistic models is their adaptation abilities to different traffic condition and materials, especially at the early stages of the life cycle where limited historical data is available [156]. However, a drawback of mechanistic models is that they are deterministic and typically do not consider the model input uncertainties [138,158]. Researchers have proposed hybrid approaches to consider uncertainty in the degradation model to overcome the problems stemming from applying purely mechanistic models. For example, Chiachío et al. [156] proposed a hybrid model based on an elastoplastic physic-based model for track settlement and a sequential model to consider model parameter uncertainty.

5.1.2. Empirical (data-driven) models

The RTMP&S problem involves various sources of uncertainty regarding railway asset degradation behaviour and model parameter estimation. Empirical models provide ways to address these uncertainties. In the RTMP&S literature, empirical models are mostly used for predicting track geometry degradation.

5.1.2.1. Stochastic models. Su et al. [114,115] addressed the uncertainty in the degradation rate of components using a stochastic process where the degradation depends on the current state and uncertainty parameter. Caetano & Teixeira [98] used a stochastic variable to represent the uncertainty to estimate the track geometry rates' degradation based on inspection data. Caetano and Teixeira [37,92] applied a two-parameter Weibull distribution to model degradation of rail and sleepers. Andrade and Teixeira [159] used a Hierarchical Bayesian model for degradation of the longitudinal level and horizontal alignment standard deviations. Letot et al. [86] used a two-parameter Wiener process to represent the stochastic dynamics of a track degradation process. Cárdenas-Gallo et al. [160] predicted track degradation by a three-parameter Gamma process models, a binary regression model, and a support vector machine model. Andrews et al. [128] used a stochastic Petri net model to consider the uncertainty in the track geometry's degradation behaviour and the uncertainty related to inspection, repair, and renewal. Vale and Ribeiro [95] and Vale and Lurdes [161] fitted a three-parameter Dagum distribution function to represent the longitudinal level's stochastic deterioration rate. Quiroga and Schnieder [18] described the degradation value of longitudinal levelling after nth tamping using a stochastic log-normally distributed variable. They used the evolution of the degradation value between consecutive tamping actions by an exponential function.

Furthermore, Mercier et al. [162] developed a stochastic decision support framework for scheduling tamping interventions using a bi-variate Gamma process to estimate the track degradation rate. Another uncertain variable in the RTMP&S problem is the predicted recovery of track geometry variables after performing maintenance. Famurewa et al. [76] used an empirically based regression model to predict the track geometry recovery after tamping interventions.

5.1.2.2. Markov chain approaches. Markov chains are common when the purpose is to model the outcomes of transformations from some states to other states; for instance, the probability that a system is functioning. This system can be built on components that can be either in a functional or a failed state. Each epoch involves calculating the probabilities of changing states, and this can include going from a functional geometry to a degraded one, or the probabilities that the system will improve, given that the system also includes maintenance operations. The Markov chain models do not need to be dichotomous but can include a range of discrete states. A continuous degradation process, for example, can be discretised into levels describing how far its degradation has progressed. Typically, maintenance regulations such as intervention limits or limits for line closure have already provided such discretised levels.

Prescott and Andrews [127] used a five-level Markov chain model that combined several geometrical parameters, degradation rates, maintenance and renewal policies, and both track and ballast states into a model consisting of 80 condition levels. They modelled maintenance and inspection policies over an expected life of 30 years for a track segment (1/8 mile $\approx$ 200m) and calculated the probabilities of the track being in a good state or in states requiring speed restrictions or line closure. Verbert et al. [38] aimed to optimise the maintenance level of a multi-component system level using Markov chain networks using the costs of different maintenance strategies. Sharma et al. [56] aimed to reduce maintenance costs of point defects using a Markov chain modelling approach for a 50-mile track. Gerum et al. [106] used random forests and neural networks to predict track defects based on inspection data. In the next phase, they used a Markov decision process to schedule maintenance activities. Sharma et al. [56] also used a Markov decision process to integrate track defects prediction and maintenance planning optimisation. Bressi et al. [109] developed a probabilistic degradation model using the Markov chains approach to find the optimal maintenance plan.

5.1.2.3. Artificial intelligence and machine learning. Recent advances in artificial intelligence and machine learning have drawn increasing attention among researchers and practitioners in railway transportation. Ghofrani et al. [163] reviewed the application of data analytics such as machine-learning methods in railway transportation operation, maintenance, and safety. Around half of the reviewed literature by Ghofrani et al. [163] focused on maintenance, in which predictive analytics remained dominant. For instance, machine learning and big data analytics have been used for track classification, degradation and recovery modelling, predictive maintenance, and condition monitoring in real-time rail traffic management [163]. Jamshidi et al. [30] used a big data analytics approach to obtain prior knowledge of the track, combining it with condition monitoring information, followed by implementing a Mamdani fuzzy inference system to develop rail health condition rules.

Nakhaee et al. [164] provided a comprehensive view of the application of machine-learning tools for predicting and diagnosing track faults. They reviewed research on shallow learning-based techniques such as support vector machines and research on deep learning-based methods such as convolutional neural networks that operate on unstructured data. They observed that deep learning techniques are used extensively in railway assets condition monitoring because of their applicability in image recognition.

Li et al. [13] presented a case where large datasets from multiple sources and various analytical learning approaches, including machine learning, were combined to produce alarm and failure predictions. They

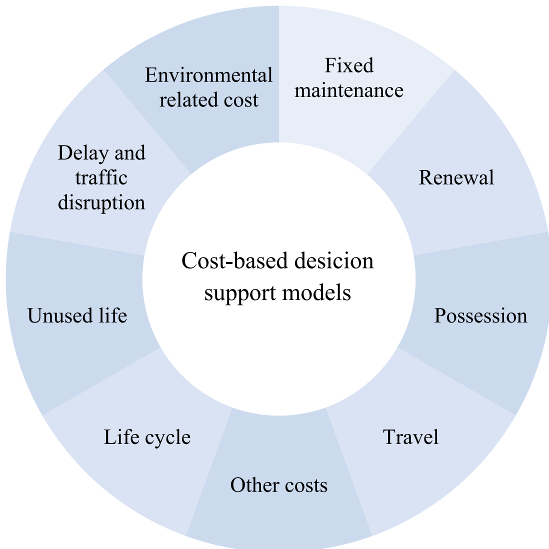

Fig. 4. Examples of RTMP&S costs used in objective functions.

found that the results improved by combining methods. Dell'Orco et al. [111] used an artificial neural network to model track deterioration.

5.2. Maintenance planning and scheduling optimisation objectives

Defining the objective function, the performance measure that the optimisation model aims, is crucial for MP&S modelling. Muchiri et al. [165] classified the maintenance objectives into five categories: functionality (availability, reliability, quality), achieving the expected design life, environmental safety, maintenance cost efficiency, and resource efficiency (energy and raw materials). Some of the main objectives in railway maintenance management are ensuring safety, reliability, cost-effectiveness, and comfort [166].

Scholars have commonly formulated the objectives mentioned above as a cost function. Cost-based decision support models cover a variety of costs to optimise different types of MP&S problems. The cost function can be formulated as a cost per maintenance or renewal activity or encompass a variety of costs such as possession, travel cost, or others (Fig. 4).

5.2.1. Life-cycle cost

The total life-cycle cost of railway transportation includes maintenance and renewal costs, construction costs, track use costs, and end of life costs. Decision-makers can use life-cycle cost to optimise investment in new construction and the maintenance and renewal of track components for a long time horizon (e.g., more than 50 years) [125]. The life-cycle cost can include tangible (e.g., construction, maintenance, renewal) or intangible costs (e.g., loss of quality, delay and traffic disruption, unused life, safety, and environment-related cost) [125]. Sasidharan et al. [123] defined four elements of the track's life-cycle cost and rolling stock as construction, operation (capacity loss, fuel or energy, environment, risk of accident, and socio-economic impact), maintenance, and end-of-life cost. Researchers have defined the railway track's life-cycle cost based on the combination of tangible and intangible costs [37,92,123,167]. For example, Zhao et al. [167] defined the life-cycle cost of the track between two consecutive renewals as a function of maintenance, renewal and penalty of poor track quality due to customers' loss and damage to track components due to poor quality.

5.2.2. Maintenance cost

It is common to estimate the planning and scheduling costs by considering a fixed cost per activity or time unit. This approach is a simple method for formulating the maintenance cost function. The sum of the estimated costs for using equipment, crew, and material can be the basis for such cost estimates. For instance, Gustavsson [112] used a general cost model to tamp track segment i at time step t as

$$Min \sum_{t\in T}\sum_{i\in N} c_{it}x_{it} + \sum_{t\in T} d_t z_t \quad (1)$$

where c_{it} is the cost estimation of the unit tamping operation and x_{it} is a binary decision variable denoting tamping on track segment i at time step t. Additionally, d_t is the cost of a maintenance occasion at time t and z_t is a decision variable indicating if at least one segment is tamped at time t. Daddow et al. [101] used Gustavsson's [112] cost formulation for unit tamping action cost. Vale et al. [16] used an objective function that minimises the total number of tamping actions where $c_{it} = 1$. Letot et al. [86] considered tamping machine cost as a fixed maintenance cost.

5.2.3. Renewal cost

Herein, we separate two categories of railway renewal cost: component renewal and complete track renewal. Caetano and Teixeira [92] used renewal cost in a multi-objective renewal planning optimisation model. They proposed the model as a decision support tool to find a trade-off between unavailability and track life-cycle cost (LCC). Furthermore, they estimated the renewal cost as a unitary cost of the renewal work and the track component's residual value. Caetano & Teixeira [37] later expanded the model to aid condition-based renewal decisions for track components. They formulated the objective function, including renewal cost, maintenance cost, and savings from grouping track segments for renewal and track components' residual value using an LCC perspective. Pargar et al. [36] proposed an integrated approach to consider equipment preparation and setup costs to balance maintenance and renewal planning. Dao et al. [25] used a fixed cost per renewal activity to consider both maintenance and renewal in the component's life cycle.

5.2.4. Possession cost

Possession cost is important for understanding the total maintenance costs, and it has been calculated using different means. One approach has been to use the time required to close the track to perform maintenance activities and then allotting an hourly cost for the possession time [78,79]. Other approaches estimate costs based on train cancellations [73] or applying a fixed cost per maintenance intervention [10]. Budai et al. [10] minimised possession and maintenance costs using a fixed possession cost per maintenance intervention time. Other studies, [36,85,87], further applied the model proposed in [10]. Zhang et al. [26] estimated the maintenance possession cost at a specific railway network arc for each maintenance based on the duration of the activity.

In some studies, track possession costs are not tangible. Instead, such costs emulate operational restrictions and their interactions within the preventive maintenance planning process. In these cases, the costs represent the difficulties in finding free maintenance possession time slots or costs for reduced traffic capacities [73,85]. Further, equipment setup cost can be another basis for calculations, as discussed in Pargar et al. [36] and Gustavsson et al. [17].

5.2.5. Travel cost

Travel costs are the estimated cost of transporting equipment and crew from one maintenance location to another [70,93,118]. Some heavy machinery such as tamping machines only travel as rolling stock. For a single track, machine transports consume the regular track time of trains, which can be considered as a cost. As discussed above, the TSN and VRP have been used to calculate travel costs [14,68,69,71]. Peng et al. [14] and Peng and Ouyang [70] used the production team scheduling problem to find the optimal total travel distance for maintenance teams.

Santos & Teixeira [118] formulated the travel cost as the distance between the yard and the maintained track segments or from one segment to another and used these costs to optimise the tamping length. Consilvio et al. [105] used the maintenance team's full travel path as the travel cost.

5.2.6. Unused life cost

Infrastructure components of the railway track have long life cycles. During their lives, maintenance and renewal actions aim to maintain an acceptable track quality. However, maintenance of one component may reduce the quality of another. One example is tamping to improve track geometry which degrades the ballast. Tamping may thus both improve current conditions but also increase the geometrical degradation rate. Therefore, the management of operations should plan maintenance and renewal actions neither too early nor too late.

The unused life cost is associated with losing useful life through premature maintenance or renewal, and it is a consequence of poor maintenance and renewal planning. We found that unused life estimations form two main categories. The first category involves track condition prediction and second PM interval recommendations.

Zhang et al. [93] used a Weibull probability function to estimate the cost for unused track life for premature maintenance in the condition-based maintenance category. Furthermore, Daddow et al. [101] applied a similar approach for the tamping's longitudinal deviation threshold. Santos et al. [75] estimated the value lost by performing early maintenance based on the differences between the predicted period for maintenance and its effective planning time.

In the preventive maintenance category, Budai et al. [10], Khalouli et al. [87], and Pouryousef et al. [85] used a penalty cost for the early implementation of work in the planning interval instead of at the end of the interval. Dao et al. [25] used the recommended PM intervals as the baseline to calculate the cost for shortening the service life in the developed plan.

5.2.7. Delay and traffic disruption cost

One objective of railway maintenance management is to maximise the track availability to cost ratio. The cost incurred by train delays and traffic disruption is significant for RTMP&S. A seminal paper by Higgins [12] proposed a formulation for delay cost. He calculated the total delay cost based on the expected interference delays, train delays, and maintenance activity delays. Simson et al. [110] estimated the train delay cost based on speed restrictions. Lidén and Joborn [78] based their estimated delay cost on the deviation from the possession plan's desired departure time. Lidén [22] applied the optimisation model presented in Lidén and Joborn [78] in the planning case. Albrecht et al. [147] proposed an integrated possession-planning model based on the train timetable and maintenance interval on the train delay and maintenance delay cost. Peralta et al. [29] calculated the delay cost through overall delay hours caused by train speed reduction due to track deterioration.

Caetano and Teixeira [113] used line shutdown costs or possession costs of track closure during renewal works as an indication of traffic disruption costs. Forsgren et al. [73] considered the number of cancelled or redirected trains as a traffic disruption cost to determine the maximum traffic flow for a fixed set of planned maintenance activities.

5.2.8. Environment-related cost

Our literature review did not find many papers that have studied the sustainability of maintenance operations and environment-related costs. Exceptions include Krezo et al. [168], Milford and Allwood [169], and Kiani et al.,[170], who quantified CO_2 emissions from railway maintenance equipment such as tampers, regulators, and stabilisers.

A research field that may need further attention is on the prediction of the effect of climate change on the railway network's maintenance. Researchers have studied the impact of climate change on railway network operation in various countries and settings [171,172]. Dépoues [171] addressed the need to consider climate change early in planning and decision-making proactively. Palin et al. [172] studied the effect of increasing temperature during the summertime and extreme weather on track components in Great Britain. The results of their studies showed that in railway track maintenance, the increasing temperature during the summer could result in track buckling, postponement of maintenance operations, and exposure of workers to heat stress during outdoor maintenance. However, we could not find any study that considered environmental factors such as temperature or effects of changed precipitation in the RTMP&S problem.

5.2.9. Other cost functions

Some objectives, such as minimising the failure costs and maximising the savings from combining maintenance activities, seem to have received less research attention. Camci [119] and Podofillini et al. [11] discussed the costs of failure or accidents. Camci [119] defined the failure cost as the direct cost of repair and the indirect cost of downtime and availability loss. This definition has also been used to calculate the failure cost as corrective maintenance costs; see Heinicke et al. [71] and Letot et al. [86].

5.3. Maintenance planning and scheduling optimisation constraints

The constraints in discrete optimisation represent the feasible solution space. In maintenance planning and scheduling, constraints correspond to the limit on availability of resources (e.g., maintenance crew, equipment, tools, and spare parts), work requirements of all maintenance work, and maintenance work sequence [134]. In RMP&S literature, we found the three main categories of constraints restricting planning and scheduling: maintenance operation constraints, track line availability, and acceptable track condition.

5.3.1. Maintenance operation constraints

In the reviewed literature, time, simultaneously and mutually exclusive activities, order of activities, preferences, track layout, regulations, and resource consumption restrict maintenance work. Time constraints can represent a variety of practical limitations for the decision-maker in maintenance scheduling. The number of extended time intervals if the maintenance is interrupted by train passage can be considered a time constraint [12]. Other forms of time constraints are the time between different maintenance activities (e.g., the time that the maintenance crew needs for transportation from one location to another [10,12,91]), the earliest and latest possible time for performing maintenance [25,84,105], the completion time [105], and equipment's setup or warm-up time [36,105,116,124].

The simultaneously and mutually exclusive constraints define which activities can be combined and cannot be performed simultaneously [10, 12,15,35,37,70,81]. Two sets of simultaneously and mutually exclusive activities can be defined and represented in constraints [81]. Moreover, technical or operational aspects can impose a sequence in which the maintenance activities need to be executed [12,14,70–72,105]. These constraints define the flow of maintenance activities' execution and precedence among maintenance activities [14,36,70,105]. Preference constraints represent the preferences to assign maintenance activities to specific crews based on geographical factors or having higher efficiency [15,70]. Preference constraints can also limit the assignment of maintenance works to specific crews [15,70].

The regulations regarding maintenance execution can come as track layout constraints [16,101,108,112,116,124]. For example, as Vale et al. [16] discussed, the tamping actions should begin and end on a straight alignment. Therefore, if a segment inside a curve needs tamping, the tamping should start from the straight section before the curve and end in a following straight section.

Resource consumption constraints represent a set of shared resources (e.g., budget, maintenance crews, and equipment) used during the maintenance execution [81]. One critical resource constraint is on ensuring that maintenance cost does not exceed the budget [12,37]. Another essential constraint in maintenance scheduling is the maintenance crews' availability [12]. However, a minority of scheduling

Table 6
Linear and integer programming approaches used in the reviewed literature.

Approach	References
Integer programming	Higgins [12], Peng et al. [14], Gustavsson et al. [17], Pargar et al. [36], Dao et al. [25], Miwa & Oyama [103], Zhang et al. [26].
Mixed-integer programming	Budai & Dekker [84], Budai et al. [10], Van Zante-De Fokkert et al. [67], Oh et al. [91], Zhao et al.[35], Pouryousef et al. [85], Nemani et al. [69], Vale et al. [16], Peng & Ouyang [70], Heinicke et al. [71], Boland et al. [72], Forsgren et al. [73], Luan et al. [77], Peng & Ouyang [15], Khalouli et al. [87], Vale & Ribeiro [95], Caetano & Teixeira [37], Consilvio et al. [96], Gustavsson [173], Daddow et al. [101], Caetano & Teixeira [98], Wen & Salling [99], Lidén & Joborn [78], Faris et al. [102], Su & Schutter [80], Dao et al. [25], Kidd et al. [81], Zhang et al. [83], Consilvio et al. [105], Consilvio et al. [23], Lidén [22], Bakhtiary et al. [124], Khajehei et al. [116], Daddow et al. [108].

models in the literature consider crew availability.

5.3.2. Track line availability

Availability and unavailability can be defined as a specific time interval in which maintenance can or cannot be performed, respectively [12,25,78]. For example, in some regions, the maintenance actions cannot be executed during some seasons, e.g., the hot summertime or cold wintertime [14,70,105]. Another form of track availability constraints is limiting the maintenance execution in different track sections to avoid heavy traffic blocking [14]. This form of constraint considers the relationship between all track sections in a corridor as either mutually exclusive sections or otherwise [14]. For example, Peng and Ouyang [70] represented the track relationships in a railway corridor by defining a graph containing a set of vertices representing track milestones and a set of edges, indicating railway tracks.

Moreover, the heavy machinery required for track maintenance needs that the track is closed for traffic during maintenance. Therefore, decision-makers need to limit the maintenance plan and schedule based on the available time windows. Constraint examples include limiting maximum hours per days or limiting work to specific days or week because of traffic volume [14,25,70,116]. The maintenance window constraint can also be represented based on an interval to which the start time and the end time of each maintenance activity must belong [83].

5.3.3. Track condition

Restoring the track condition after degradation is one of the main purposes of performing maintenance actions such as tamping. Therefore, the evolution of track degradation and maximum level of track degradation based on a predefined limit can be considered as constraints [16,91,95,99,101,108,112,116,124]. One can also set a safety limit on the longest accepted time interval between maintenance [35]. In addition, recovery of the track condition after performing maintenance may also be modelled as constraints [16,37,95,99,101,108,112,116,124].

5.4. Solution approaches

To finally solve an RTMP&S problem, a suitable approach should be chosen to solve a mathematical formulation of the problem, considering the decision-making level and resulting decision variables, track condition data, the objectives, and the constraints. Here, we provide an overview of these approaches, starting with linear and integer programming, the most commonly proposed method. RTMP&S problems involve complex relationships between various planning and scheduling activities, thereby producing more decision variables and side constraints. These problems can often be considered non-deterministic polynomial-time hard (NP-hard) [12,105]. Consequently, researchers often use heuristics or metaheuristics to provide satisfactory solutions faster. We also provide an overview of the search methods used in the

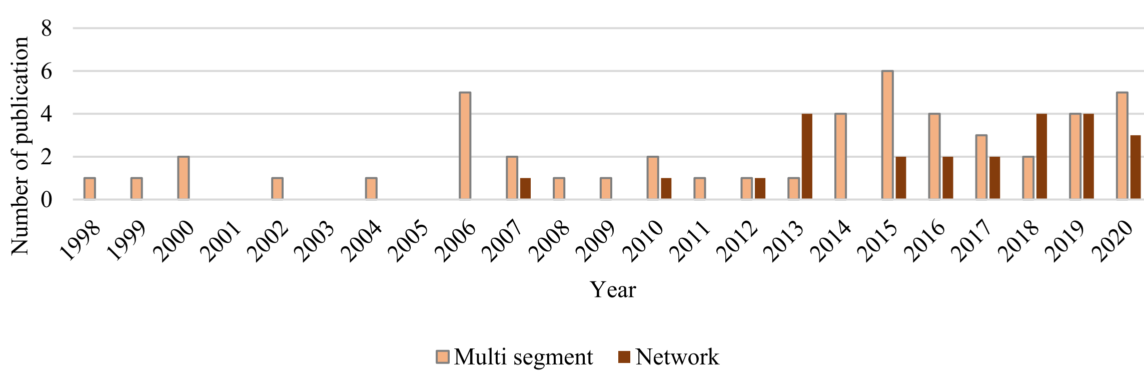

Fig. 5. Historical trend of RTMP&S at multi-segment vs network levels in the reviewed literature. Table A.1 and A.2 in the Appendix provide further details.

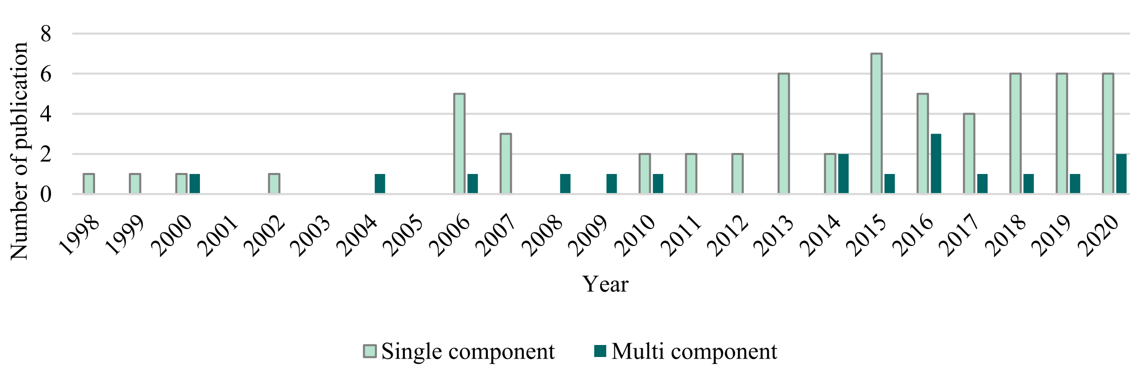

Fig. 6. Historical trend of RTMP&S using single- or multi-component perspectives in the reviewed literature. Table A.1 and A.2 in the Appendix provide further details.

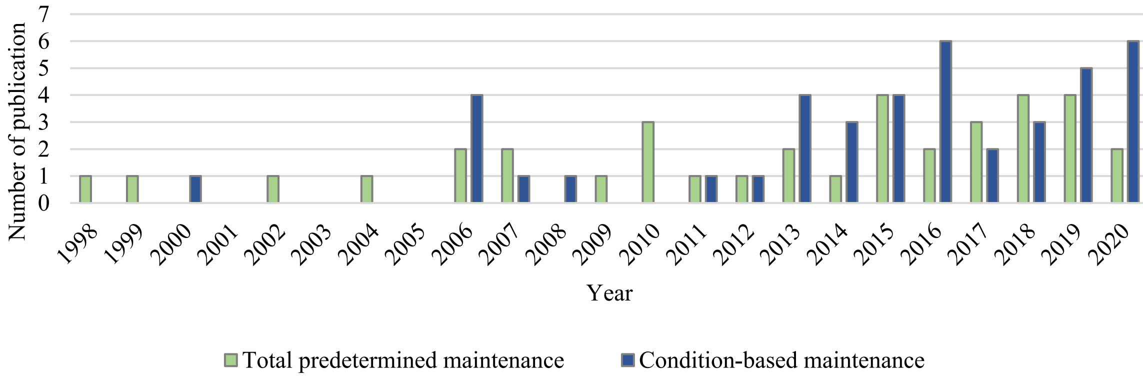

Fig. 7. Historical trend of research on predetermined and condition-based maintenance. Table A.1 and Table A.2 in the Appendix provide further details.

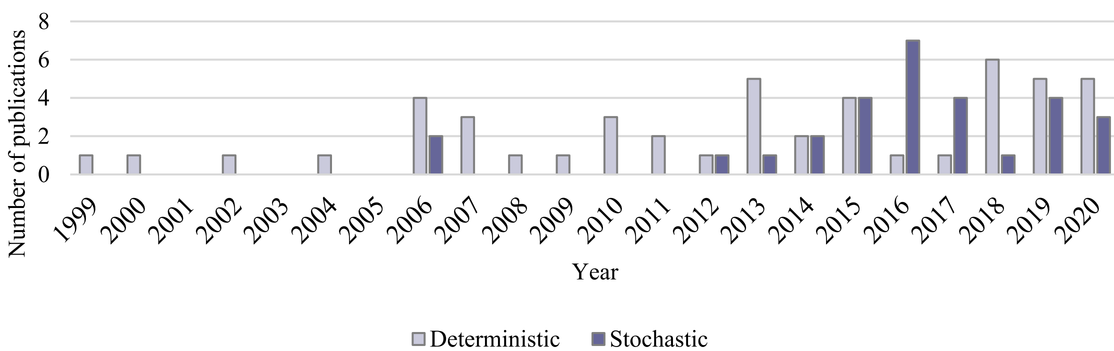

Fig. 8. Historical trend of using deterministic or stochastic approaches in degradation modelling.

surveyed articles.

5.4.1. Linear and integer programming

The nature of the decision variables in RTMP&S makes linear or non-linear programming suitable. Additionally, integer programming fits well with integer decision variables, such as whether or not to take maintenance actions or allocate resources.

5.4.1.1. Single objective function models. Most of the surveyed literature used a single objective function, often a piecewise construction of various objectives presented in Section 5.2. The time of maintenance intervention and selected segments' location for maintenance intervention can be both integer and continuous variables. Often, these models include both continuous and integer variables, leading to mixed-integer linear programming approaches. Table 6 illustrates how mixed-integer linear programming is the most common approach used.

The studies presented in Table 6 most commonly relied on commercial solvers such as CPLEX [10,14,16,25,36,80,81,83,84,95,108], Gurobi [22,78], or FICO Xpress [37,103]. Additionally, various heuristics and metaheuristics were used. Nemani et al. [69] used decomposition-based heuristics to solve the curfew planning problem (CPP) for railway maintenance. Peng and Ouyang [70] used multiple neighbourhood search heuristics, i.e., decomposition and restriction method and block interchange, while Luan et al., [77] and Zhang et al., [26] used a Lagrangian relaxation-based solution framework. Peng & Ouyang [15] used three algorithms, greedy, local search, and a feasibility heuristic iteratively to improve the solution. Higgins [12] used a tabu search heuristic. Consilvio et al. [105] used customized meta-heuristic algorithms to decompose the original problem into smaller problems. Zhang et al. [93], Bakhtiary et al. [124], and Khajehei et al. [116] used a genetic algorithm to solve the optimisation model.

5.4.1.2. Multi-objective function models. Multi-objective optimisation provides the possibility of measuring the trade-off between multiple conflicting or non-conflicting objectives for decision-makers. Caetano and Teixeira [92] proposed a multi-objective optimisation approach for the RTMP&S problem considering two railway track unavailability objectives caused by maintenance and life cycle cost of track components. Peralta et al. [29] developed a multi-objective model addressing maintenance operation costs and train delay costs caused by track deterioration. D'Ariano et al. [28] used a bi-objective model to identify Pareto-optimal solutions for the integrated planning of both the train timetabling problem and tactical maintenance planning. One objective function addresses the minimisation of train dispatching deviation from the nominal timetable, and the second objective function maximises the number of paired maintenance work executions [28].

Bressi et al. [109] formulated railway track-bed maintenance strategy selection as a bi-objective problem minimising mean vertical alignment and the present value of total maintenance and renewal cost. The solution approach in [109] was a genetic algorithm involving weighted sums and Pareto optimality.

5.4.2. Non-linear programming

While linear programming was the most used choice in RTMP&S formulation and optimisation, some researchers preferred non-linear programming. Zhao et al. [117] used a non-linear formulation for sleeper maintenance scheduling and used the steepest gradient as a search method. In another application of non-linear programming for maintenance scheduling, Zhang et al. [93] used an enhanced genetic algorithm. In articles by Lake and Ferreira [65] and Lake et al. [64], simulated annealing was found to be the best heuristic [64] and used as the final step after finding a feasible solution in [65].

Su et al. [114,115] used multiple level Model Predictive Control approaches for maintenance planning. They used different solution approaches at different model levels; a pattern search, MILP conversions, a Dantzig-Wolfe decomposition, and converting the arc routing problem to a node routing problem. A later article by the same authors [115] used a similar approach for clustering maintenance actions and noted that clustering could be solved either through a MILP conversion or with gradient-free algorithms like pattern search or genetic algorithms.

5.4.3. Simulation

Researchers have increasingly considered connecting simulation models to an optimisation engine in RTMP&S problems [174]. Alrabghi and Tiwari [174] found discrete event simulation to be the most common technique to model maintenance systems. Simulation models have high capabilities and flexibility to consider the practical complexities of maintenance planning and scheduling problems [20,174].

Monte Carlo simulation techniques rather than discrete-event simulation have also been used to model the track geometry's degradation behaviour, and recovery after maintenance. Monte Carlo simulations rely on repeated random sampling through computational algorithms to obtain numerical results. Khajehei et al. [104] used Monte Carlo simulation for the track geometry behaviour to study the effect of different maintenance limits on maintenance cost. Letot et al. [86] modelled the track degradation and recovery behaviour using stochastic approaches and used Monte Carlo simulation to determine the optimal tamping intervention time. Andrews et al. [128] used the Monte Carlo simulation to analyse the effectiveness of asset management strategy by changing the inspection frequency, track degradation behaviour, maintenance intervention time, and the track degradation threshold that triggers the maintenance intervention. Quiroga and Schnieder [18] used Monte Carlo simulation to simulate track geometry degradation and recovery to optimise a tamping schedule.

5.4.4. Other approaches

In this subsection, we discuss other approaches not falling under the categories presented above. In some cases, particular types of problems were posed and then solved using heuristics or metaheuristics. Santos and Teixeira [118] studied the optimum length of track to be maintained by a single machine and solved their formulation through simulated annealing. Bueno et al. [24] used simulated annealing to find optimal placements for maintenance windows, further evaluated through what was dubbed as the Train Scheduling Planner. Lee et al. [34] determined the optimal frequency for tamping and renewing a ballasted track using a nondominated sorting genetic algorithm to solve a problem with two objective functions. Albrecht et al. [147] used another metaheuristic, the problem space search, to reschedule timetables. Li et al. [82] discuss the complex problem of joint workforce scheduling and routing during disruption recovery and propose a solution approach based on the ant colony optimisation metaheuristic.

The decision rules model has primarily been used in dynamic decision problems under uncertainty in robust optimisation and multi-stage stochastic programming [175]. In RTMP&S, Santos et al. [75] used a decision rules model to provide planning and scheduling solutions by considering a set of practical rules.

Another approach is the fuzzy decision-making methods to analyse the track quality index and degradation factors to plan maintenance actions, e.g., Phanyakit and Satiennam [122]. Dell'Orco et al. [111] used a fuzzy C-means clustering method for maintenance planning optimisation, suggesting that fuzzy decision-making methods are more flexible in considering approximate values and linguistic terms than traditional decision-making methods based on binary logic.

6. Research trends in RTMP&S and future directions

6.1. Railway system structural characteristics

The structural characteristics of railway systems play a central role in developing practical planning and scheduling models. The reviewed literature analysis indicates that a majority of prior research (~65%) investigated RTMP&S at multi-segment levels. Our analysis shows that 35% of the studies focus on the network level, which Su et al. [115] noted to be a precursor for obtaining an optimal maintenance schedule. In recent years, the number of studies on optimal maintenance planning and scheduling at the network level has increased, as shown in Fig. 5. We expect this trend to continue as means of handling the computational complexity of optimising RTMP&S at a network level keep also developing.

Quatrini et al. [39] observe an increased research interest in the multi-component perspective. They note this to be fundamental for CBM advancement and for increasing the cost efficiency of RTMP&S. Fig. 6 shows that the number of studies that have considered the dependence between the railway track components has increased. However, the literature lacks investigation of the stochastic and structural dependencies between railway track components, which may be an important area for future research. Quatrini et al. [39] also indicated that resource dependency is less investigated overall in CBM research.

6.2. Maintenance management decisions

Recently, the condition-based maintenance policy in railway track maintenance has attracted increased attention (Fig. 7). A more detailed analysis of the RTMP&S literature shows that 42 papers (54%) studied condition-based maintenance, while 36 papers (46%) considered predetermined maintenance. These trends highlight how the development of more accurate prediction models and enabling technologies are shifting improvement efforts towards predictive condition-based maintenance, as noted in a more general CBM context by Quatrini et al. [39]. Such enabling technologies include improved data infrastructure, inexpensive and better sensors, and advanced monitoring systems. However, Quatrini et al. [39] consider data management for CBM as an immature research area. Given the continuous development of sensors and advances in artificial intelligence and machine learning methods, we expect that this trend of an increased interest in condition and prediction-based maintenance will continue, both in practice and in research.

Track quality prediction has gained considerable attention in planning decision-making areas compared to maintenance identification and prioritisation. Few studies have proposed approaches to select the required maintenance action types based on track measurement data effectively. Reliability centred maintenance (RCM) is a popular approach in maintenance planning to identify the correct maintenance action types [176]. However, as Lee et al. [34] discussed, RCM practice usually only uses track quality predictions in railway infrastructure. However, the adaptation of RCM in railway maintenance planning appears in need of further research.

Another less apparent trend is systemic RTMP&S approaches such as developing multi-level decision-making frameworks to integrate different levels of planning and scheduling decisions. Jointly solving train scheduling and CBM planning would result in more optimal plans for both, but is also challenging due to its complexity and the shorter-term nature of train scheduling, as pointed out by Su et al. [115]. The main advantages of these frameworks are their capabilities to capture the interaction between different decision-making levels.

In scheduling decision-making areas, simultaneous possession scheduling and multi-component grouping policies are two research trends that can improve maintenance management efficiency. Previous studies show promising results of cost savings by incorporating grouping policies [36,88]. However, to the best of our knowledge, only predetermined preventive maintenance costs and not the effect of grouping policy on corrective maintenance costs have been considered. Dao et al. [88] also identified integrating multiple types of maintenance activities as a future research topic. Another research gap is the lack of exploring the efficacy and efficiency of different grouping policies for condition-based maintenance activities.

In other contexts, the maintenance planning literature has suggested spare parts and material supply, procurement contracts, and budget planning as planning decision-making areas [4,134]. However, the railway track literature does not cover these areas comprehensively. Aldenlöv et al. [173] explored procurement contracts in the Swedish railway infrastructure maintenance in four key areas of maintenance contract management: partnering, contract incentives, financing, and maintenance management practices. In our literature review, Van Zante-De Fokkert et al. [67] is the only study we found that considered the contractor workload and worker safety in scheduling maintenance activities. Zhu et al. [177] investigated spare part forecasting in the RTMP&S context.

Reviewing the literature, we found only a handful of articles that included ecological or social sustainability perspectives in addressing RTMP&S problems. Given the increased societal focus and research funding directed toward improving sustainability, we expect to see more research integrating sustainability in RTMP&S more explicitly.

6.3. Decision-making framework

The optimal planning and scheduling of maintenance activities can increase the efficiency and effectiveness of railway infrastructure management. This complicated task starts with modelling degradation, which will provide input for performing various maintenance tasks. In this area, the stochastic approaches to model the track degradation are gaining popularity (Fig. 8). Directly integrating this stochasticity to a maintenance optimization model's inputs is a promising area of future research, as pointed out by Consilvio et al. [105].

A critical factor in defining the optimisation objective is to have a realistic estimation of the maintenance cost in practice. Therefore, oversimplified cost functions may result in an inadequate analysis of the RTMP&S strategies and decisions. In practice, the decision-maker needs to consider multiple and often conflicting objectives [124], yet cost remains the most used criterion in Section 5.1. How to integrate sustainability perspectives through, e.g., "environmental costs", may also be a promising research area in our opinion. Achieving higher reliability and safety levels is equally vital for maintenance management. In practice, there is a conflict between maximising the reliability and safety of railway infrastructure and minimising maintenance costs. Su et al. [115] also noted this conflict and suggested combining multiple track health performance criteria in the track condition function or formulating multiple objective problems.

A single objective function MILP formulation for RTMP&S optimisation was the prevalent approach and most often solved using a commercial solver, as seen in Section 5.4. However, as discussed earlier, there is a recognized need for larger models combining different time horizons, different types of maintenance work, networks and even different stakeholders. To solve these problems in a reasonable amount of time, more efficient [82] and dedicated [28] solution algorithms should be developed to respond to practical events such as speed restrictions or disruptions [28]. These can be evolutionary algorithms [88] or distributed methods for multi-objective optimization. Solution algorithms could also include efficient heuristics or metaheuristics [115]. Such models will further enable the application of formal scheduling and optimization techniques to practice, including possession planning, see, e.g., Armstrong and Preston [148].

Finally, Consilvio et al. [23] suggested using digital twins in rail asset management and that these are developed by combining data processing, machine learning, and simulation to provide prescriptive results within one real-time decision support system. Such digital twins would enable integrating degradation models directly to the maintenance scheduling engine in a network context [88] and studies of the stochasticity's effect on infrastructure manager's decision-making [137]. Regarding machine learning, their application in remaining useful life and future state prediction life in CBM was noted to be an open topic by Quatrini et al. [39].

Methods based on artificial intelligence and machine learning approaches are often opaque on how results are produced, but human interpretability of the rule set producing predictions is a crucial facilitator of decision making, as pointed out by Li et al. [13]. Nakhaee et al. [164] also note the effect of this lack of transparency in the railway maintenance context. Other issues concerning artificial intelligence and machine learning methods in railway maintenance applications include incompatibility in data collected from different spatial and temporal points by multiple detectors in different locations [13]. Such data collection schemes may result in heterogeneity, inconsistency, and incompleteness. [163]. Other related problems include skewed data due to failures being scarce, a lack of labelled datasets, and a lack of public datasets [164]. Additionally, these approaches require care for processing large datasets [13,163], augmenting models with domain knowledge [164], and data ownership issues [163].

7. Conclusions

This article provides a review of the literature focusing on decision support models for RTMP&S. We propose a taxonomy for classifying research on RTMP&S based on three main categories: (1) railway system structural characteristics, (2) maintenance management decisions, and (3) decision-making framework. Each of these main categories has underlying attributes and sub-attributes, which we apply to structure our literature review. We argue that the taxonomy's value is to provide an overview of the attributes that the railway infrastructure maintenance management needs to consider. Furthermore, the taxonomy provides an overview of costs and constraints that maintenance managers should quantify when defining an optimisation objective. Finally, the article provides an overview of the optimisation objectives and solution approaches that researchers have used to solve them.

We identified some trends in the research on RTMP&S and found an increased research interest on such problems from a multi-component and railway network perspectives. The condition-based maintenance policy has attracted more attention from researchers working on railway track maintenance than predetermined maintenance has. This trend highlights the need for more accurate prediction models to handle the ever-increasing possibilities for gathering data from railway infrastructure assets to predict the track condition. Additionally, there is a trend for a systemic perspective in dealing with RTMP&S problems. This line of research includes developing multi-level decision-making frameworks that also integrate planning and scheduling decisions (strategic, tactical, and operational).

We observed that cost-based decision support models must often combine various costs to minimise the overall cost. We believe that future research on how to 'best' formulate the objective function may be valuable. Furthermore, with sustainability being a global megatrend, we expect a stronger emphasis on environmental and other sustainability-related costs. We also observed an increase in stochastic degradation modelling, complementing the general trend towards more complex models, including networks, multi-component systems, multiple decision-making levels, and more elaborate objective functions.

As decision-makers frequently need to consider multiple, often conflicting objectives, such as maintenance costs and safety, we believe future research should aim to develop frameworks for multi-objective optimisation. In the studied RTMP&S literature, artificial intelligence and machine learning-based approaches have only received limited attention, and researchers have primarily used them to create predictions to support the existing decision-making system. Considering how fashionable the topic is across all industries, we expect a surge in research on how artificial intelligence and machine learning methods can improve decision frameworks based on predictive condition-based maintenance.

In this article, we follow the established logic of an integrative literature review; the current status of RTMP&S research is thoroughly reviewed, and future trends are discussed based on these results. It would be interesting to complement this work with a different type of review, relying on a more narrow article base and reviewing it with a critical tone. Other complementary approaches could be based on reviewing current practice through, e.g., interviews or surveys of decision-makers, or reviews of professional literature and available software solutions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Summary of the literature review

Table A1 and Table A2

Table A.1
Summary of the articles with predetermined maintenance policy.

References	Infrastructure configuration		Component level			Decision-making areas	Modelling approach
	Single component	Multi-components	Single-segment	Multi-segments	Network		
Higgins [12]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Integer Programming
Cheung et al. [63]	✓			✓		Possession scheduling	Constraint-handling model, Resource allocation
Lake et al. [64]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Heuristics
Lake & Ferreira [65]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Trial of four heuristic optimisation models, Simulated Annealing, Tabu Search, Local Search, and Multiple local searches
Budai & Dekker [84]		✓		✓		-Possession scheduling, -Grouping policy: Integrating maintenance activities	Mixed Integer Programming
Budai et al. [10]		✓		✓		-Possession scheduling, -Grouping policy: Integrating maintenance activities	Mixed Integer Programming
Huisman [66]	✓				✓	Maintenance sequencing, vehicle routing, and crew scheduling	Column generation-based algorithm
Van Zante-De Fokkert et al. [67]	✓			✓		Contractor workload optimisation	Mixed Integer Programming
Zhao et al. [35]		✓		✓		Grouping policy: Mixed approaches	Mixed Integer Programming
Gorman & Kanet [68]	✓				✓	Crew scheduling	Integer Programming, Constraint Programming, and genetic algorithms
Pouryousef et al. [85]		✓		✓		-Possession scheduling, -Grouping policy: Integrating maintenance activities	Mixed Integer Programming
Nemani et al. [69]	✓			✓		Crew scheduling	Mixed Integer Programming
Peng et al. [14]	✓					Possession scheduling	Integer programming, Time-Space Network (TSN)
Peng & Ouyang [70]	✓				✓	Crew scheduling	Mixed Integer Programming
Heinicke et al. [71]	✓			✓		Vehicle routing	Mixed Integer Programming, Multi-Depot Vehicle
Routing Problem							
	Single component	Multi-components	Single-segment	Multi-segments	Network		
Boland et al. [72]	✓				✓	Possession scheduling	Mixed Integer Programming, Vehicle Routing Problem
Forsgren et al. [73]	✓				✓	Possession scheduling	Mixed Integer Programming
Peng & Ouyang [15]		✓		✓		Grouping policy: Grouping segments	Mixed Integer Programming
Lannez et al. [74]	✓				✓	Inspection scheduling	Integer Programming
Santos et al. [75]	✓			✓		Maintenance sequencing	Decision Rule Model
Famurewa et al. [76]	✓			✓		Maintenance intervention timing	Simulation Model
		✓		✓			Mixed Integer Programming

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Table A.1 (*continued*)

References	Infrastructure configuration		Component level			Decision-making areas	Modelling approach
	Single component	Multi-components	Single-segment	Multi-segments	Network		
Khalouli et al. [87]						-Possession scheduling, -Grouping policy: Integrating maintenance activities	
Letot et al. [86]		✓		✓		Grouping policy: Grouping segments	Stochastic model
Luan et al. [77]	✓				✓	Possession scheduling	Mixed Integer Programming
Pargar et al. [36]		✓		✓		Grouping policy: Integrating activities	Integer Programming
Lidén & Joborn [78]	✓				✓	Possession scheduling	Mixed Integer Programming
Lidén et al. [79]	✓				✓	Possession scheduling	Mixed Integer Programming
Dao et al. [88]		✓		✓		Grouping policy: Integrating activities	Mixed Integer Programming
Su & Schutter [80]	✓				✓	Maintenance sequencing, vehicle routing, and crew scheduling	Integer programming
Kidd et al. [81]		✓		✓		Grouping policy: Integrating activities	Mixed Integer Programming
Zhang et al. [83]	✓				✓	Possession scheduling	Mixed Integer Programming
D'Ariano et al. [18]	✓				✓	Possession scheduling	Bi-Objective Mixed-Integer Linear Programming, Pareto optimal solutions
Lidén [22]	✓				✓	Possession scheduling	Mixed Integer Programming
Zhang et al. [26]	✓				✓	Possession scheduling	Integer Programming, solve with a heuristic algorithm using Lagrangian relaxation

Table A.2
Summary of the articles with condition-based maintenance policy.

References	Infrastructure configuration			Component level		Decision-making areas	Modelling approach
	Single component	Multi-components	Single-segment	Multi- segments	Network		
Simson et al. [110]		✓		✓		Grouping policy: Grouping segments	Simulation Models
Dell'Orco et al. [111]		✓		✓		Grouping policy: Grouping segments	Neuro-Fuzzy Inference Engine
Oyama & Miwa [89]	✓			✓		Equipment logistic	Integer Programming
Meier-Hirmer et al. [90]	✓			✓		Maintenance intervention timing based on track quality prediction	Stochastic Model for track geometry degradation
Podofillini et al. [11]	✓				Not specified	Inspection interval planning	- Markovian model of failure states, -A metaheuristic for scheduling (Multi-objective Genetic Algorithm)
Oh et al. [91]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Mixed Integer Programming (Heuristic Algorithm)
Zhao et al. [117]	✓			✓		Maintenance action identification and prioritisation	Nonlinear Integer Programming (Steepest Gradient Method)
Vale et al. [16]	✓			✓		- Maintenance intervention timing -Mixed Integer Programming,	-Stochastic Model
Santos & Teixeira [118]	✓			✓		Equipment logistic	Meta-Heuristic Algorithm
Peng et al. [14]	✓				✓	Maintenance sequencing, vehicle routing, and crew scheduling	Mixed Integer Programming
Zhang et al. [93]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Meta-Heuristic Algorithm (Genetic Algorithm)
Caetano & Teixeira [92]		✓			✓	Grouping policy: Integrating activities	-A stochastic model for ballast, sleepers, and rail degradation -Scheduling: Multi-objective Optimisation, Genetic Algorithm

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Table A.2 (*continued*)

References	Infrastructure configuration			Component level		Decision-making areas	Modelling approach
	Single component	Multi-components	Single-segment	Multi- segments	Network		
Lovett et al. [94]	✓				Not specified	Multi-level: -Maintenance sequencing, Vehicle routing, and crew scheduling -Maintenance timing based on track quality prediction,	Not specified
Gustavsson et al. [17]		✓		✓		Grouping policy: Grouping segments	Integer Programming
Vale & Ribeiro [95]	✓			✓		Maintenance intervention timing	-A stochastic model for track degradation -Planning: Mixed Integer Programming
Consilvio et al. [96]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Mixed Integer Programming
Gustavsson [112]		✓			✓	Maintenance timing based on track quality prediction	Mixed Integer Programming
Camci [119]	✓			✓		Maintenance sequencing, vehicle routing, and crew scheduling	Genetic Algorithm
Famurewa et al. [97]	✓			✓		Maintenance timing based on track quality prediction	Optimisation Algorithm
Caetano & Teixeira [113]		✓			✓	Grouping policy: Integrating activities	Mixed Integer Programming
Caetano & Teixeira [98]	✓			✓		Inspection timing based on track quality prediction	-Stochastic Model, -Multi-objective Optimisation (Genetic Algorithm)
Wen & Salling [99]	✓			✓		Maintenance timing based on track quality prediction	Mixed Integer Programming
Su et al. [120]	✓			✓		Multi-level: -Maintenance timing based on track quality prediction, -Maintenance sequencing, Vehicle routing, and crew scheduling	Model Predictive Control (MPC), Mixed Integer Programming
Consilvio et al. [121]	✓				✓	Maintenance sequencing, vehicle routing, and crew scheduling	Mixed Integer Programming
Villarejo et al. [100]	✓			✓		Maintenance timing based on track quality prediction	Data-Driven Model
Daddow et al. [101]	✓			✓		Maintenance timing based on track quality prediction	Mixed Integer Programming
Su et al. [114]	✓			✓		Multi-level: -Maintenance timing based on track quality prediction, -Maintenance sequencing, Vehicle routing, and crew scheduling	Model Predictive Control (MPC), Mixed Integer Programming
Peralta et al. [29]	✓			✓		Maintenance timing based on track quality prediction	Multi-Objective Models
Faris et al. [102]	✓		Not specified	Maintenance sequencing	Mixed Integer Programming		
Phanyakit & Satiennam [122]	✓			✓		Maintenance action identification and prioritisation	Fuzzy Multi-Attribute Decision Making
Su et al. [115]	✓			✓		Multi-level: -Maintenance timing based on track quality prediction, -Maintenance sequencing, Vehicle routing, and crew scheduling	Model Predictive Control (MPC), Mixed Integer Programming
Sharma et al. [56]						Maintenance timing based on track quality prediction	Data-driven approach, decision process
Khajehei et al. [104]	✓			✓		Maintenance timing based on track quality prediction	Monte Carlo Simulation
Consilvio et al. [105]	✓				✓	Maintenance sequencing and crew routing	Mixed Integer Programming
Gerum et al. [106]	✓				✓	Maintenance timing based on track quality prediction	Data-driven approach, Machine learning methods
Rahimikelarijani et al. [107]	✓			✓		Inspection timing based on track quality prediction	Monte Carlo Simulation
Daddow et al. [108]	✓			✓		Maintenance timing based on track quality prediction	Mixed Integer Programming

(continued on next page)

Table A.2 (*continued*)

References	Infrastructure configuration			Component level		Decision-making areas	Modelling approach
	Single component	Multi-components	Single-segment	Multi- segments	Network		
Consilvio et al. [23]	✓			✓		Maintenance action identification and prioritisation	-Bayesian Network (BN) Model, -Mixed Integer Linear Programming
Bakhtiary et al. [124]	✓		✓		-	Maintenance timing based on track quality prediction -Grouping policy: Grouping segments	Mixed-integer programming (Genetic algorithm)
Sasidharan et al. [123]	✓				✓	Maintenance timing based on track quality prediction	Monte Carlo Simulation
Khajehei et al. [116]		✓		✓		-Maintenance timing based on track quality prediction -Grouping policy: Grouping segments	Mixed Integer Programming (Genetic Algorithm)
Bressi et al. [109]	✓			✓		-Maintenance timing based on track quality prediction	Multi objective optimisation (Genetic Algorithm)

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