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TOPICAL REVIEW

Applications of Genetic Algorithm and Its Variants in Rail Vehicle Systems: A Bibliometric Analysis and Comprehensive Review

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ABSTRACT Railway systems are time-varying and complex systems with nonlinear behaviors that require effective optimization techniques to achieve optimal performance. Evolutionary algorithms methods have emerged as a popular optimization technique in recent years due to their ability to handle complex, multi-objective issues of such systems. In this context, genetic algorithm (GA) as one of the powerful optimization techniques has been extensively used in the railway sector, and applied to various problems such as scheduling, routing, forecasting, design, maintenance, and allocation. This paper presents a review of the applications of GAs and their variants in the railway domain together with bibliometric analysis. The paper covers highly cited and recent studies that have employed GAs in the railway sector and discuss the challenges and opportunities of using GAs in railway optimization problems. Meanwhile, the most popular hybrid GAs as the combination of GA and other evolutionary algorithms methods such as particle swarm optimization (PSO), ant colony optimization (ACO), neural network (NN), fuzzy-logic control, etc with their dedicated application in the railway domain are discussed too. More than 250 publications are listed and classified to provide a comprehensive analysis and road map for experts and researchers in the field helping them to identify research gaps and opportunities.

INDEX TERMS Genetic algorithm, railway systems, NSGA, multi-objective algorithm, scheduling, energy saving, particle swarm optimization, railway energy management systems, ant colony optimization, neural network.

I. INTRODUCTION

The railway system (RS) is a critical part of the transportation infrastructure in many countries, providing efficient and safe transportation of passengers and goods. However, it is a complex and dynamic system that requires careful optimization to ensure its efficient operation.

Optimization techniques can play a significant role in improving the efficiency, safety, and reliability of the RSs. By using optimization techniques, it is possible to reduce operating costs, increase capacity, improve the accuracy of train schedules, and minimize the risk of accidents. In railway systems, there are wide scopes for improvements including mechanical domains like train operation and rolling stock optimizations, electrical domains like energy consumption and power systems optimizations, or systems integration optimization like maintenance, signal and communication, and safety optimizations which can be achieved by using different optimization techniques.

Evolutionary algorithms (EAs) have been widely used to optimize different aspects of engineering issues in recent years [1], [2]. They are a class of optimization algorithms inspired by natural selection and genetics. They use a population of candidate solutions and iteratively apply genetic operators, like mutation and crossover, to develop the solutions toward an optimal solution. EAs are also used widely in RSs due to their complexity, nonlinearity, and uncertainty [3], [4].

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Genetic algorithm (GAs) is one of the earliest and most widely used types of EAs in RSs. It is inspired by the process of natural selection and uses a population of candidate solutions to find an optimal solution. It is a computational optimization technique that is based on the principles of natural selection and genetics. It is a popular metaheuristic optimization technique that has been applied in various fields, including transportation systems such as railways. The application of GA in RSs has been growing in recent years due to its ability to optimize various aspects of railway systems including designing, development, operation, and utilization. Especially in scheduling, energy, forecasting, designing, fault diagnosis, maintenance, allocation, and network planning domains.

Scheduling is one of the significant challenges in railway systems due to the complexity of the system and the need to ensure that trains operate efficiently and on time. Several studies have applied GA to optimize train scheduling in railway systems. For instance, the hybrid multi-objective GA-based approaches to solve the train scheduling problem, which considers both the speed and the capacity of the railway network are presented in [5], [6], and [7]. The proposed approaches are able to optimize train schedules and reduce the waiting times for trains.

Energy consumption is also an important area that requires optimization. The railway system is a significant energy consumer [8], and optimizing energy consumption can reduce operating costs and improve environmental sustainability. GAs have also been used to optimize energy-related processes and increase energy efficiency, especially by optimization of regenerative braking energy. One example of the application of GA in regenerative braking energy optimization is the work by Che et al. [9]. They proposed a promising utilization method of regenerative braking energy according to power regulation with a GA to ensure that it is completely consumed by other adjacent traction trains. The proposed scheme consists of railway power conditioners, energy transfer converters, and a central controller. The results showed that the utilization rate after implanting the method increased to 93.3%. Regarding optimum utilization of the regenerative braking energy, there are also some other studies developing hybrid GAs optimizing the train timetable, train synchronization, and train driving method [10], [11]. Overall, GA-based optimization methods for regenerative braking energy in electric RSs have been widely utilized.

Another significant application of GA in railway systems is in the optimization of railway network design. The railway network design involves determining the location and size of railway stations, the location and number of tracks, and the location of maintenance and repair facilities. GA has been used in several studies to optimize railway network design [12]. Resource allocation is another critical aspect of railway operations that can be optimized using GA [13]. Resource allocation involves determining the optimal allocation of resources, such as locomotives, wagons, and crew, to ensure efficient and effective railway operations. According to the wide range of applications and new variants of GA utilized in the railway section, there is a need for a review study to classify all these important aspects and compares the new variants together with their pros and cons from a different application point of view.

Some comprehensive reviews about applications of GA have also been conducted in the literature in other domains. These reviews cover a broad spectrum of subjects like engineering design, scheduling, and forecasting. One of the most complete reviews is conducted by Katoch et. al [14], which considered around 220 papers covering the description of well-known GA algorithms and their implementation together with their pros and cons. In [15] the basic GA and its recounts history in the electromagnetics literature is described. Meanwhile, the application of advanced genetic operators within the realm of electromagnetics is presented. There are some other studies investigating the applications of GA in hybrid electric vehicles [16], medicine [17], and operation management [18]. These publications are out of the scope of the railway context and definitely require further and specific investigations and improvements to solve railway issues. Overall, the authors could not find any review paper dedicated to the application of GA in RSs. Accordingly, this paper is prepared to cover this gap providing an understanding of the development of GA and its variants in the railway domain and recognizing the most significant applications to give a roadmap to help experts on im-proving the efficiency and reliability of ERSs. Meanwhile, this paper presents a literature review together with a bibliometric analysis of the application of GA in railway systems, including the various optimization problems that have been addressed using GA.

The subsequent sections of the paper are arranged in the following manner: Section II discusses the review methodology and bibliometric analysis of the GA-based publications in the railway section. Some basics of GA are briefly reviewed initially in section III; then, the strategy for searching the literature and the examination of GA implementations in the railway sector are introduced. Section IV is dedicated to study the most important GA variants in RSs together with their applications and performances. In section V the main optimization methods used in RSs that have been combined with GA known as hybrid GAs are discussed. Finally, section VI gives some future trends and concludes the paper.

II. REVIEW METHODOLOGY AND BIBLIOMETRIC ANALYSIS

The purpose of the keyword survey is to identify and categorize the different re-search streams and evolutionary algorithm methods.

To achieve this, the Scopus Web of Science database was used as the primary source for publications, and a Boolean search was conducted to obtain a comprehensive collection of articles. A total of 1147 documents were included in the search from 2008 to 2022, with additional restrictions on language (English) and research areas (engineering, energy, environmental science, computer science, multidisciplinary,

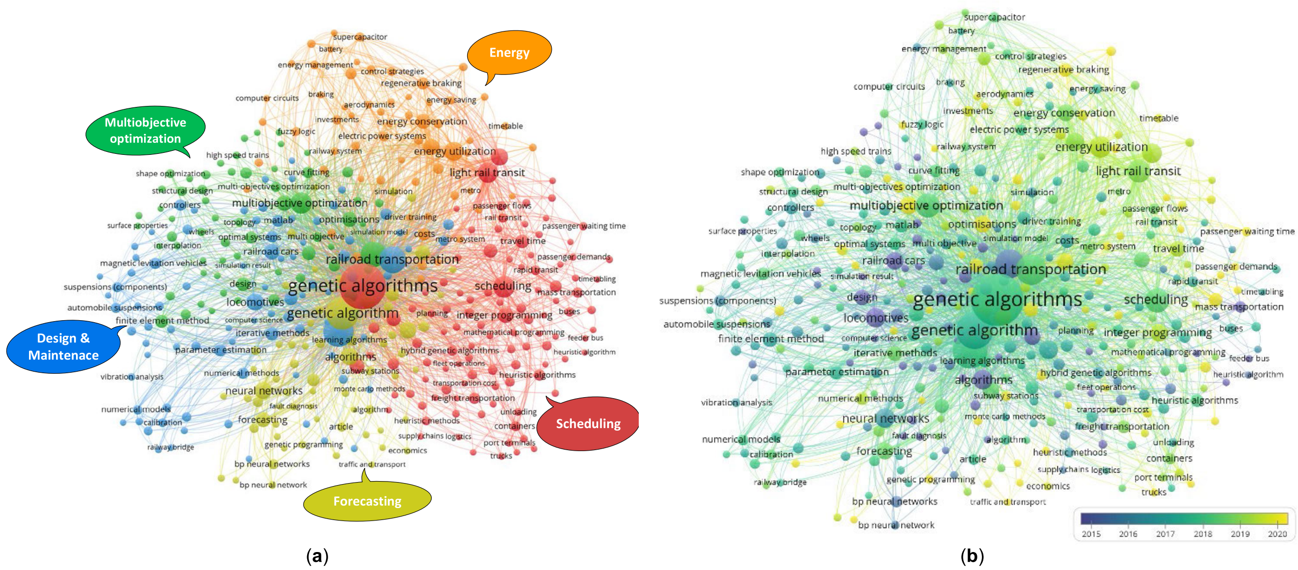

FIGURE 1. Extracted maps regarding bibliometric analysis of the keywords in the genetic algorithm method in railway section. a) network cluster map. b) time overlay visualization map.

and mathematics). The VOS Viewer software was chosen as the analytical tool to extract key terms and research streams. The resulting cluster map, depicted in Figure 1.a., shows that the keywords can be grouped into five main clusters that represent different topics of research combined with genetic algorithms in evolutionary methods. The size of each circle represents the frequency of the selected keyword, while the distance and lines represent the relationships between keywords in the same group. The clusters are classified and can be labeled based on their content, which included energy, scheduling, forecasting, design & maintenance, multi-objective optimization, and neural networks. The analysis revealed that the strongest relationships were between the " design & maintenance " cluster and the other clusters. These clusters were identified as the main topics to be discussed in the paper. The most commonly used keywords among these clusters were "genetic algorithm," railroad", "optimization," "scheduling," "energy utilization," and "multi-objective optimization". Meanwhile, the most commonly used keywords related to the application of GE method in different aspects of railway systems are found as "scheduling", "energy", "forecasting," "sensitivity analysis", "maglev suspension, "plants & structures", passenger flows", "maintenance", "fleet operation", "reliability", "railway bridge", "timetable" and "vibration".

A time overlay visualization map of the analysis, shown in Figure 1.b., indicates that these keywords, along with others related to the "multi-objective optimizations" and "energy" clusters, have become increasingly significant since 2019 and have received significant attention in recent years.

According to the bibliometric analysis and results, the study on the application of GA method in railway systems and each of the mentioned aspects and clusters is likely to spread more in the coming years. According to the research stream and gap founding, the next sections present an overview of the different methods found as clusters, their pros and cons with challenges, and future works.

III. GENETIC ALGORITHM METHODOLOGY

GA is an evolutionary algorithm method inspired by the process of natural selection and genetics. In GA, a population of potential solutions is iteratively evolved through the application of genetic operators such as selection, crossover, and mutation. These operators simulate the biological processes of reproduction, crossover between parents, and random mutations that occur in natural evolution. The fitness of each individual in the population is evaluated using an objective function that quantifies the quality of the solution. GA has been successfully applied to a wide range of optimization problems, including those in the fields of engineering, finance, and biology. One of the key strengths of GA is its ability to search a large and complex search space efficiently, making it suitable for problems with a large number of variables or constraints. Additionally, GA can incorporate prior knowledge or constraints into the fitness function, which can help to generate solutions that align with domain-specific knowledge. However, GA has some limitations, such as its susceptibility to premature convergence and the difficulty of handling constraints or non-continuous optimization problems.

A. GA METHOD DESCRIPTION

The GA was one of the first stochastic algorithms that utilized a population-based approach. The concept of GA was derived from Darwin's theory of evolution [19], which focused on the survival of the fittest species and their genes. Each potential solution is viewed as a chromosome, with each parameter serving as a gene. An objective function is used to measure the fitness of each individual in the population. To enhance weak solutions, the selection process chooses the best solutions at random using a mechanism such as a roulette wheel. This operator favors the best solutions due to the probability being proportional to their fitness, but it also helps to avoid local optima by allowing poorer solutions to be selected. This implies that if fit solutions become caught in a local solution, they can be extracted by other solutions.

The reliability of the GA algorithm stems from its stochastic nature, as it maintains the best solutions within each generation and employs them to enhance other solutions; therefore, with each successive generation, the whole population improves. GA algorithm is based on four steps as follows [20]:

1) INITIAL POPULATION

The population in the genetic algorithm consists of various solutions that correspond to the chromosomes of individuals, and each chromosome contains a collection of variables that simulate genes. During the initialization stage, the primary goal is to distribute the solutions evenly throughout the search space to maximize the population's diversity and increase the likelihood of identifying promising areas.

2) SELECTION

The fundamental basis for this part of the GA is derived from natural selection. In nature, the strongest individuals have greater odds of food and get-ting mated, leading to their genes being more prevalent in the next generation. Consequently, the GA utilizes a roulette wheel to allocate probabilities to individuals based on their fitness levels and selects them to create the subsequent generation in proportion to their objective values.

Due to the stochastic nature of a roulette wheel, individuals who are not fit have a low chance of contributing to the formation of the next generation. However, if a poor solution is selected, its genetic makeup can still be passed on to the next generation. Therefore, it is important to avoid eliminating such solutions, as doing so would decrease the variety within the population.

3) CROSSOVER

Once the selection operator has identified individuals, they must be utilized to generate the next generation. Naturally, the chromosomes from a male and female mix to create a new chromosome. As depicted in Figure 2. in a genetic algorithm, two selected solutions (parent solutions) are combined using techniques such as single-point or double-point crossover, to generate two new solutions (children's solutions).

The single-point crossover involves exchanging the chromosomes of two parent solutions at a single point, both before and after it. On the other hand, the double-point crossover involves two crossover points, where only the chromosomes between these points are changed.

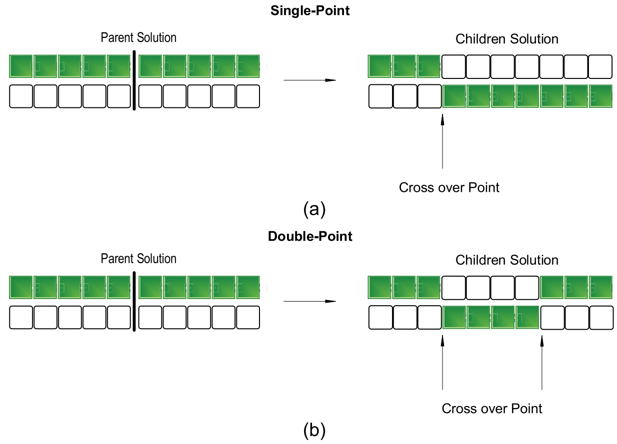

FIGURE 2. Technique in crossover step. a) Single point. b) double point.

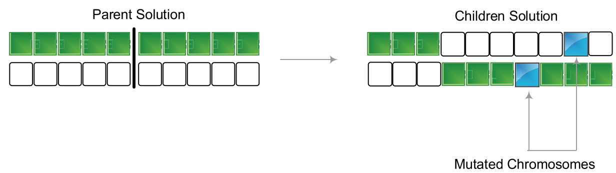

FIGURE 3. Mutation operator.

4) MUTATION

In order to prevent a genetic algorithm from becoming a basic random search, the mutation rate is kept low, as high mutation rates can have this effect. The mutation operator is used to add an additional level of randomness to the population, which helps to maintain diversity and prevents solutions from becoming too similar; as a result, the likelihood of avoiding local solutions is increased within the genetic algorithm. Figure 3. provides a concept of how this operator works, where minor alterations are made to randomly chosen genes following the recombination (crossover) phase.

B. APPLICATION OF GA IN RAILWAY SYSTEMS

As demonstrated in the bibliometric analysis section, in the context of railway systems, based on the most commonly used keywords related to the application of GA method, they can be used for various purposes such as scheduling, energy saving, forecasting, sensitivity analysis, plants & structures, passenger flows, maintenance, fleet operation, reliability, timetable, and vibration.

According to the publications discovered during the analysis, the exploration of GA applications in the railway industry is not a new area of research and has been ongoing for quite some time. Nevertheless, in recent years, the research community has demonstrated greater attention to this matter. To verify this assertion, the analysis collected publications of all types between 2008 and 2022.

Figure 4 depicts the quantity of GA publications within the railway sector per annum including journals, conferences, and book/chapter. Between 2008 and 2011, there were

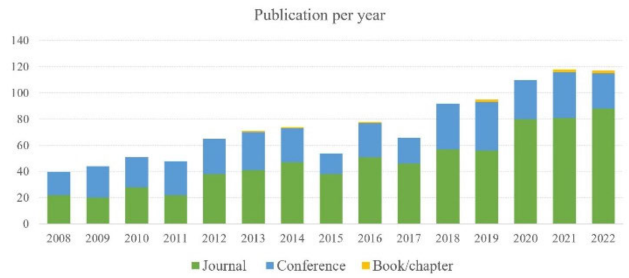

FIGURE 4. Number of GA method publications in railway domain by year.

relatively few studies conducted in this area. Accordingly, the data presented in this figure highlights three distinct phases for GA publications in the railway domain: 2008-2014, 2015-2017, and 2018 to the present day. Since 2018, there has been a significant rise in annual publication rates for both journals and conferences, such that nearly 48% of all publications are concentrated within the 2018-2022 timeframe.

Table 1 lists the GA applications found in railway-related publications, which are divided into seven main categories: scheduling, control optimization, network planning, and allocation, designing, driving and energy, forecasting, fault diagnosis, and maintenance. It is recognized that categorizing applications is challenging because numerous applications encompass several areas and may belong to several categories. Each of the subcategories may be included in other subjects. Maybe some of them could be placed in other categories too since there is a lot of connection between some of the clusters. However, the categories and classifications in Table 1 are according to the authors' engineering knowledge and expertise. For each category, the highly cited papers are addressed with their specified purposes and area of application.

1) SCHEDULING

According to the bibliometric results, it is evident that a significant portion of GA applications in the railway sector is focused on scheduling, which comprises about 28.9% of the total papers. Scheduling applications are primarily concerned with timetable optimizations [5], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], travel time [24], [28], [33], [34], [35], [36], [37], [38], [39], [40], [41], train scheduling/rescheduling [5], [24], [31], [42], [43], [44], [45], [46], [47], [48], where a train schedule provides information on the specific routes taken by different train types, along with their departure and arrival times at various stops along the way. Rescheduling is implemented in response to delays, which require the generation of new schedules that cause minimal disruption to the existing schedules. Train routing also is dedicated to the train scheduling subcategory, but with more concentration on the routes. Train routing typically offers several routes or stop plans to select from, while the routes and stop plans for train scheduling may be fixed and unable to be altered.

Furthermore, GA has been applied to scheduling tasks such as rolling stock and crane scheduling in railway systems [49], [50], [51], [52], [53], and train crew scheduling [54], [55], [56]. In such scheduling applications, GA is used directly to pinpoint the best possible mix of plans or schedules. Additionally, scheduling applications have been utilized for vehicle/train maintenance and power supply substations for electrified railways which are dedicated to energy and maintenance categories.

2) ENERGY

Energy demonstrates the second biggest application area with almost 18.5% of total publications. This reveals that energy is an important area that requires optimization. The RS is a significant energy consumer, and optimizing energy consumption can reduce operating costs and improve environmental sustainability [57]. Meanwhile, integrating renewable energy sources and other distribution generations has increased the necessity of energy optimization and intelligent control by smart energy management systems [58], [59], [60]. According to the literature and bibliometric analysis, GAs have been used to optimize energy-related processes including energy utilization or energy efficiency [61], [62], [63], [64], [65], energy saving/conservation [27], [39], [74], [75], [76], [77], [78], [66], [67], [68], [69], [70], [71], [72], [73], energy storage systems [27], [79], [80], [81], [82], [83], [84], and regenerative braking energy [9], [10], [85], [86], [87], [88], [89]. According to the time overlay-based visualization map shown in Fig.1b, energy subcategories are trends and hot topics which became more significant since 2018 and have been given great attention in recent years.

Subcategories like energy utilization, energy efficiency, and energy saving/conservation are also interlinked with the scheduling domain in terms of optimal train scheduling and speed control to reduce the consumption of energy. However, due to the terms regenerative braking energy, power supply system optimization, optimal voltage control, energy storage systems, and optimal locations of power infrastructures they have been considered in the energy domain. As a new trend in the integration of ESS and RSs, GA can be used to optimize the operation of the system and improve its performance in terms of optimizing the control strategy and finding the optimal setpoints for charging and discharging [81], designing optimal size and configuration of the ESS, and finding the optimal locations [90], [91].

3) CONTROL

Active controls, which are utilized for achieving adaptive or semi-adaptive systems, constitute the third largest application area, accounting for almost 18.2% of the total publications. Controllers represent a fundamental aspect of active control, and various controllers have been employed across different applications.

According to the literature and bibliometric analysis, GAs have been used together mostly with model predictive control (MPC) [92], [93], [94], [95], fuzzy logic [21], [56], [84], [96],

TABLE 1. Main application of GA method in different aspects of railway systems.

Main Domain	General objective		Specified purpose & related references
Scheduling	Timetable optimization		timetable optimization of train arrival and departure time [5] timetable optimization incorporating energy allocation and passenger assignment [22]
	Travel time		finding an optimal timetable and driving strategy to reduce travel time by 3.26% [28] optimizing running time, departure time, dwell time and arrival time train [40]
	Train scheduling		optimizing a passenger train timetable in a heavily congested urban rail corridor [26] train scheduling problem for an urban rail transit network [41] adaptable and stable train scheduling for long-term use in rail transit networks [45]
	Rolling stock, crane scheduling		optimizing rail-mounted gantry crane scheduling [49] flexible schedule for the gantry crane operation in intermodal transport yard [50] railway container freight yard crane scheduling [51] optimization model for the train timetable, rolling stock assignment, and short-turning strategy [53]
	Crew scheduling		crew scheduling problems with attendance rates [55] optimizing the crew-scheduling problem in the rail-freight industry [56] optimizing a passenger rail crew scheduling problem in North America [54]
	Routing		train routing on high-speed railway network [7]
Energy	Energy utilization/efficiency		single-train trajectory optimization by ATC [62] energy-efficient scheduling and speed control of train reducing energy consumption of Beijing Metro Line around 25% [65]
	Energy saving & conservation		timetables of urban rail transit systems based on energy-saving strategies and service quality levels [68] optimize the actual speed curve for energy-saving operation of High-Speed trains [69]
	Energy storage, Batteries, Supercapacitor		optimal energy management strategy and sizing of ESS for tramway [79], [84] optimizing locations of wayside energy storage devices and speed profiles [83]
	Regenerative braking		energy-efficient scheduling and timetable approach to improve the use of regenerative braking energy [87], [86] energy supplementation strategy utilizing regenerative energy of trains in power interruptions [85]
	Costs		energy consumption minimization and cost reduction in a subway ventilation system [92] reducing the operating capacity and costs of compensators [89]
Control	MPC		GA combined with MPC for energy consumption minimization in a subway ventilation system [92] real-time optimal speed control and scheduling with MPC [93] real-time control of a metro reducing wait times by 24.0% and travel times by 5.5% [94]
	Fuzzy		eco-driving and schedule of high speed train for minimizing energy consumption [21] adaptive EMS for a tramway with hybrid ESS [84] optimization of a road-rail intermodal transport system [98]
	NN		train re-scheduling with GA and ANN [47] fault diagnosis of railway rolling bearing with GA and NN [107] optimizing the speed profile of the trains using GA and ANN [108] optimization program of rail profiles [116]
	SMC		speed curve optimization and tracking [70] intelligent control of maglev [121]
	PID		controller design for maglev system [123] vibrations control and active suspension of the train [125] active control strategy on a catenary–pantograph dynamic interaction [126] optimized control for a maglev [127]
Design	Bogies, rolling stock		suspension parameters design for the monorail vehicle [12] bogie frame design [157]
	Automobile suspension & dynamics		analysis of bogie dynamics [130] optimized design of bogie suspension components [131] suspension parameters design of high-speed trains [149]
	Railway bridge, catenaries		modeling and design of a stone masonry railway bridge [132] geometric optimization design of railway catenaries [137] calibration and design of the numerical model for a bowstring-arch railway bridge [150] design of a long-span suspension bridge [154]
	Multi-modal network		designing multimodal freight transport network [128] coordination method for an integrated multimodal transit network [138]
	Route design		designing train routing [7] mass transit route network design [139] routing a metro track inspection vehicle [147] bus bridging route design integrated with metro system [151]
	Station design		designing the support system of a subway station [101] indoor air quality design in subterranean train stations [134] ventilation design in a subway station [140]
Network Planning and Allocation	Track layout/alignment		design rail transit alignment [160] optimization of rail transit alignments and station locations [161] mountain railway alignment [162] design of existing railway horizontal alignment geometry [163]
	Optimal location	Station/sites	optimizing the location and capacity of rail-based park-and-ride sites [164] optimization of traction substation converter characteristic [165]
		Maintenance facility	Balise location for speed error reduction in railway signaling systems [166]
		Bridge and tunnel	method to optimize and limiting tunnel-induced damages [191]
		Electric compensators	finding optimal location of FACTS devices [167]
		energy storage system	optimal location and sizing for stationary ESS [90], [91] installation of wayside ESS in DC railway [168]
	Monitoring sensors		maximizing life time of wireless railway infrastructure condition monitoring network [169]

TABLE 1. ***(Continued.)*** **Main application of GA method in different aspects of railway systems.**

	Signaling and communications devices		error reduction in railway signaling systems [166] verification of railway signaling data [171]
	Power sources		multi-objective optimization of the AC railway power supply system [172]
	Allocation	Platform	railway capacity allocation [173] railway station platform and resources allocation [174] optimization system for earthworks of railway systems [175]
		Vehicle	route planning approach for automated vehicle allocation [176] vehicle routing for earthwork allocation optimization [177] railway wagon management and optimal empty wagons allocation issue [178]
		Crews	intelligent crew allocation for railway sleepers precast [179]
		Resource	energy planning and time allocation maximizing regenerative energy utilization [13] bus resource allocation integrated with Metro [151] reduce the problem of resource allocation and capital occupation of high-speed railway [202]
Fault diagnosis and maintenance	Damages		limiting tunnel-induced damages [191]
	Rolling elements		fault diagnosis of railway rolling bearing [107] fault diagnosis for track circuit [203]
	Inverter		fault diagnosis of subway auxiliary inverter [105]
	maintenance scheduling		optimal scheduling of track maintenance [25] improved rail profile and its maintenance for Stockholm underground [180] optimization of maintenance strategy for railway track-bed [181] maintenance scheduling data-rich complex infrastructure [182]
	track maintenance		optimal scheduling of track maintenance [25] optimization of railway track maintenance [184]
	Calibration		finite-element model calibration of a train [185] calibrating rail transit assignment [186] optimization and calibration of automotive diesel engine [187]
	Vibration		dynamic model of a composite steel-concrete railway viaduct and vibration analysis [189] analyze the track vibration behavior and minimize the chance of rail corrugation [188]
	Sensitivity analysis		sensitivity analysis of railway bridges [190] sensitivity analysis of railway tunnels [191]
Forecasting/ Prediction	Trains traffic		rail transit system planning and traffic prediction [192] traffic congestion prediction in park-and-ride area [193]
	Passengers traffic		railway passenger volume forecasting [194] holiday passenger flow forecasting in metro [195]
	Ticket pricing		optimization of pricing and subsidies for urban rail transit [196]
	Thermal capacity		thermal capacity estimation for traction transformers in high-speed railway [197]
	Damage and Risk identification		railway dangerous goods transportation system risk identification [198] damage identification of railway bridges [199] [200] metro station safety status prediction [201]

[97], [98], [99], [100], neural network (NN) [47], [90], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], sliding mode control (SMC) [70], [119], [120], [121], PID [70], [122], [123], [124], [125], [126], [127].

For instance, fuzzy logic combined with GA was implemented in [21] to reduce energy consumption in railways traffic operation, particularly in high-speed lines. In [84] a modified energy management system with GA and fuzzy logic to optimally size a tramway with a hybrid energy storage system is presented.

Meanwhile, Acıkbas et al. presented a novel method using ANN and GA as coasting schemes to reduce the energy consumption of mass rail transit systems [108]. Train rescheduling problems and optimizing the rail profile for high-speed railways also has been addressed with GA and ANN in [47] and [116] respectively.

Proportional integral derivative (PID) controller-based systems are presented in [123] and [127] to control MAGLEV systems and regulate the levitation process of maglev vehicles. Vibration control of the train and pantograph-catenary control is also done by using PID and GA in [125] and [126].

Strategies based on model predictive control (MPC) and numerical optimization of an objective function using GA for real-time control of a metro system are proposed in [93] and [94]. In another study [92], an energy consumption minimization method in a subway ventilation system is presented based on combined MPC and GA.

Sliding mode control (SMC) is another common control method that is applied along with GA. A random reinforcement GA to avoid the local optimum efficiently combined with SMC is developed for speed curve tracking with bounded disturbance for subway trains in [70]. In [121], a novel electromagnetic guiding system with current control modules for MAGLEV system is proposed and to remove the sensitivity of the proposed method to system parameters, a control strategy based on a combination of cascade sliding mode and GA is applied.

4) DESIGN

Design represents the next largest application area of GA in RSs. According to bibliometric study results, it can be subdivided into subcategories of designing vehicles like bogies or rolling stock, designing system layouts like railway bridges and catenaries, suspension and dynamic of trains, multi-modal and intermodal network design, route design and station design [7], [12], [101], [128], [129], [130], [131],

[132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157], [158], [159].

As optimizations of train designs, [12] outlines an approach to create a dynamic model for an articulated monorail, which is then optimized using a genetic algorithm to enhance its curving dynamics. This model features six car bodies and seven straddle-type bogies. Furthermore, the other study explores the theoretical and experimental aspects of quasi-static load spectra on bogie frame structures of high-speed trains [157].

System layout optimizations are discovered for railway bridges [132], [150], [154], overhead catenary [137], and suspension and dynamics of vehicles [130], [131], [149], [158].

Another absorbing design optimization was detected for the multimodal and intermodal station for optimizing the transportation of goods and passengers in a railway system that involves multiple modes of transport or intermodal transfers [128], [141], [142], [143], [145], [146], [152]. Furthermore, route design optimizations in RSs referring to the use of GA to determine the most efficient and cost-effective routes for railway trains are noticed in [7], [136], [139], [147], [151], and [159]. The use of GA to optimize the layout, configuration, and operation of railway stations and facilities are the other domains that are discovered [101], [134], [135], [140], [148].

5) NETWORK PLANNING/ALLOCATION

Both allocation and network planning applications involve usually determining the destination or recipient of certain items. Allocation applications are mainly concerned with allocating train sets and vehicles, platforms, crews, and resources. Some other aspects of applications in this category include alignment, optimal locations, monitoring sensors, signaling and communications, and power sources.

Using GA to optimize the alignment and layout of railway tracks aiming to improve the performance of the track system in terms of safety, capacity, and speed while minimizing construction and maintenance costs are found in [160], [161], [162], and [163]. Optimizing location and capacity of stations/sites [164], [165], balise locations [166], power quality compensators [167], the best energy management strategy, location, and size for ESS [90], [91], [168], the locations of monitoring sensors [169], [170], signaling devices [166], [171], designing dimensioning of the electric railway system based on neutral zones location optimizations [172] are found as the other interesting optimization areas.

Allocating platform optimization using GA involves optimizing the assignment of train platforms to arriving trains at a station or terminal aiming to maximize the use of available platforms while minimizing the waiting times for trains and passengers discovered in [173], [174], and [175].

Allocating vehicle optimization in RS involves optimizing the assignment of train sets and vehicles to specific routes, stations, and services [176], [177], [178]. The objective is found to improve the efficiency and utilization of train sets and vehicles, minimize delays, and enhance the overall performance of the railway system.

Allocating crew optimization involves optimizing the assignment of crew members to specific train services or tasks in a railway system [179] and allocating resources optimization is found as the other application domains.

6) FAULT DIAGNOSIS AND MAINTENANCE

Fault diagnosis and maintenance applications by GA in railway systems usually involve the determination of the health condition of components or subsystems of the RS, detecting faults or failures, predicting their future occurrence, and performing maintenance actions to prevent or minimize their impact on the system's performance.

Fault Diagnosis of different parts of RS, like rolling bearing, track circuit, auxiliary inverter, etc. are discovered as one of the common subcategories [107].

Maintenance scheduling and track optimization in RS involve the use of GA algorithms to optimize the timing and frequency of maintenance activities to minimize system downtime and maximize operational efficiency [25], [180], [181], [182].

The GA algorithm analyzes data from various sources such as track condition monitoring, historical maintenance records, and train scheduling to determine the optimal timing for track maintenance activities to maximize the lifespan of the track and minimize downtime due to maintenance [25].

Calibration found as the other main application which involves the use of GAs to optimize the calibration of measurement systems used in railway operations, and determine the optimal settings for sensors and measurement devices such as accelerometers, strain gauges, and temperature sensors, which are used to monitor various aspects of railway operations [25], [183], [184], [185], [186], [187].

Vibration optimization in RS using GAs to optimize the vibration characteristics of trains, tracks, and other components is found as other main applications [188], [189]. Vibration is a major issue in RS as it can lead to wear and tear on the tracks, vehicle components, and surrounding infrastructure. GAs can be used to analyze data from various sources such as vehicle acceleration data, track geometry data, and environmental data to determine the optimal settings for various parameters such as track stiffness, vehicle suspension, and damping. The GA algorithm can also determine the most effective vibration mitigation strategies such as the use of active suspension systems or the addition of damping materials to reduce vibration levels. Last but not least is the sensitivity analysis in RSs using GAs to analyze the sensitivity of different variables on the overall performance of the RS [130], [190], [191].

7) FORECASTING

Forecasting was discovered as the last main domain in RSs involving GAs to predict future events or trends based on historical data. These applications are typically used for predicting demand for railway services, forecasting train delays, traffic, possible risks or damages, predicting maintenance needs, and estimating future energy consumption. By analyzing large amounts of historical data, GA can identify patterns and trends that can be used to make accurate predictions about the future.

Forecasting train and passenger traffic [154], [192], [193], [194], [195] includes the use of GAs to predict the future behavior of both train and passenger traffic to optimize the use of resources, such as trains and tracks, by accurately predicting the number of passengers and trains that will use the system at different times. This can be achieved by collecting and analyzing historical data on train and passenger traffic, train schedules, routes, and other variables to predict future train traffic patterns. Prediction of tickets [196], thermal capacity [197], and risk identifications [198], [199], [200], [201] are found as the other subcategories in this domain.

IV. GA VARIANTS APPLICATIONS IN RAILWAY SYSTEMS

GA variants emerged to address the limitations and challenges of the original GA algorithm and to adapt the algorithm to different types of optimization problems. The original GA was introduced by John Holland in the 1970s [204] and was inspired by the process of natural selection. While the original GA was successful in solving many optimization problems, it had some limitations and challenges. For example, it could get stuck in local optima, it could be slow to converge, and it was not suitable for certain types of optimization problems such as those with continuous decision variables. To address these limitations and challenges, researchers developed various variants of GA. These variants introduced new techniques and strategies for selection, crossover, mutation, and adaptation. Some variants were designed for specific types of optimization problems, such as binary optimization, real-valued optimization, and multi-objective optimization. Other variants were designed to address general challenges in optimization, such as premature convergence, diversity maintenance, and scalability.

There are many variants of GA that have been developed over the years. Here are some of the commonly used and well-known variants of GA specially used in railway section:

- Binary-coded Genetic Algorithm
- Real-coded Genetic Algorithm
- Integer-coded Genetic Algorithm
- Permutation-based Genetic Algorithm
- Niching Genetic Algorithm
- Non-dominated Sorting Genetic Algorithm
- Adaptive/ Self-Adaptive Genetic Algorithm
- Parallel Genetic Algorithm
- Memetic Algorithm
- Multi-Objective Genetic Algorithm
- Hybrid Genetic Algorithm

These variants of GA have different characteristics and are suited for different types of optimization problems.

Hybrid genetic algorithm is a type of optimization algorithm that combines two or more optimization techniques to improve its performance and efficiency such as a local search method, a simulated annealing algorithm, or a particle swarm optimization algorithm. Accordingly, we have separated it and discussed it in section V.

A. BINARY-CODED GA (BCGA)

In this variant, the solution is represented as a string of 1s and 0s. Each element of the string represents a binary digit, and the entire string represents a candidate solution. BCGA is commonly used for combinatorial optimization problems.

One of the critical applications is the optimization of train scheduling, which involves determining the arrival times of trains, their routes, and stops [205]. BCGA can be used to minimize the total delay, reduce waiting times, and maximize the use of track and train capacities. Another application is the optimization of track occupancy time, where the algorithm can minimize track usage time, reduce conflicts, and enhance safety. Train traffic control systems can also benefit from the use of BCGA by optimizing signal settings and minimizing waiting times, collisions, and maximizing throughput [206]. Finally, BCGA can be used also in ATO and train formation optimization by determining the optimal sequence and length of carriages that reduce empty carriage movements, and total weight, and minimize damage to track and rolling stock components [207].

B. REAL-CODED GENETIC ALGORITHM (RCGA)

RCGA is a variant of the traditional GA that allows the optimization of problems with continuous variables. In this algorithm, the chromosome is represented by a vector of real numbers, which allows the representation of the actual values of the decision variables. The RCGA approach has been widely applied to various optimization problems in different fields, including railway systems, due to its ability to handle real-valued decision variables and its capability to converge to optimal solutions effectively.

One of the primary applications of RCGA in RSs is in train scheduling optimization problems. The optimization problem involves a large number of decision variables, such as the departure and arrival times of the trains, the routes to be taken, and the speeds of the trains. RCGA is a suitable optimization technique for such problems because it can handle the continuous decision variables and optimize the schedules in a more efficient way [208], [209].

Another application of RCGA in RSs is in the optimization of railway vehicle maintenance. The maintenance of railway vehicles is an essential aspect of RSs because it directly affects the safety and reliability of the system. The optimization problem involves deciding when and how to perform maintenance activities, such as inspections, repairs, and replacements, in a way that minimizes the overall cost and maximizes the availability and reliability of the vehicles [210]. RCGA has been used to optimize the maintenance schedules and decisions in RS, resulting in improved system performance and reduced maintenance costs.

C. INTEGER-CODED GENETIC ALGORITHM (ICGA)

Integer-coded genetic algorithm (ICGA) is a variant of genetic algorithms specifically designed to work with integer representation of problem solutions. In this variant, the solution is represented as a vector of integers. Like real-coded GA, this algorithm optimizes the value of this vector by creating new solutions through reproduction, crossover, and mutation. ICGA is commonly used for optimization problems that require discrete variables.

In recent years, ICGA has gained significant attention due to its versatility, computational efficiency, and application potential in various areas, including transportation management and optimization. In the RSs, they can be used for various applications such as train scheduling, rail network design, and maintenance planning.

ICGA can be used for train scheduling [206], where the chromosome represents the train's departure and arrival times at different stations. Fitness function can be defined based on the number of conflicts and the utilization of resources such as tracks and platforms. Meanwhile, ICGA can be used to optimize the rail network design by defining the chromosome as the placement of stations, tracks, and other infrastructure. The fitness function can be defined based on factors such as total distance, connectivity, and capacity.

D. PERMUTATION-CODED GENETIC ALGORITHM (PCGA)

In this variant, the solution is represented as a vector of numbers that represent the order in which elements should appear. The algorithm optimizes the order of these elements by creating new solutions through reproduction, crossover, and mutation. PCGA is commonly used for optimization problems that require sequences or arrangements of elements, such as the traveling salesman problem. PCGA can also be applied to various aspects of RSs, especially in optimizing complex and large-scale problems. One of the significant applications of PCGA is the optimization of crew scheduling, where the algorithm can allocate tasks, shifts, and rest periods to crews while minimizing operational costs, labor hours, and fatigue. Another application is the optimization of routing and scheduling of multiple trains, where the algorithm can determine the combination of routes and departure times that maximize throughput, minimize delay and interference, and optimize resource utilization. PCGA can also be applied to the optimization of railway maintenance, where the algorithm can determine the optimal allocation of maintenance tasks to minimize downtime, reduce maintenance costs, and optimize resource allocation [211], [212].

E. MULTI-OBJECTIVE GENETIC ALGORITHM (MOGA)

MOGA is a type of genetic algorithm that is used to solve optimization problems with multiple, often conflicting, objectives. MOGA works by generating a population of candidate solutions, evaluating their fitness based on multiple objectives, and then evolving the population through selection, crossover, and mutation to generate new candidate solutions. MOGAs have been widely used in railway systems to address complex optimization problems involving multiple conflicting objectives. In RSs, MOGAs have been applied to various problems such as scheduling, routing, resource allocation, and train control, among others [7]. For example, in train scheduling, objectives may include minimizing travel time, maximizing passenger satisfaction, and minimizing costs. These objectives are often conflicting, and it is not possible to optimize one objective without affecting the others. MOGAs can be used to find a set of optimal solutions that represent a trade-off between these conflicting objectives.

In addition, MOGAs can also be used for optimal design of different elements RS like ventilation and aerodynamic design of substation [140], [213] or energy distribution analysis [214].

F. PARALLEL GENETIC ALGORITHM (PGA)

A PGA is a type of optimization algorithm used to solve complex problems in a faster and more efficient manner by running multiple instances of the algorithm simultaneously on multiple processors. It is a population-based search algorithm that emulates the process of natural evolution to find optimal solutions. In PGA, multiple populations are created and evolved simultaneously, with each population running on a separate processor or computational unit. The populations exchange information periodically to improve the diversity of the search and avoid premature convergence to suboptimal solutions.

PGA has been used in RSs for various applications, such as scheduling [5], planning model [192], [215], alignment [216], and network design optimization [217]. PGAs can effectively solve complex problems with large solution spaces and multiple objectives, which is often the case in RSs.

Real-time control involves making decisions during the operation of the RSs, such as controlling train speed, routing, and signaling in implementing the digital twin concept can be other applications of PGA [218].

G. NICHING GENETIC ALGORITHM (NGA)

NGA is used to find multiple solutions in the same problem space by using the concept of niches, which represent different regions of the search space with diverse solutions.

NGA is a type of GA that aims to maintain diversity in the population by preserving multiple niches or subpopulations in the search space. In the RSs, NGAs can be applied in several areas, including:

Generation of driving profiles in the context of railway system design [219], for clustering of system environmental variables and analysis of railway driving missions [220]. Aerodynamic shape optimization of trains and the design of hybrid locomotives are the other application found in the literature [221], [222].

H. NON-DOMINATED SORTING GENETIC ALGORITHM II (NSGA-II)

NSGA-II is a variant of MOGA that was developed by Kalyanmoy Deb in 2002 [223]. It is an extension of the original NSGA algorithm, which was proposed in 2000 [224].

NSGA-II is a popular multi-objective method that is specifically designed to solve optimization problems with multiple objectives, where traditional optimization methods may not be effective. NSGA-II is based on the idea of non-dominated sorting, which involves sorting solutions into multiple layers, where each layer represents a set of solutions that are not dominated by any other solution in the same layer.

In RSs, NSGA-II has been widely used for train scheduling and routing problems [38], time table optimizations [22], [225], ATO and energy consumption [226], optimal allocation of tunnels for limiting damages [191], multistage energy distribution for whole vehicles in high-speed train collisions [227], optimization of a railway wheel profile [228], railway freight operation planning [229], optimization of the AC railway power supply system [172], and maintenance [230].

I. IMMUNE GENETIC ALGORITHM (IGA)

IGA is a hybrid algorithm that combines the principles of GAs and immune systems to solve optimization problems. In IGA, the population of candidate solutions is represented as a set of antibodies, and the optimization process is modeled as an immune response. It is a variant of GAs that mimics the immune system's behavior to improve the algorithm's performance. In RSs, IGA has been used for train scheduling, routing, and optimization problems [231], [232], ATO [233], sustainable urban land use planning approach [234], and site selection of the emergency supply railway station [235].

J. MEMETIC GENETIC ALGORITHM (MGA)

Memetic Genetic Algorithm (MGA) is a type of genetic algorithm that combines the traditional genetic algorithm with local search techniques. This hybrid approach is used to improve the optimization process and find better solutions to complex optimization problems. In RSs, MGA is found to be applied to various optimization problems such as train operation optimization, scheduling, track maintenance, and crew scheduling [63], [236]. The main application of MGA has been found to optimize intermodal transport networks, considering factors such as cost, transit time, and modal shift [98], [237], [238].

The main applications of the above-mentioned GA variants together with the related papers are summarized in Table 2. According to the bibliometric results, the variant's application distribution in publications is plotted in Fig. 5. It is obvious that the NSGA and MOGA are the most widely used variants in RSs. It is due to the MOGA and NSGA capabilities to handle multiple objectives simultaneously.

Overall, the choice of which variant of genetic algorithm to use depends on the specific problem at hand and the characteristics of the search space. Each variant has its own strengths and weaknesses, and the best approach may involve a combination of different algorithms.

TABLE 2. Application of GA variants in different domains of railway systems.

Variant name	Specified purpose & Related papers
BCGA	train and route scheduling [205] Train traffic control [206] ATO, minimizing damage and track maintenance [207]
RCGA	train traffic control and design [208] train scheduling and traffic design [209] fault diagnosis induced by tunnels and maintenance [210]
ICGA	train scheduling and optimizing stopping patterns [206]
PCGA	scheduling, maintenance [212] designing of wagon [211]
MOGA	train routing and scheduling [7] designing ventilation system of substation [140] aerodynamic design [213] energy distribution and saving analysis [214]
PGA	scheduling [5] forecasting train traffic [192] network planning and allocation [215] network design and alignment [217]
NGA	optimizing driving profile[219] railway driving optimization [220] designing of locomotive[221], [222]
NSGA-II	train scheduling, routing and timetable optimization [22], [38] [225] optimization of power supply system [172] optimal allocation and reducing tunnel damage [191] energy consumption reduction [226] energy distribution and saving analysis [227] optimizing railway wheel profile [228] operation planning and network allocation [229] maintenance [230]
IGA	train scheduling, routing and timetable optimization [231], [232] ATO [233] network planning and allocation [234] allocation resources [239]
MGA	train scheduling, routing and timetable optimization, track maintenance [63], [236] intermodal/multimodal transport networks[98], [237], [238] [240]

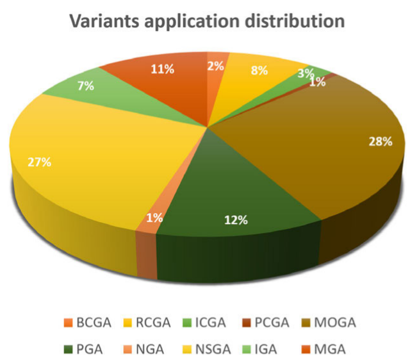

FIGURE 5. GA variants application distribution in railway domain.

V. HYBRID GENETIC ALGORITHMS

As mentioned before, Hybrid Genetic Algorithms (HGAs) are types of optimization algorithms that combine the principles of GA with other optimization techniques to overcome the limitations of traditional GA. The objective of HGAs is to enhance the search process by exploiting the complementary strengths of different optimization algorithms.

There are several HGAs that have been used in railway systems to optimize various aspects of railway operations and improve system efficiency. Some of these HGAs are discussed in this section with their specific application in railway section.

A. GENETIC ALGORITHM WITH TABU SEARCH (GATS)

GATS is a hybrid algorithm that combines the exploration ability of genetic algorithms with the local search capability of tabu search. This algorithm has been used for the optimization of train scheduling and crew rostering in railway systems. The nature of the connections between these two methods, and revealing different kinds of opportunities that exist for creating such a hybrid approach to the benefits of their supplementary properties are shown in [241].

In [225] a novel method is formulated for the train synchronization problem and timetable Synchronization of mass rapid transit systems using improve NSGA II, combined with differential evolution, and a hybrid combination with local search techniques like heuristic hill climbing, tabu search, and simulated annealing.

A model for efficiently expand of multimodal freight transport network systems based on genetic local search and GATS is accomplished in [128] by comparing the performances. Minimizing the objectives of the passengers' waiting and trip times and trains' travel times were also found in [242] done by GATS.

B. GENETIC ALGORITHM WITH SIMULATED ANNEALING (GASA)

GASA is a hybrid algorithm that combines the global search ability of genetic algorithms with the local search capability of simulated annealing. This algorithm has been used for the optimization of train scheduling, route planning, and crew rostering in railway systems.

In [225] a novel method is formulated for the train synchronization problem and timetable synchronization of mass rapid transit systems using improved NSGA II, and a hybrid combination with and simulated annealing.

An improved method based on improved crossover and selection methods with-out breaking the fixed track utilization rule constraint is proposed in [243] for real-time track Reallocation in busy complex railway stations.

In [244], GASA was presented as a method of solution for the dynamic fleet-sizing and for rail freight car fleet-sizing problem and the results showed the high efficiency and effectiveness of the proposed algorithm.

A GA and simulated annealing are proposed to find the optimal preventive maintenance scheduling and spare parts problems for a rolling stock system considering intervals and the optimal spare parts number of all components [245].

C. GENETIC ALGORITHM WITH PARTICLE SWARM OPTIMIZATION (GAPSO)

GAPSO is a hybrid algorithm that combines the population-based search ability of genetic algorithms with the swarm intelligence of particle swarm optimization. This algorithm has been used for the optimization of train scheduling and the allocation of railway resources such as tracks and trains.

GAPSO applications to reschedule high-speed railway timetables with the consideration of primary delays as a case study in China are discussed in [246]. It is shown that the objective values calculated by the developed GAPSO are reduced by 15.6%, 48.8%, and 25.7% compared with the other methods.

A novel model which takes advantage of the GAPSO algorithm with fuzzy logic controller to realize the integrated scheduling of multi-AGV with conflict-free path planning is studied in [100]. It is shown that from the convergence speed point of view, the proposed method is more effective and reliable than GA algorithms, especially on largescale problems.

The authors of [78] presented an integrated model to reach the global optimality of energy-efficient operation by optimizing the timetable and train trajectory simultaneously. The results confirmed that hybrid GAPSO obtains the best results compared with the results obtained by the other traditional heuristic algorithms.

As an other application of GAPSO, the railway alignment optimization in mountainous regions has been studied in [247]. The outcomes demonstrated that it can provide more favorable solutions when compared to options created by skilled designers, or those produced using a non-stepwise particle swarm algorithm or simple GA.

D. GENETIC ALGORITHM WITH ANT COLONY OPTIMIZATION (GACO)

GACO is a hybrid algorithm that combines the global search ability of genetic algorithms with the self-organizing behavior of ant colony optimization. This algorithm has been used for the optimization of train scheduling, resource allocation, and routing in railway systems.

The optimal speed control of a multiple-mass train for minimum energy consumption using GACO is studied in [64]. In this study, the GACO is applied to the energy efficiency problem of electrical trains for various track gradients and curvatures.

In [248], the carrier's delivery route model using railway stations is simulated by the optimized routing strategy based on an integrated ant colony algorithm and genetic algorithm. Therefore, GACO is designed for this problem.

The computational results showed that the method could be a feasible solution for handling the ''last-mile'' problem.

E. GENETIC ALGORITHM WITH DIFFERENTIAL EVOLUTION (GADE)

GADE is a hybrid algorithm that combines the exploration ability of genetic algorithms with the mutation and crossover operators of differential evolution. This algorithm has been used for optimization problems such as train scheduling and crew rostering.

In [225] a multifunctional method is proposed for the train synchronization problem and timetable synchronization of mass rapid transit systems using improve NSGA II GA, combined with differential evolution, and a hybrid combination with local search techniques. It is revealed based on the results that the use of the proposed GADE-based scheme outperforms the original NSGA-II in terms of convergence and spread of solutions generated for this application.

An evolutionary framework to automatically plan navigation paths for crowds in public spaces is proposed in [249]. In this study mainly according to the fitness evaluation mechanism, a structure based on differential evolution is developed to efficiently evolve path planning strategies. Meanwhile, since the population is bigger after the generation of new individuals, the selection is important to maintain the population, for which the NSGA-II is adopted.

F. GENETIC ALGORITHM WITH HARMONY SEARCH (GAHS)

GAHS is a hybrid algorithm that combines the global search ability of genetic algorithms with the improvisation ability of harmony search. This algorithm can be used for optimization problems such as train scheduling and resource allocation.

The authors couldn't find any papers that specifically discuss the applications of genetic algorithms combined with harmony search in the railway section. However, the integration of these two methods is studied in [250].

G. GENETIC ALGORITHM WITH ARTIFICIAL BEE COLONY (GABC)

GABC is a hybrid algorithm that combines the population-based search ability of GAs with the intelligent foraging behavior of artificial bee colony. This algorithm also can be used for optimization problems such as train scheduling and route planning. The authors couldn't find any papers that specifically discuss the applications of genetic algorithms combined with ABC in the railway section. However, the advantages of hybridization in some other areas which can also be implemented in RS found in [251], [252], and [253].

H. GENETIC ALGORITHM WITH FUZZY LOGIC (GAFL)

GAFL is a hybrid algorithm that incorporates fuzzy logic for making decisions during the optimization process. This algorithm has been used for optimization problems such as train scheduling and crew rostering.

A fuzzy-logic controlled GA proposed for the solution of the crew scheduling problem in the rail-freight sector is presented in [56]. The proposed GAFL utilizes a hybrid approach that combines a fuzzy-logic controller with a GA to enhance its performance. The fuzzy-logic controller is embedded in the GA to dynamically adjust the mutation and crossover probabilities based on the GA's performance. The computational findings indicate that this hybrid approach produces a schedule with a 10% lower cost compared to a GA that uses fixed mutation and crossover rates.

In a study published in [99], a new fuzzy logic supervision strategy was devised to integrate renewable production and storage units into a railway power substation. This strategy helped to limit the power drawn from the grid and to increase the consumption of locally-produced renewable energy by using empirically-supervised parameters. The optimization method employed an experimental design to reduce the number of design variables and mitigate the ''curse of dimensionality'' before iteratively applying the GA method through the Sophemis platform for parallel optimization and Simulink GUI interface. The numerical outcomes indicated that the economic indicator (i.e., the objective function) could be easily improved with the optimal solutions obtained using this method, but the simulation results showed only minimal changes in hybrid railway power substation supervision behavior.

In [84] an adaptive energy management system is presented for a tramway that utilizes a hybrid energy storage system comprising both batteries and supercapacitors. The hybrid ESS is sized using MOGA optimization, and the system also employs a fuzzy logic-based control strategy. The proposed approach has been shown to achieve cost savings of up to 25.5% (compared to just super capacitor-based system) while maintaining an overall efficiency of approximately 84.4%.

A novel model which takes advantage of the GAPSO algorithm with fuzzy logic controller to adaptive auto-tuning to solve the model aiming realization of the integrated scheduling of multi-AGV with conflict-free path planning is studied in [100]. It is shown that from the convergence speed point of view, the proposed method is more effective and reliable than GA algorithms, especially on largescale problems.

The purpose of the study in [97] is to develop an eco-driving model that can generate efficient driving commands while taking into account the uncertainties of climatological conditions. The uncertainties related to temperature, pressure, and wind are represented using fuzzy numbers, and a Genetic Algorithm with fuzzy parameters is employed to solve the optimization problem. To ensure accuracy, a railway simulator is used in the process. The proposed model is applied to a realistic Spanish high-speed railway scenario, demonstrating the importance of considering climatological parameters to adapt driving commands. Results indicate that energy savings of up to 34.7% can be achieved during summer conditions when the uncertainty of climatological parameters is taken into account, as opposed to the 29.76% savings that can be achieved without considering these factors.

I. GENETIC ALGORITHM WITH NEURAL NETWORKS (GANN)

GANN is a hybrid algorithm that combines the genetic algorithm with neural networks to optimize the weights and architecture of neural networks for various problems such as function approximation, classification, and prediction.

A novel method based on artificial neural network and GA combined method is presented in [116] to optimize the rail profile for high-speed RS. The results obtained from the computational analysis indicate that the rail profile that has been optimized performs better in terms of contact conditions and wear between the wheel and rail. Additionally, the optimized rail profile retains good dynamic performance.

A strategy is proposed for real-time controlling of a Maglev system based on the combination of neural networks and GA [254]. The suitable control inputs were calculated utilizing a back propagation-based learning mechanism. Simulations based on Delphi 7 environment revealed that the proposed method was successful and effective.

GANN is also used for the weight optimization problem [106]. In this context, a combination approach involving, finite element analysis, Neural Networks and GA has been successfully used to optimize the weight of bogie frame such that the safety factor at all three critical locations are above 2.5. For the modified design, a weight reduction of 7.6% in the existing bolster is presented.

After examining the current state of using the generalized regression neural network (GRNN) in railway freight volume prediction, [113] has enhanced the model's performance by incorporating an improved neural network. The improved method employs a GA to search for the optimal spread, which is the only factor of the GRNN, and then uses the optimal spread for forecasting in the GRNN. In the process of forecasting railway freight volume, this method employs data increments during calculation and uses the goal values obtained after the calculation as the forecasted results. Compared to the results of the GRNN, the GA-improved GRNN achieves higher prediction accuracy. Finally, based on this method, the railway freight volumes for the next 2 years are forecasted, and this improved method offers a new approach to predict railway freight volume.

The main applications of the above-mentioned HGAs together with the related papers are summarized in Table 3. According to the bibliometric results, the HGAs application distribution in publications is plotted in Fig. 6. It is obvious that the GANN and GATbS are the most widely used HGAs in RSs. It may show their capabilities in terms of effectiveness, performance, and accessibility.

Overall, these hybrid GAs have been successful in optimizing various aspects of railway systems and have helped improve system efficiency, reduce costs, and increase resource utilization. These HGA have proven to be effective in optimizing various aspects of railway systems, and their success has led to further research and development in the field of railway operations optimization.

TABLE 3. Application of HGAs in different domains of railway systems.

Hybrid method	Specified purpose & Related papers
GATbS	multimodal network designing [128] scheduling, timetable optimization [225] travel time, timetable optimization [242]
GASA	scheduling, timetable optimization [225] real-time track allocation [243] designing fleet and network planning [244] maintenance [245]
GAPSO	timetable optimization, energy saving [78] scheduling, allocation [100] scheduling, timetable optimization [246] network planing and alignment [247]
GACO	control, timetable optimization, energy saving [64] delivery route model using railway stations [248]
GADE	scheduling, timetable optimization [225] forecasting traffic, scheduling [249]
GAFL	scheduling, crew scheduling [56] energy, energy storage system optimal location and sizing [84] eco-driving, ATO [97] design, railway substation optimization [99] scheduling, allocation [100]
GANN	bogie design and optimization [106] fault diagnosis, forecasting [107] forecasting and prediction [113] rail profile optimization, safety and maintenance [116] traffic forecasting, network planning and alignment [117] active and suspension control, identification [254]

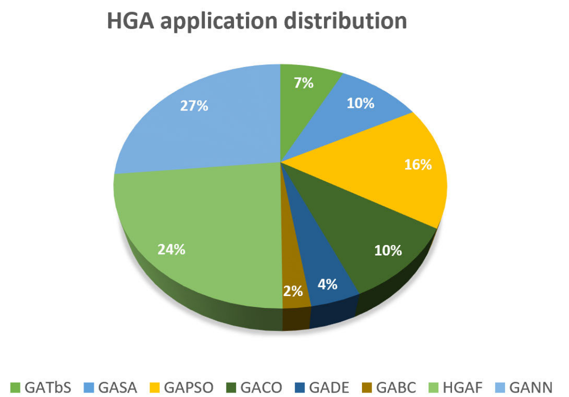

FIGURE 6. Hybrid GA application distribution in the railway domain.

The choice of which HGAs to use depends on the specific problem at hand and the characteristics of the search space. Each method has its own strengths and weaknesses, and the best approach may involve a combination of different algorithms.

VI. CONCLUSION AND FUTURE TRENDS

In this paper, a comprehensive review study is conducted to examine the use of GA and its various variants in the railway section. More than 250 publications were reviewed and summarized. The study encompassed a wide range of applications, including optimization of railway networks, maintenance, scheduling, fault diagnosis, design, forecasting, energy, etc. Additionally, the paper discussed the most popular GA variants and hybridization of GAs with other optimization techniques to enhance their effectiveness in solving railway-related problems. The bibliometric analysis further highlighted the trends in research in this field and identified the most prominent research directions. Overall, this review demonstrates the potential of GA and its variants in improving various aspects of railway operations and highlights the need for further research in this area to tackle emerging challenges and develop more efficient and effective solutions.

As research in the field of GAs progresses, new developments and trends emerge, which can be used to improve railway operations and safety. One promising future trend is the integration of GAs with other optimization techniques. For instance, GAs can be combined with swarm intelligence or machine learning algorithms to produce hybrid approaches that leverage the strengths of multiple optimization techniques. This integration can improve the efficiency and accuracy of railway optimization problems, leading to more effective solutions. Another trend is the use of GAs in conjunction with big data and IoT technologies. These technologies enable the collection of vast amounts of data from various sources, which can be utilized to optimize railway systems. GAs can be used to analyze and model this data, and to generate optimized solutions for complex problems, such as train scheduling and predictive maintenance.

Moreover, there is a growing interest in developing intelligent decision support systems using GAs. These systems can assist railway operators in making real-time decisions by providing accurate and timely information and realizing the digital twin concept. Accordingly, the main research gaps of this study are studying the integration of GA with emerging technologies such as artificial intelligence, machine learning, or big data analytics and exploring the practical implementation of GA-based solutions in real-time railway operations.

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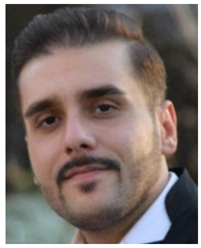

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