Review Article

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Evolutionary Computation for Intelligent Transportation in Smart Cities: A Survey

Abstract

As the population in cities continues to increase, large-city problems, including traffic congestion and environmental pollution, have become increasingly serious. The construction of smart cities can relieve large-city problems, promote economic growth, and improve the quality of life for citizens. Intelligent transportation is one of the most important issues in smart cities that aims to make transportation safe, efficient, and environmentally friendly. There exist many optimization problems to achieve intelligent transportation, and most of them contain large-scale data and complex features that challenge traditional optimization methods. With the powerful search efficiency, evolutionary computation has been widely used to solve these optimization problems. In this paper, a two-layer taxonomy is introduced to review the research of evolutionary computation for intelligent transportation in smart cities. In the first layer, related studies are classified into three categories (land, air, and sea transportation) based on the application scene of the optimization problem. In the second layer, three categories (government, business, and citizen perspectives) based on the objective of the optimization problem are introduced for further classification. A detailed review of related studies is presented based on the two-layer taxonomy. Future research directions and open issues are also discussed to inspire researchers.

I. Introduction

According to the report by Ritchie [1], the number of people living in cities reached 4.1 billion in 2017, and it is estimated that more than two-thirds of the people in the world will live in cities by 2050. The process of urbanization brings great challenges to city planning and management. To address these challenges, researchers have proposed the concept of a *smart city*, which is based on the use of advanced information technologies to achieve better city planning and management. In recent years, smart cities have gained extensive attention from researchers and have become a hot research topic [2], [3].

Intelligent transportation is a critical issue in smart cities. Various mathematical methods, such as linear programming and dynamic programming, have been used to solve transportation optimization problems in the literature [4], [5]. However, certain new features in modern cities make transportation optimization problems more complex. First, the scale of the optimization problem has become larger. Based on a report from the United Nations [6], 548 cities in the world had more than one million inhabitants by 2018, and it is estimated that the number of such large cities will grow to 706 in 2030. Massive populations will lead to

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massive transportation demand, which yields large-scale optimization problems. Second, complex application scenes yield NP-hard optimization problems, which typically make mathematical methods perform unsatisfactorily or even make them inapplicable. Tuning the model of the optimization problem to make it suitable for mathematical methods will cause an unacceptable modeling error. Third, many transportation optimization problems have complex features (e.g., dynamic environment and multiple objectives) due to real-world application demands, making them more difficult to solve.

Evolutionary computation (EC) is a kind of computational intelligence and artificial intelligence technique that imitates intelligent behaviors or phenomena in nature and human society. A salient feature of EC algorithms (approaches) is that they do not require a delicate mathematical model (e.g., linear programming model) and can obtain optimal or near-optimal solutions in an acceptable time. With a powerful search capacity, great robustness, and potential parallelism, EC has been widely used to solve various kinds of complex optimization problems [7]–[9].

In recent years, EC algorithms have also been extensively used to solve transportation optimization problems, helping to achieve intelligent transportation in smart cities. However, to the best of our knowledge, there are still few literatures that comprehensively survey the conjunction of EC algorithms and intelligent transportation in smart cities. To fill this gap, a two-layer taxonomy is introduced to classify related studies, as shown in Fig. 1. In the first layer, the related studies are classified into three categories based on the application scene of the optimization problem. These three categories are "For Land Transportation," "For Air Transportation," and "For Sea Transportation." The construction of smart cities is oriented to different types of cities. Land transportation is the most basic transportation mode in cities. Air transportation is essential to cities with airline hubs, such as Los Angeles and Beijing. Sea transportation is essential to coastal and port cities, such as Shanghai. Thus, it is necessary to review the related studies on all three transportation modes. Then, in the second layer, related studies are further classified from the perspectives of government, business, and citizens. The government perspective focuses on public infrastructure and municipal management, the business perspective focuses on the profit and service quality of transportation companies, and the

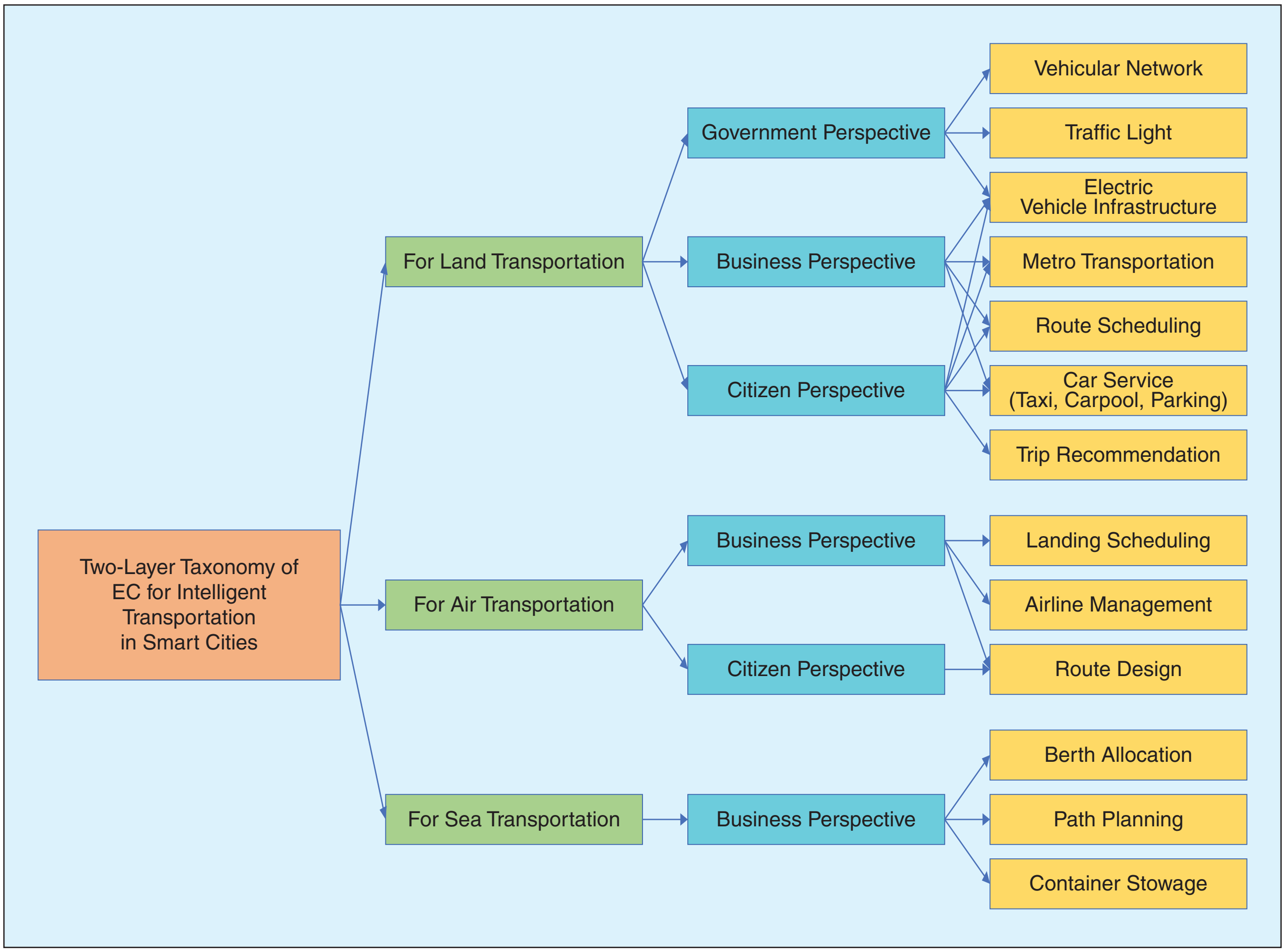

FIGURE 1 Two-layer taxonomy of EC for intelligent transportation in smart cities.

citizen perspective focuses on transportation services and planning for citizens. Finally, the last column of Fig. 1 shows the specific intelligent transportation application scenes in smart cities.

The contributions of this paper are as follows: 1) A two-layer taxonomy is proposed to classify related studies on EC for intelligent transportation in smart cities; 2) Related studies are reviewed in detail based on the two-layer taxonomy; 3) Certain future research directions and open issues are discussed. This paper hopes to provide readers with a comprehensive overview of EC for intelligent transportation in smart cities and promote more follow-up research.

The remainder of the paper is organized as follows. Section II presents background knowledge about intelligent transportation in smart cities and EC algorithms. Sections III–V review related studies on land, air, and sea transportation, respectively. Section VI discusses future research directions and open issues. Finally, Section VII draws conclusions.

II. Background

Transportation is a foundational component in modern cities. The supply of daily necessities, citizen travel, and commercial activities all require the support of transportation. In recent years, the technology of the Internet of Things (IoT) has developed rapidly, which enables the collection of transportation data from multiple sources (e.g., citizens, vehicles, and infrastructure). By analyzing these data, efficient planning and management schemes can be generated, making transportation more intelligent in smart cities. There are four essential objectives of intelligent transportation: maximizing transportation efficiency (e.g., speeding up transportation, reducing traffic congestion), maximizing economic profit, minimizing environmental pollution, and maximizing benefits to citizens. Optimization problems of intelligent transportation in smart cities often involve large-scale data and complex features. EC algorithms that have powerful search efficiency have been widely used to solve these problems. Therefore, this paper focuses on related studies on EC for intelligent transportation in smart cities.

EC is a group of optimization algorithms inspired by natural phenomena or social behaviors. Genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and differential evolution (DE) are typical and widely used EC algorithms. GA [10] and DE [11] are inspired by the crossover and mutation of chromosomes. PSO [12] and ACO [13] are inspired by the foraging behavior of birds and ants, respectively. Based on their search behavior, GA and ACO are more suitable and easier to apply in solving discrete optimization problems, while PSO and DE may be better choices for continuous optimization problems. Generally, an EC algorithm first generates an initial population, in which each individual represents a candidate solution of the optimization problem. Then, a problem-dependent process to evaluate each individual's fitness (i.e., the quality of its corresponding candidate solution) is performed. Next, a reproduction process that generates or updates individuals biased by fitness based on the Darwinian notion is performed, which is the key component of an EC algorithm. The algorithm executes the fitness evaluation and reproduction process iteratively until the termination condition (e.g., the maximum number of function evaluations) is met. Finally, the algorithm outputs the optimization result.

The application of EC algorithms for intelligent land transportation is classified into the following seven categories: vehicular network, traffic light, electric vehicle infrastructure, metro transportation, route scheduling, car service, and trip recommendation.

III. EC for Intelligent Land Transportation

Land transportation is the most basic and extensive mode of transportation, particularly in citizens' daily travel and short-distance goods transportation. Land vehicles include cars, trucks/lorries, and trains. The application of EC algorithms for intelligent land transportation is classified into the following seven categories: vehicular network, traffic light, electric vehicle infrastructure, metro transportation, route scheduling, car service, and trip recommendation.

A. Intelligent Vehicular Network

The vehicular network [14] is a fundamental component of an intelligent transportation system in smart cities. With the development of IoT, cloud computing, edge computing, and 5G technology, the application of vehicular networks has become practical. The communication unit deployed in vehicles enables vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications. An example of a vehicular network with V2I and V2V communications is shown in Fig. 2. Transportation data can thus be transmitted and gathered for further analysis to generate planning and management schemes. The deployment of vehicular networks includes a large amount of infrastructure, which requires a large amount of investment but yields little profit. Such a project is typically led by a government; thus, the application of vehicular networks is considered from the government perspective. There are three critical optimization problems in vehicular networks: infrastructure deployment, network routing, and resource scheduling.

First, although vehicles can communicate with each other, the function of the vehicular network also relies on the deployment of certain infrastructure. Lin and Deng [15] considered the deployment optimization problem of wireless sensors and roadside units (RSUs). Wireless sensors are used to collect traffic data and detect environmental events, while RSUs are a kind of communication device to transmit data to vehicles. Wireless sensors and RSUs all have limited coverage radii, which raises the optimization problem of how to deploy a minimal number of wireless sensors and RSUs while guaranteeing full coverage of the targeted area and network communication. A PSO-based algorithm is proposed to optimize the deployment scheme.

Second, the network routing problem in vehicular networks has been widely researched in the literature. The routing of vehicular networks has certain special features [16]. One feature is that relay nodes of the network (i.e., the vehicles) are mobile, making the network dynamic. The routing path is thus unstable and has a limited lifetime. To address the situation in which the route may break down at any time, Eiza *et al.* [17] proposed an ACO-based algorithm integrated with situational awareness that can prepare countermeasures for quick reconnection. Li *et al.* [18] used ACO to construct a routing path for maximizing quality of service (QoS) while subjecting the path to the maximum delay constraint. Sun *et al.* [19] used ACO to generate routing paths under a dynamic environment, in which buses were treated as primary relay nodes since they had regular timetables and travel trajectories, while other vehicles were treated as secondary relay nodes. The optimization objective is to find a routing path with a longer lifetime and lower delay. In Sun *et al.*'s other research [20], they used ACO to construct routing between vehicles in adjacent intersections. Another feature in the routing of vehicular networks is that certain vehicles may be malicious (i.e., they transmit incorrect data, regardless of intention, or even launch cyber-attacks) in the V2V communication. Such malicious vehicles will lead to severe safety threats, as decision-making for traffic planning and management highly depends on stable and authentic data collection. To address this problem, Eiza *et al.* [21] proposed an ACO-based routing algorithm. Plausibility checks are incorporated into the proposed algorithm to ensure the consistency of routing control messages. In addition, Safavat and Rawat [22] first proposed an effective malicious vehicle detection method and then used ACO to obtain a routing path with low delay, short distance, and no malicious vehicle. Based on these studies, ACOs are shown to be popular because vehicular network routing is a discrete optimization problem, in which ACOs are efficient.

Third, the incorporation of edge computing and 5G in vehicular networks creates the complex scheduling problem of computational and communication resources. Tan *et al.* [23] focused on the edge computing scene. A PSO algorithm is used to generate a solution representing the caching strategy of RSUs and the computation allocation scheme of mobile edge computing servers for optimizing the overall operating cost of the vehicular network, which includes communication, storage, and computation costs. Chen *et al.* [24] proposed a graph-based GA and a heuristic algorithm to schedule computational and communication resources for optimizing resource utilization, QoS, and support for concurrent requests. Edge computing also enables vehicles to be computational nodes. Some studies [25], [26] considered the influence of the mobility of vehicles and used EC algorithms to assign computational tasks to vehicles to optimize task completion time. Khan *et al.* [27] focused on the 5G communication scene, where the baseband unit was the basic transmission device. Each zone controller should be linked to a baseband unit, and through the transmission of the baseband unit, the zone controller can connect to the software-defined networking controller. A hybrid-fuzzy logic-guided GA is proposed to determine links between baseband units and zone controllers. The optimization objective includes the number of baseband units used, delay of data transmission, and load balance of the vehicular network.

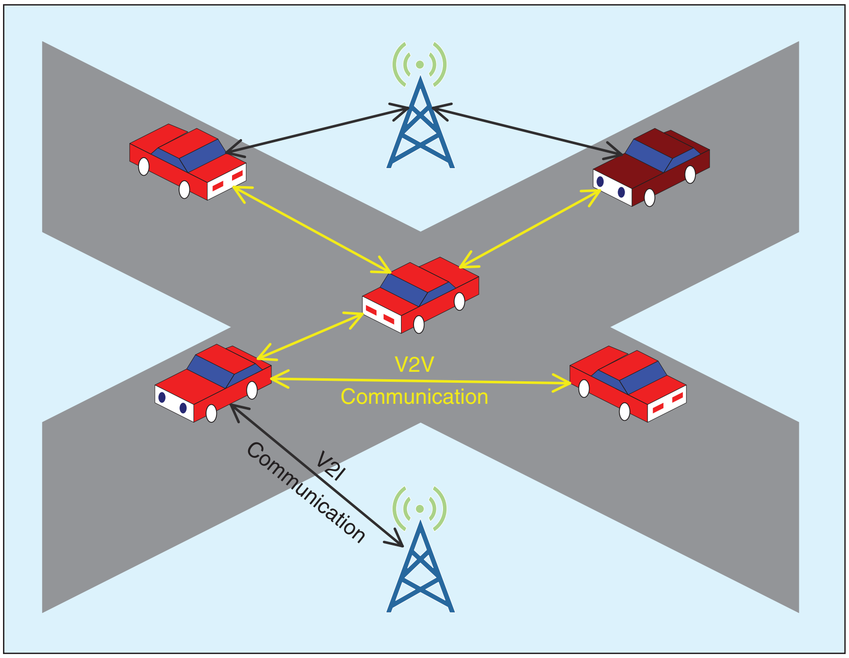

FIGURE 2 Example of a vehicular network with V2I and V2V communications.

B. Intelligent Traffic Light

With the development of the economy and the manufacturing technology of cars, the number of cars in cities increases rapidly, which produces a strong pressure on the traffic system and leads to congestion. Besides improving infrastructure, such as constructing new roads and broadening the current roads, optimizing the signal pattern of traffic lights is a more economical approach to reduce traffic congestion. Based on the vehicular network, traffic flow on the road can be monitored in real time. Some studies further used machine learning methods to predict short-term traffic flow, in which EC algorithms were used for parameter optimization [28], [29]. With this information, the signal pattern of the traffic light can be adjusted intelligently. Traffic light scheduling belongs to the scope of municipal administration; thus, this application is considered from the government perspective.

Related studies focused on optimizing the duration of each signal phase. A signal phase represents the signal of each traffic light in an intersection. Two examples of a signal phase are shown in Fig. 3. The decision variables for an intersection are a sequence of signal phases and the duration of each phase. Typically, several intersections are simultaneously considered to generate an efficient traffic network. Sanchez-Medina *et al.* [30] used a binary GA to solve this problem with the optimization objective of the average travel time for cars to arrive at their destination. The duration of the signal phase is restricted as an integer for binary encoding. The cellular automata technique is used to simulate the traffic flow and obtain the fitness of a solution (i.e., the average travel time). Li *et al.* [31] also used GA and set the same optimization objective (i.e., the average travel time) but with integer encoding. To simulate traffic flow, a modified Dijkstra algorithm that considers congestion is proposed to assign a route to each car. The integer encoded PSO algorithm proposed in [32] maximizes the number of cars that can reach their destinations and minimizes the traveling time of cars. Ferrer *et al.* [33] focused on the adaptation of the traffic light scheduling approach to highly dynamic and uncertain traffic flow. Bi *et al.* [34] proposed a multi-agent type-2 fuzzy logic control system to address uncertainties in traffic flow, where DE was used to optimize the parameter configuration of the system. Bie *et al.* [35] dealt with traffic light scheduling for controlling the headway between buses. Two buses on the same bus line must maintain a certain distance and time interval, but the uncertain number of passengers makes the stop time of a bus unpredictable. Thus, they used GA to schedule the traffic light and the speed of buses to maintain the regularity of the bus line. Rather than only considering the traffic flow of vehicles, some studies also considered the traffic flow of pedestrians during traffic light scheduling. Zhang *et al.* [36] proposed a discrete harmony search algorithm to optimize the weighted sum of the delay times of vehicles and pedestrians. In [37], the delay times of vehicles and pedestrians were set as two separate objectives, and the harmony search and artificial bee colony algorithms (both integrated with a local search operator) were used to solve this multiobjective model. Some of the studies mentioned above conducted experiments based on real-world road networks; for example, the road network in Saragossa, Spain is used in [30], and the road network in Jurong, Singapore is used in [37].

C. Intelligent Electric Vehicle Infrastructure

Electric vehicles (EVs) are a new type of vehicle powered by electric or traction motors. EVs are more environmentally friendly (e.g., can reduce greenhouse gas emissions) than traditional petrol vehicles [38] and are thus considered to be the trend of future vehicle development. EV charging requires specific facilities so new infrastructure should be deployed to support the usage of EVs. First, the government and EV manufacturers should deploy charging facilities in parking lots and construct specific charging stations. Intelligent charging strategies should also be developed to reduce expenditure and improve service quality. In addition, energy companies should deploy a power grid for the charging of EVs. The government often engages in the construction and management of EV infrastructure, related companies want to earn profits, and citizens benefit from the intelligent EV infrastructure in terms of travel convenience. Thus, the intelligent EV infrastructure is considered from the government, business, and citizen perspectives.

In the domain of infrastructure deployment, Zhang *et al.* [39] used a PSO-based algorithm to optimize the deployment of charging facilities. Specifically, the algorithm determines the number of fast-charging stations along a roadside and the location and charging capacity of each station. The optimization objective consists of the following four factors: investment cost, operation and maintenance cost, electricity cost, and time efficiency. Herein, time efficiency refers to the time that drivers spend in arriving at the charging facilities and waiting for the charging process to be complete. Zeng *et al.* [40] investigated the location of parking lots, the number of charging facilities, and the incentive policy to optimize the profit. Alegre *et al.* [41] optimized the location

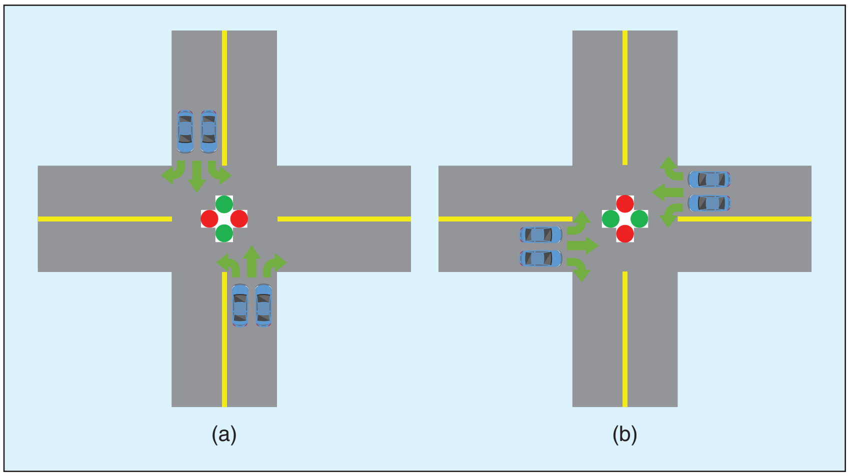

FIGURE 3 Two examples of a traffic light signal phase. (a) Signal phase for the up-down direction. (b) Signal phase for the left-right direction.

of charging stations to minimize investment for constructing charging stations and to maximize the service quality. Sadeghi-Barzani *et al.* [42] optimized the location and charging capacity of fast-charging stations, where the objective included investment, grid loss, and traveling cost of EVs to reach fast-charging stations. The above three studies [40]–[42] all used GA to solve their corresponding problem. Ko *et al.* [43] considered a special charging facility for electric public buses. These charging facilities support wireless power transmission and are deployed underground along a bus route; a bus can thus be charged while driving. The deployment of such charging facilities must be able to maintain the buses' battery level within a normal range. A PSO-based algorithm is proposed to determine the location of charging facilities and the battery capacity of buses to optimize the overall cost of such a public bus charging system.

In addition to the infrastructure deployment mentioned above, certain studies have focused on developing charging strategies from the citizen perspective based on the existing charging infrastructure. Moghaddam *et al.* [44] and Liu *et al.* [45] investigated the selection of charging stations and options, and planned the route for each EV to reach the corresponding charging station. Moghaddam *et al.* [44] proposed an ACO-based algorithm to optimize the traveling time, queueing time, and charging cost of EVs, while Liu *et al.* [45] proposed a DE-based algorithm to optimize the traveling time, charging cost, and difference between the real battery state and the expected battery state. Unlike refueling petrol vehicles that only require several minutes, the charging of EVs may require much more time (e.g., several hours). To reduce the time cost, battery swapping is a promising charging strategy. In battery swapping, an EV unloads the near-empty battery and replaces a full battery from the exchanging station [46]. The near-empty battery is then charged in the exchanging station and can be provided for the other EVs. Kang *et al.* [47] considered battery swapping from the perspective of exchanging stations. By using a hybrid algorithm of PSO and GA to schedule the charging time and location of the batteries, the charging cost, power loss, and voltage deviation are optimized. Wu *et al.* [48] investigated the selection of charging options for the batteries in the exchanging station. Different options have different features in terms of charging speed, charging cost, and battery damage. The proposed algorithm is also a hybrid algorithm of PSO and GA.

For energy companies, Yang *et al.* [49] built a probabilistic model to describe an EV's charging load on a power grid, in which an ACO-based algorithm was proposed for parameter identification. Amini *et al.* [50] used GA and PSO to allocate distributed renewable resources to parking lots to minimize power grid loss. Rahmani-Andebili *et al.* [51] simultaneously investigated two optimization problems: deployment optimization and charging scheduling. The first optimization problem refers to the selection of parking lot locations, which aims to optimize the initial investment and operation cost over the next 30 years. The second optimization problem aims to schedule the charging time of EVs to avoid using expensive electricity generation units to maximize the profit of energy companies. A simulated annealing algorithm is used to solve the first optimization problem, while GA is used to solve the second. Wind farms produce power from wind energy, which is clean and renewable. Both wind power and EVs are considered environmentally friendly. Some researchers have thus focused on the economic dispatch problem involving the charging of EVs and wind power, which aimed to determine the optimal electricity generation output to meet the load demand. Zhao *et al.* [52] used PSO to minimize the electricity generation cost of wind farms. Qiao *et al.* [53] proposed a nondominated sorting-based DE to solve a multiobjective model that minimized the electricity generation cost and pollutant emissions simultaneously. In this multiobjective model, thermal power is also considered to cooperate with wind power to meet the load demand, and the pollutant emissions are caused by the usage of thermal power.

D. Intelligent Metro Transportation

An increasing number of cities, particularly large cities, have built metro systems. Metro transportation is a convenient and efficient choice for commuting because it rarely has delays. It can also reduce the traffic congestion on roads. There are mainly two research topics within intelligent metro transportation: timetable design and speed control. These topics are related to the expenditure of metro corporations and the travel convenience for citizens; thus, they are considered from both the business and citizen perspectives.

First, timetable design includes the design of arrival and departure times of trains in each station along their route. The most widely considered optimization objective is to minimize the waiting time of transfer passengers [54]. Zhong *et al.* [55] proposed a dual-population DE, in which two populations focused on search diversity and convergence, respectively. Hassannayebi *et al.* [56] used PSO and proposed an adaptive parameter control strategy to enhance search efficiency. In addition to the waiting time of transfer passengers, Nitisiri *et al.* [57] further considered the operating cost of metro corporations and proposed a parallel multiobjective GA to optimize these two objectives. Certain studies focused on the timetable design for reusing energy. In detail, when a train brakes, the generated kinetic energy can be reused by another train in the same substation concurrently for acceleration. Lin *et al.* [58] used GA to schedule the dwell time of a train in each station for efficient reuse of the regenerative energy from braking. However, the classic version of GA is used and there is no specific strategy to enhance the algorithm's performance. Liu *et al.* [59] proposed an artificial bee colony-based algorithm to schedule the headway and dwell time of trains for optimizing the utilization of regenerative energy.

Second, speed control handles the operational status of trains. The operational status can be described as pulling, holding, coasting, or braking. Fernández-Rodríguez *et al.* [60] proposed a multiobjective PSO to minimize the running time and energy consumption of trains. Cao *et al.* [61] scheduled the coasting time of trains by GA to optimize punctuality, passenger comfort, and energy consumption. Feng *et al.* [62] used GA to manage the timetable design and speed control simultaneously to maximize the utilization of regenerative braking energy.

E. Intelligent Route Scheduling

Route scheduling aims to allocate vehicles and assign each vehicle a driving route to achieve certain objectives. The well-known vehicle routing problem (VRP) is a typical route scheduling problem, in which a delivery company should design the driving route of each truck/lorry for delivering the goods from the depot to the customers and finally going back to the depot. The route scheduling is related to the service quality and profit of delivery companies from the business perspective. City VRPs [63] consider both the benefit of delivery companies (e.g., service quality and route cost) and the benefit of citizens (e.g., traffic congestion and environmental pollution). In this regard, route scheduling is also considered from the citizen perspective.

In recent years, some new VRPs are studied to meet the demands in smart cities, including multi-echelon VRPs, green VRPs, VRPs with EVs, VRPs with crowdshipping, and VRPs with drones. Multi-echelon VRPs are common in city logistics, in which the delivery process is divided into multiple steps rather than directly delivering the goods from the depot to the customers [64]. To optimize the route cost, Yan *et al.* [65] proposed a graph-based evolutionary algorithm that incorporated the fuzzy logic to enhance the search efficiency. In addition, Wang *et al.* [66] proposed a hybrid algorithm of PSO and GA to minimize the total cost of a multi-echelon logistics network. Green VRPs [67], [68] focus on environmental pollution. Poonthalir and Nadarajan [69] proposed a PSO-based algorithm with a greedy mutation operator to optimize not only the route cost but also the fuel consumption for reducing emissions of greenhouse gas. Li *et al.* [70] proposed an improved ACO algorithm to optimize four objectives: revenue, cost, transportation time, and CO_2 emissions.

With the development of EVs, certain studies considered the scenario of using EVs to transport goods. The usage of EVs can also reduce vehicle exhaust emissions and improve the air quality in cities. Thus, the VRPs with EVs have connections to the green VRPs. There are two critical issues: one is that the charging of EVs requires a lot more time than the refueling of traditional petrol vehicles; the other is the time-of-use (TOU) electricity price. TOU electricity price means the electricity price is time-varying throughout the day, which is common in the current electricity market. Considering these two issues, Yang *et al.* [71] proposed a GA-based algorithm and Miao *et al.* [72] proposed a DE-based algorithm to generate route schemes for optimizing charging cost and battery loss. Li *et al.* [73] further considered the carbon taxes that aimed to reduce greenhouse gas emissions. An ACO-based algorithm is proposed to optimize the charging cost, payment for EVs and employees, service quality, queuing time of EVs for charging, and cost for carbon taxes. Note that for readers who are interested in VRPs with EVs, the resources (including a benchmark set) in https://mavrovouniotis.github.io/EVRPcompetition2020/ can help them start a study.

Crowdshipping, derived from sharing economy, is a new delivery mode that allows ordinary people to join the delivery process using their own vehicles [74]. To minimize the total cost of crowdshipping delivery, Wu *et al.* [75] proposed a scale-adaptive fitness evaluation method and embedded it into GA. Feng *et al.* [76] proposed a GA-based evolutionary multitasking algorithm that can solve multiple instances simultaneously while obtaining promising results through knowledge transfer.

Drones can also be used to deliver goods, which can reduce labor cost and improve delivery efficiency. Due to the low carrying capacity of drones, drones usually cooperate with traditional vehicles (e.g., trucks) and undertake the last-mile delivery. To deal with this new scene, simulated annealing-based algorithms are proposed in [77] and [78]; Shao *et al.* [79] considered the route length of drones and the number of landing depots along the route to formulate an objective function and proposed a hybrid algorithm of ACO and A* algorithm; Das *et al.* [80] proposed an ACO-based multiobjective algorithm to minimize the route cost and to maximize the service quality simultaneously.

In the future, large-scale highly dynamic delivery systems will be promising in smart cities. Some studies have focused on this topic. To deal with the challenge of large-scale delivery demand, Xiao *et al.* [81] used the well-known NSGA-II [82] to divide the large-scale VRPs into a set of subcomponents; Jabir *et al.* [83] proposed a hybrid algorithm of ACO and the variable neighborhood search. To deal with the challenge of dynamic delivery demand, Jia *et al.* [84] proposed a set-based PSO algorithm; Xiang *et al.* [85] proposed an ACO-based algorithm that used a pairwise proximity learning method to help the algorithm adapt to the change of delivery demand.

F. Intelligent Car Service

Car service in smart cities includes the following three services: taxi, carpool, and parking. These services are considered from the business perspective since the operators of these services want to earn profits. In addition, these services are typically used by citizens and are thus also considered from the citizen perspective. In the domain of taxis, taxi dispatch is a critical problem to be solved. Traditionally, taxi drivers do not know where passengers are currently, and they typically seek passengers based on their own experience. Thus, some passengers tend to wait a long time for a taxi, and some taxi drivers tend to drive without finding passengers. Taxi booking apps such as Uber, which have recently become popular, can gather information from both passengers and taxis. This information can be used to make a global dispatch of taxis for passengers. Situ *et al.* [86] proposed an ACO-based algorithm to generate a taxi-passenger matching scheme for maximizing profit. To address a large number of passengers and taxis, a region is divided into several subregions, and dispatch in each subregion is conducted in parallel. Gong *et al.* [87] considered both the profit and QoS when formulating the taxi-passenger matching scheme. Specifically, a fuzzy logic control system is proposed to score each potential taxi-passenger pair based on the profit and QoS, in which DE is employed to optimize membership functions and fuzzy rules. Jung *et al.* [88] focused on the shared-taxi scenario that allowed a taxi to detour to pick up other passengers when some passengers were already in the taxi during rush hours. A simulated annealing-based algorithm is proposed to minimize the passenger travel time and to maximize the profit. In the shared-taxi scenario, some passengers need to spend more travel time due to the detour so they expect lower prices. However, the profit of drivers should also be considered. To satisfy both passengers and drivers, Zhang *et al.* [89] proposed a GA-based algorithm to optimize the pricing scheme. Liang *et al.* [90] investigated the dispatch of electric taxis. Since the charging of electric taxis requires much more time than the refueling of traditional petrol taxis, the dispatch of electric taxis should consider the remaining battery capacity and the location of charging facilities. The primary objective of this problem is to maximize the number of passenger requests that are satisfied, while the secondary objective is to reduce the total waiting time of passengers whose requests are satisfied. An ACO-based algorithm with a pre-selection strategy and local pruning strategy is proposed in [90] to solve this problem.

Carpooling is also called ride-sharing, and an example is shown in Fig. 4. People nearby may have the same or nearby destination(s) (e.g., people living in the same block also work in the same company). Rather than driving to the destination in separate cars, several people could share one car. In Fig. 4, Charles will drive the blue car and take Amy and Jack together, while Fiona will drive the gray car and take John, Linda, and Susan together. There are three benefits of carpooling. The first benefit is that the fuel cost of drivers can be shared by the other passengers, and the passengers also spend less money compared to driving by themselves. The second and third benefits are reducing traffic congestion and the emission of greenhouse gas, respectively, because fewer cars are on the road. However, drivers must detour from their shortest route to pick up passengers, which incurs additional driving distance, fuel costs, and time costs. Passengers also have certain demands, including the pick-up time of cars. Thus, efficient algorithms for matching drivers and passengers should be developed to provide high-quality carpool services.

To manage carpooling, Huang and Jiau investigated various optimization objectives in carpooling [91]–[98]. The details of the objectives considered in the related studies are compared in Table I. In [94] and [98], the concept of a time window (i.e., a specific window of time when passengers require cars to pick them up) is considered. Early arrival or a delay will affect the user experience. To address multiple optimization objectives, integrated models that combine several objectives into a single objective function are formulated in [91] and [96], while dual-objective

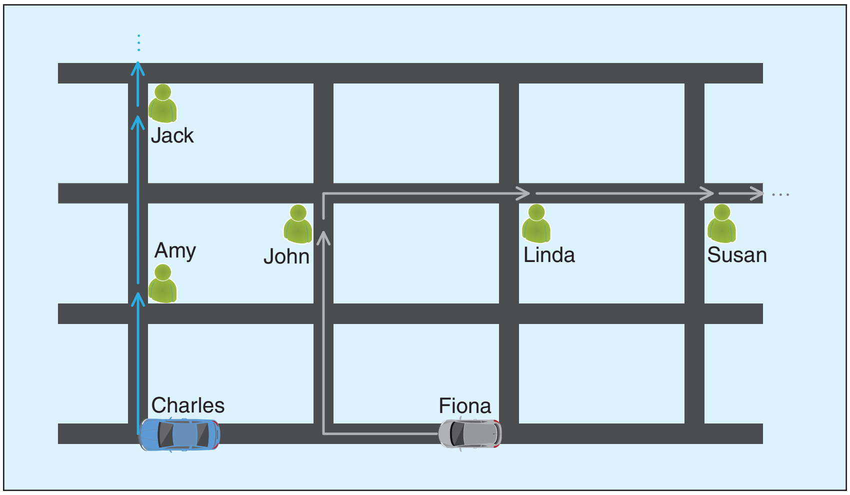

FIGURE 4 Example of carpooling.

TABLE I The objectives considered in the related studies on carpooling.

REFERENCE	DRIVERS' TRAVEL DISTANCE	PASSENGERS' TRAVEL DISTANCE	NO. OF MATCHED PASSENGERS	PASSENGERS' WAITING DISTANCE	SEAT USAGE RATE
[91]	✓	✓	✗	✓	✗
[92]	✓	✗	✓	✓	✗
[93]	✓	✓	✓	✗	✓
[94]	✓	✓	✓	✗	✓
[95]	✓	✓	✓	✓	✗
[96]	✓	✗	✗	✗	✓
[97]	✓	✓	✓	✗	✗
[98]	✓	✓	✓	✓	✗

models that set the primary and secondary objectives are formulated in [92], [94], and [95]. In [93], [97], and [98], multiobjective models are directly formulated, and nondominated sorting GA-based algorithms are proposed to obtain a set of Pareto optimal solutions.

The number of privately owned cars has grown rapidly in recent years. By the end of 2019, the number of privately owned cars is projected to exceed 200 million in China [99]. This large number of cars leads to difficulties in finding parking space. Typically, in the central business district of a city, the supply of parking spaces cannot meet demand. The deployment of smart parking systems is a promising way to relieve the parking difficulty, which has been widely studied in recent years [100]. Parking reservations are an important part of smart parking systems [101], which allow drivers to reserve a parking space before arriving at a parking lot. However, if all parking spaces are reserved, other drivers on the road cannot park in parking lots. Therefore, some parking spaces should be made available only to non-reservation drivers. Mei *et al.* [102] used GA to optimize the proportion of parking spaces for reservation in parking lots. Two optimization objectives are considered: 1) social benefits, which include travel time, travel distance, and queuing time of drivers for parking; and 2) parking lot revenue, which primarily refers to parking fees paid by drivers. Liu *et al.* [103] introduced a parking guidance system. In their proposed system, a wavelet neural network is used to predict the available parking spaces for drivers, and PSO is used to optimize the network configurations. The selection of parking lots for users is based on a multivariate logit model, and an adaptive GA is used to provide a route with a short distance and time for drivers to reach the selected parking lot.

G. Intelligent Trip Recommendation

With economic development and increasing income levels, people increasingly travel for vacations. A tourism city always has various trip items (e.g., tourist attractions and entertainment activities). However, tourists typically have limited time and budgets. How to efficiently plan the itinerary of a trip to obtain the best experience is the most important concern of tourists, which creates a large demand for trip recommendation services [104]. Thus, this application is considered from the citizen perspective. A general trip recommendation scheme includes the following three parts: a set of trip items to be visited, the visit sequence of the trip items, and the traveling route/vehicle between two trip items.

Luan *et al.* [105] proposed an ACO-based algorithm for trip recommendation. The solution from this algorithm is constructed by adding trip items one by one until all items are included or the user's time or budget has been exceeded. The selection of trip items is based on two factors: trip relevance and trip diversity. Trip relevance represents the interest of a tourist in a kind of trip item or a specific trip item, which is obtained based on users' scores. However, if only trip relevance is considered, the trip recommendation scheme may include too many similar trip items, which is not what tourists expect. To address this problem, trip diversity is incorporated, which represents the difference level among the selected trip items. Huang *et al.* [106] also considered trip diversity. In addition, the rating of trip items and transportation time are further considered. Since some tourists do not have specific interests, they may prefer high-rated trip items (e.g., must-see attractions). In addition, with limited time, tourists prefer to minimize transportation time. A niching GA is proposed to generate multiple candidate itineraries for users. Migliorini *et al.* [107] considered crowding. For example, during a public holiday, many tourists will flock to tourism cities, creating dense crowds at tourist attractions. Dense crowds have a poor impact on the trip experience and induce longer visiting time at attractions. Thus, the balance of tourists among the attractions is incorporated into the trip recommendation. A simulated annealing algorithm is proposed to solve this problem. Dotoli *et al.* [108] focused on planning vehicles during the itinerary, including bikes, buses, metros, and cars. Three optimization objectives are considered: cost, time, and gas emissions. GA is used to solve this problem, in which the fitness of the chromosome is set to the weighted sum of the three optimization objectives above.

IV. EC for Intelligent Air Transportation

Air transportation is the most modern mode of transportation. For the construction of smart cities, the transportation issues related to the airport are essential, especially for those cities with airline hubs. The application of EC algorithms for intelligent air transportation is classified into the following three categories: landing scheduling, airline management, and route design. These three categories are introduced as follows.

A. Intelligent Landing Scheduling

Air traffic is typically busy in large cities. For example, the total traveler throughput of the Beijing Capital International Airport reached more than 100 million in 2019 [109]. However, the limited number of runways in an airport may not meet the demand of take-off and landing (i.e., an airplane may not take off or land immediately when it is ready). Constructing new runways is a potential solution but is expensive and may not be possible due to insufficient free space. An alternative solution is scheduling the take-off/landing sequence of airplanes to reduce delays. Most studies have focused on landing scheduling. However, the take-off and landing of airplanes both refer to the occupation of runways so these studies are also applicable to hybrid take-off and landing scenarios. Landing scheduling is related to the service quality of airlines from the business perspective.

A simple example of landing scheduling on a runway is shown in Fig. 5. The arrival time of airplanes is typically known in advance based on the timetable of the airline. The decision variable is the landing sequence of airplanes. An important constraint is that the landing of two airplanes on the same runway must have a certain time interval, which depends on the models of the two airplanes. First-come-first-serve (FCFS) is the most direct method to determine the landing sequence but may not be the best choice due to the constraint of the landing interval. As shown in Fig. 5, the total delay of the three flights in FCFS is (0 + 110 + 220) = 330 seconds, while that in intelligent scheduling is (0 + 250 + 0) = 250 seconds. Certain exact algorithms (e. g., branch-and-cut [110] and branch-and-price [111]) have also been proposed to deal with landing scheduling. However, these exact algorithms require specific mathematical features of the landing scheduling model and thus cannot be extended in more complex scenarios. Differently, EC algorithms have fewer restrictions of the model and are therefore applicable in various scenarios. The related studies on EC algorithms for landing scheduling are compared in Table II. Xu [112] proposed a GA-based algorithm to optimize the landing sequence with the goal of minimizing the landing time of the last airplane. Hu and Paolo [113] used an adjacency matrix to encode the landing sequence and proposed a binary GA to minimize the total delay of all flights. Specifically, the receding horizon control is incorporated, which divides the timeline into a set of time windows. The proposed algorithm sequences airplanes in each time window respectively, rather than sequencing all expected landing airplanes simultaneously. Based on the receding horizon control framework in [113], Zhan *et al.* [114] proposed an ACO-based algorithm with integer encoding to solve the problem. The above three studies focused on the single-runway scenario, but modern airports usually have multiple runways. Thus, considering the multi-runway scenario may be more practical. In this domain, Liu [115] proposed a GA-based approach. Salehipour *et al.* [116] constructed a mixed-integer programming model and proposed a simulated annealing-based algorithm to plan the landing sequence and landing times of airplanes. Salehipour [117] also proposed a two-step approach to solve this mixed-integer programming model. The first step is to obtain the landing sequence by a simulated annealing-based algorithm. With the landing sequence, the mixed-integer programming model can be transformed into a linear programming model and be solved by an exact solver. Wu *et al.* [118] extended the method in [114] to address multi-runway scenarios. A greedy heuristic is proposed to distribute the airplanes to multiple runways based on the landing sequence obtained by the ACO algorithm in [114].

Although flights are expected to follow a pre-established timetable, many uncertainties exist in real operation. For example, the arrival and taxiing times of airplanes cannot be as accurate as planned, and there may be additional airplanes expecting to land. Caprì and Ignaccolo [119] considered the uncertainty of flight arrivals. When new request-landing airplanes emerge, the landing sequence must be rearranged. GA is used to solve this problem, where the optimization objective is to minimize the sum of the landing time of airplanes. In addition, Bencheikh *et al.* [120] proposed an ACO-based algorithm to address the uncertain airplane arrival scenario. The optimization objective consists of two parts: the delay penalty and the rearrangement penalty. The rearrangement penalty is related to the change in landing time of an airplane

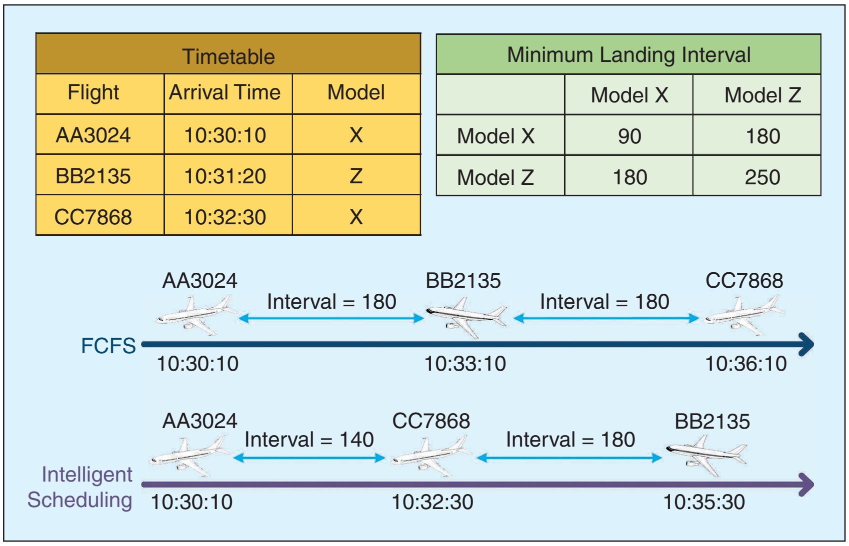

FIGURE 5 Example of landing scheduling on a runway.

TABLE II The comparison of the related studies on landing scheduling.

SCENARIO	REFERENCE	BASIC OPTIMIZER	CONSIDER UNCERTAINTY
SINGLE-RUNWAY	[112]	GA	✗
	[113]	GA	✗
	[114]	ACO	✗
	[119]	GA	✓
	[121]	PSO	✓
MULTI-RUNWAY	[115]	GA	✗
	[116]	SIMULATED ANNEALING	✗
	[117]	SIMULATED ANNEALING	✗
	[118]	ACO	✗
	[120]	ACO	✓

after rearrangement because a rearranged timetable with less change compared to the original timetable is preferred. Hong *et al.* [121] considered the uncertainty of flight time, which induced an uncertain arrival time. The proposed approach not only addresses the landing sequencing problem but also schedules the flight routes of airplanes to enter the airport. PSO is used to generate a landing sequence, while flight route scheduling is modeled as a mixed-integer linear programming problem and solved by the CPLEX Optimizer (software developed by IBM).

B. Intelligent Airline Management

Airline management refers to the management of various affairs in airline operations. The objective of airline management is to maintain the orderly operation of airlines and to maximize profit. Thus, airline management is considered from the business perspective. EC algorithms are widely used to solve airline management problems, including flight planning, airplane assigning, airplane maintaining, crew scheduling, and shuttle arranging.

1) Flight Planning

Flight planning aims to generate a flight schedule that maximizes the profit of the airline and includes the following two steps. The first step is to select a set of flights from many candidate flights to operate. This selection is restricted by the number of available airline resources (e.g., number of airplanes and employees). Kölker and Lütjens [122] used GA to solve this problem. After selecting a set of flights, the second step is to specify the timetable of these flights to obtain a complete flight schedule. Abdelghany *et al.* [123] used GA to solve this problem and considered three optimization objectives: maximizing ticket revenues and the number of flight rotations, and minimizing the idle time of airline resources. The number of flight rotations refers to the number of flights that an airplane and a group of crew members can conduct consecutively.

However, during the operation of the flight schedule, certain disruptions may occur, such as poor weather, air traffic control restrictions, and airplane breakdown. In this case, the flight schedule must be rearranged to maintain flight operations and to minimize delays [124]. Another possible solution for disruptions is inserting buffer time when arranging the original timetable. In addition to the necessary ground turnaround time between two consecutive flights (e.g., boarding/offboarding time, airplane maintenance time), some buffer time is added. Thus, if a previous flight is delayed, the subsequent flight can still be on time. Ahmed *et al.* [125] used PSO to determine the buffer time between two consecutive flights to avoid flight delays. Although the insertion of buffer time may lose some potential profit, buffer time can avoid rearranging the flight schedule and enhance the on-time performance of an airline, which is one of the issues that passengers are concerned about the most.

2) Airplane Assigning

After determining the flight schedule, airlines should assign airplanes to fly all planned flights. Zhang *et al.* [126] used ACO to minimize the time required to finish all flights. Chou *et al.* [127] proposed a multiobjective GA with the two objectives of ensuring sufficient ground turnaround time between two consecutive flights and minimizing the number of no-profit flights. If the destination of the previous flight is different from the departure of the subsequent flight, the airplane needs to conduct a flight to the departure of the subsequent flight with no passenger. Such a flight refers to a no-profit flight.

In addition, different flights have different numbers of potential passengers. The flights between two large cities typically have many passengers. Different types of airplanes have different capacities (e.g., the number of seats). Thus, assigning a suitable airplane for each flight can yield more profit. Anzoom and Hasin [128] used an ACO-based algorithm to optimize the profit of an airline, where the profit was calculated by subtracting the flight operating cost from the ticket revenue. Yazdi *et al.* [129] made a more comprehensive calculation of the revenue, which considered ticket revenues and the revenue obtained from ticket cancelations and overbooking. A binary DE is used, and the solution is encoded by a matrix representing the map between airplanes and flights.

In recent years, scientists find that a large number of carbon emissions will cause global climate warming. Therefore, the assignment of airplanes should also consider carbon emissions [130]. The European Union (EU) has launched the EU Emissions Trading System (EU-ETS) that restricts the carbon emissions of flights whose departure or destination is in EU countries. If the carbon emissions exceed the limit, the airline should pay a fine based on the exceeded emissions. Ko *et al.* [131] dealt with the regulation of EU-ETS by assigning airplanes with low carbon emissions for flights in the EU, and GA is used to optimize the profit of the airline.

3) Airplane Maintaining

Safety is the primary issue in flight. Insufficient maintenance can cause an airplane to crash, yielding many casualties. The crash of China Airlines Flight 611 in 2002 killed all 225 people in the airplane, and the investigation showed that it was caused by metal fatigue in the tail skin [132]. To ensure the safety of flights, airplanes require regular maintenance. Because airplanes continuously fly from one destination to the next to earn profits, an airline must determine when and where to perform maintenance of airplanes in accordance with the regulation made by the International Civil Aviation Organization. For example, routine maintenance must be performed if an airplane meets the maximum cumulative flight time. Flights may be delayed for various reasons, which will cause the maintenance plan to fail to proceed as scheduled. Eltoukhy *et al.* [133] proposed an ACO-based algorithm to address the coordination between flight operation and maintenance operation. A bilevel model is proposed, which uses the upper and lower levels to minimize the delay of flights and the employment cost for maintenance work, respectively. Ip *et al.* [134] focused on the scheduling of maintenance tasks in an airport. The maintenance tasks of airplanes should be assigned to several maintenance teams, and the maintenance sequence should also be determined. They proposed a GA-based algorithm to minimize the total delay of all flights. Eltoukhy *et al.* [135] considered disruptions when planning the maintenance schedule, and proposed an ACO-based algorithm to minimize the delay of flights. The proposed algorithm is validated based on real-world data from a major Middle Eastern airline.

4) Crew Scheduling

Crew scheduling consists of two parts: pairing and rostering [136]. With a set of flights that an airline plans to operate, a pairing is a flight sequence in which the first flight begins from the base of the crew, the other flights start from the destination of their previous flight, and the last flight should return to the base of the crew. The airline must construct pairings that can cover all planned flights; this situation describes the crew pairing problem. Each pairing is operated by a crew, and there are two important constraints in the construction of pairings. One is that the duty time of a crew over a given period cannot exceed the maximum working hours in law. The other is that the crew members, particularly the pilots, must have sufficient rest time between two flights. The resulting pairings are then assigned to airline employees to determine the crew members for each pairing, which describes the crew rostering problem. The primary objective of crew pairing is to minimize the employment cost of crews, while crew rostering typically considers the fairness of workload assignment and the satisfaction of employees.

To solve the crew pairing problem, Deng and Lin [137] proposed an ACO-based algorithm. Rather than the direct construction of pairings, Deveci and Demirel [138] first enumerated all possible pairings via Depth-First-Search; then, a GA-based algorithm is proposed to pick up certain pairings that can cover all planned flights and with minimal cost. To solve the crew rostering problem, Zhou *et al.* [139] constructed a multiobjective model that simultaneously considered the fairness and satisfaction of the workload assignment. The proposed multiobjective ACO algorithm is based on the multiple populations for multiple objectives framework [140], [141], which uses two ant colonies to optimize the two objectives. Chen and Chou [142] considered disruptions in crew rostering, such as mechanical malfunctions of airplanes and crew member sickness. If a disruption occurs, the rostering plan must be rearranged. The overall objective is to minimize the changes between the new and original plans. Six optimization objectives are considered, and the proposed algorithm is based on NSGA-II.

The studies mentioned above only deal with one of the two problems in crew scheduling. However, crew pairing and crew rostering are not two independent problems. The crew pairing is the premise of crew rostering, i.e., solving the crew rostering problem requires a set of pairings as input. Due to the large scale of data and the complex features of these two problems, it is very challenging to solve these two problems simultaneously. Researchers have made some attempts. Souai and Teghem [143] proposed a GA-based algorithm that contained three heuristic strategies to make the solution feasible. Chen *et al.* [144] encoded the solution by two matrixes that represented the pairing and rostering schemes, respectively. Five optimization objectives are considered: maximizing the day-offs of employees and minimizing the number of deadheads, the overnight cost, the waiting time between two consecutive flights, and the workload deviation among employees. A deadhead represents that a crew member should take a flight as a passenger to get to a specific destination for work. Overnight cost refers to the cost needed for crew members to stay overnight in a place other than their base. An improved NSGA-II algorithm is proposed to solve this multiobjective optimization problem.

5) Shuttle Arranging

Airports are usually located in suburbs. Airport shuttle service is a common approach that makes it convenient for people to travel from downtowns to airports, which typically refers to the arrangement of shuttle buses. Öner *et al.* [145] proposed a simulated annealing-based algorithm to arrange the schedule of a fixed bus line between the airport and city center, aiming to maximize the profit. The travel time through shuttle buses may be influenced by traffic conditions, but passengers must arrive at the airport on time to catch the flight. Thus, Bao *et al.* [146] focused on optimizing the reliability of the airport shuttle service. The reliability refers to the probability that shuttle buses arrive on time. A hybrid algorithm of GA and a hill-climbing algorithm is proposed to solve this problem. Usually, the airport shuttle bus lines are between airports and city centers because there are many potential passengers. For people who do not live in the city center, certain airlines provide demand-responsive services, in which people request pick-up service via telephones or the Internet and the airlines arrange vehicles and routes to deliver these people to the airport. Wei *et al.* [147] used NSGA-II to optimize the operating cost, fuel consumption, and carbon emissions of the arrangement.

C. Intelligent Route Design

Route design includes the design of the flight route in various scenes, and the optimization objectives of route design are often related to the safety of flight, fuel consumption, and impact on residents. Thus, route design is considered from both the business and citizen perspectives. There are two typical issues to consider: noise handling and danger handling.

The flight of airplanes will generate much noise, which has a marked impact on nearby residents, particularly when airplanes fly at low altitudes. A direct solution is designing flight routes far away from residential areas. However, such routes may induce more fuel consumption that reduces the profit of the airline. To address this problem, Ho-Huu *et al.* [148] constructed a multiobjective model that considered noise impact and fuel consumption simultaneously and proposed a two-stage approach to solve the model. In the first stage, MOEA/D [149] is used to determine a set of Pareto optimal routes. Then, in the second stage, NSGA-II is used to assign airplanes to the routes obtained in the first stage.

In addition, the flight route of airplanes should remain away from dangers such as poor weather, crowding traffic, and no-fly zones. González-Arribas *et al.* [150] constructed a dynamic model to represent thunderstorms in airplane route design. Han *et al.* [151] planned the routes of multiple airplanes simultaneously. The flight speed of each airplane is assumed to be the same. A DE-based algorithm is proposed to adjust the flight direction of each airplane in each time window, guaranteeing that the minimal distance between any two airplanes will not be smaller than a certain threshold to avoid collisions. Wang [152] proposed a hybrid algorithm of the artificial immune algorithm and ACO to design a route with minimal distance while avoiding no-fly zones.

V. EC for Intelligent Sea Transportation

For coastal and port cities, sea transportation is a significant part of the intelligent transportation in smart cities. The application of EC algorithms for intelligent sea transportation is classified into the following three categories: berth allocation, path planning, and container stowage. These three categories all considered the profit and service quality of either shipping companies or port operators, and are thus considered from the business perspective. Details of these three categories are introduced as follows.

A. Intelligent Berth Allocation

A number of ships arrive at a given port every day. Containers must be loaded or unloaded by quay cranes in the berths of the port, which typically requires dozens of hours. Therefore, due to the limited number of berths in the port, arriving ships may not be able to dock at the berths for container loading/unloading immediately. This situation could benefit from an intelligent berth allocation approach that reduces ship waiting time and avoids delays of subsequent trips [153]. Berth allocation includes assigning ships to the berths and determining the handling sequence of each berth. In the literature, certain exact algorithms (e. g., branch-and-cut [154] and branch-and-price [155]) have been applied to the berth allocation and have obtained great performance on small- and medium-scale instances. However, they may suffer from poor time efficiency in solving large-scale instances. In comparison, EC algorithms can obtain optimal or near-optimal solutions on instances of various scales within an acceptable execution time. Ting *et al.* [156] used PSO to optimize the time-in-port, which includes the waiting and handling times of all ships. Cheong and Tan [157] constructed a multiobjective model where waiting and handling times were set as the two optimization objectives. A multi-colony ACO is proposed to solve the model. Şahin and Kuvvetli [158] used DE to minimize the penalty of delay and non-optimal berthing position. Hu [159] used NSGA-II to minimize delays and night work. Night work is not preferred by employees and is also less efficient than daytime work.

Heterogeneous berths are considered in [160] and [161]. The difference among berths is described in size (i.e., length and width) and water depth. Large ships cannot dock at a small berth, while several small ships may dock at the same large berth and be handled simultaneously. Tsai *et al.* [160] used GA to minimize total waiting time. Ji *et al.* [161] considered the total time-in-port as the optimization objective, and the constraints of the problem are considered to be the other optimization objective. Thus, a multiobjective model is constructed. NSGA-II is used to solve this model.

In addition, some studies created more detailed berth allocations by considering additional resources in ports (e.g., quay cranes and yard trucks). Quay cranes can be flexibly allocated to the berths based on the handling workload [162]. Hsu [163] proposed an improved PSO algorithm to solve berth allocation and quay crane assignment simultaneously. De *et al.* [164] used a chemical reaction optimization algorithm to optimize the time-in-port of ships and the additional rental cost of quay cranes. Liang *et al.* [165] considered two objectives. One is the total time-in-port of ships, and the other is the movements of quay cranes. Specifically, if two consecutive ships at the same berth require different numbers of quay cranes, some quay cranes must be moved. The proposed algorithm is a multiobjective GA. Yard trucks are used to transfer containers between the berth and warehouse. Li *et al.* [166] considered the time-in-port of ships and the transfer distance between the berth and warehouse. A PSO-based algorithm is proposed to solve this multiobjective optimization problem.

B. Intelligent Path Planning

When planning the navigation path of ships, feasibility, safety, and economic benefit are three critical issues. Feasibility issues refer to the avoidance of various obstacles, such as reefs and shallow seas (i.e., where ships easily run aground). Liang *et al.* [167] used ACO to construct a feasible path with minimized length.

Safety issues refer to the handling of weather influences and the control of multi-ship traffic. Maki *et al.* [168] considered the influence of winds and waves, and used GA to optimize fuel cost and path safety. Lin *et al.* [169] proposed a ship weather routing system that consisted of four modules for ship motion, ocean environment, navigation, and routing optimization. PSO is used in the routing optimization module to optimize fuel consumption and travel time. For the control of multi-ship traffic, researchers have focused on planning the path of multiple ships in the same area for maintaining a safe distance between ships and avoiding collisions [170]. Zlapczynski and Szlapczynska [171] used GA to generate paths, where the solution was encoded by a set of points and the corresponding path was the polyline connecting these points.

Economic benefit issues refer to the profit of shipping companies. The ports of call during the sailing itinerary and the total transportation task (i.e., the number of goods loaded and unloaded at each port) are known in advance. De *et al.* [172] proposed a PSO-based algorithm to determine ship routes, and the optimization objective is set as the sum of handling cost, docking cost, berthing cost, fuel cost, total operating cost, bunkering cost, and charges for berthing outside the given time window. In addition, De *et al.* [173] set profit and carbon emissions as two optimization objectives. Then, they used NSGA-II and a non-dominated sorting-based PSO to solve the problem. Jeong *et al.* [174] considered the imbalanced distribution of containers because certain countries or regions import more goods than they export, while others import fewer goods than they export. Thus, in addition to minimizing transportation cost, the transportation of empty containers during navigation is also considered to avoid the shortage or surplus of containers. A PSO-based algorithm integrated with a heuristic algorithm is proposed to solve the problem. Kang *et al.* [175] focused on a specific transportation scene where a car manufacturer planned to transport cars to other locations by sea. The optimization objective is to minimize transportation cost, handling cost, and carry-forward penalties. Carry-forward penalties occur when certain cars produced in the current time period cannot be transported immediately and are postponed to the next time period.

C. Intelligent Container Stowage

The cargo transported by ships is typically stored in containers. The containers are stacked on ships' decks, as shown in Fig. 6(a). Fig. 6 (b) shows an example that illustrates two issues in container stowage, where each rectangle represents a container, and the number represents its weight. The first issue is container movement. A ship needs to load and unload containers in a number of ports during a given sailing itinerary. However, to move containers in the lower layer (e.g., the blue containers), the corresponding containers in the upper layer (e.g., the yellow containers) must be moved first. Since the loaded and unloaded containers in each port are known in advance, certain studies have focused on using EC algorithms to generate a stowage scheme that minimized container movements and thus reduced handling time at berth [176], [177]. Jovanovic *et al.* [178] used ACO to optimize the handling time of quay cranes, while Hottung and Tierney [179] proposed a biased random-key GA to minimize container movements.

The second issue is the stability of ships. The containers are typically of the same size, but the weight of cargos they carry is not the same. Thus, the stowage scheme should maintain the stability of ships. For example, in Fig. 6(b), the weight of containers on the left side is far greater than that on the right side, which will make the ship imbalanced and increase the risk during navigation. Some studies considered these two issues by setting the weighted sum of container movements and stability factor as the optimization objective [180], [181]. Zhang and Lee [182] directly considered these two issues as two optimization objectives and used NSGA-II as the solver.

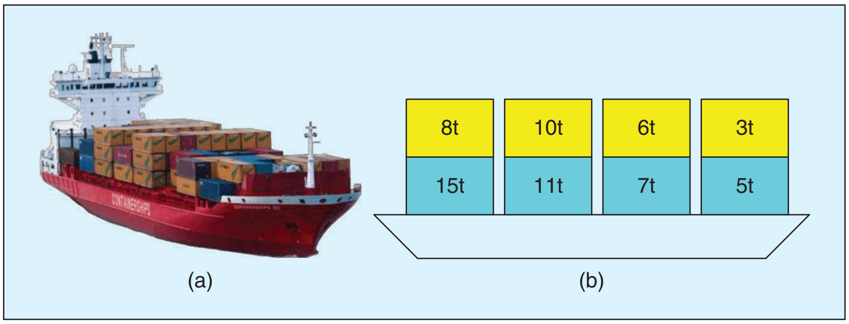

FIGURE 6 Container stowage on ships. (a) A typical container ship. (b) An example of container stowage on a ship.

VI. Future Research Directions and Open Issues

In this survey, the literature on EC for intelligent transportation in smart cities is reviewed and discussed in detail. In the future, EC algorithms will be promising for solving optimization problems of intelligent transportation in smart cities. Several future research directions and open issues are discussed, which include the "problem" aspect (e.g., how to model intelligent transportation problems more accurately), the "algorithm" aspect (e.g., how to enhance EC algorithms to make them more efficient in solving intelligent transportation problems), and the "application" aspect (e.g., how to apply EC algorithms to broader real-world scenes related to intelligent transportation in smart cities). This section hopes to inspire researchers in their future work.

A. Multi-Source Data Fusion-Enhanced Problem Model

In smart cities, many IoT devices (e.g., roadside cameras and wireless sensors) collect multi-source transportation data from the environment. Traditionally, raw data related to the optimization problem will be directly used to formulate the problem model. However, such an approach has two shortcomings. First, the scale of raw data is typically large, which makes problem-solving challenging. Second, raw data may be incorrect or imprecise: unreliable data sources and device malfunctions will cause incorrect and imprecise data collection, respectively. Data fusion is a promising approach to address these shortcomings. In data fusion, multi-source raw data are analyzed first. Then, a subset of them is extracted, and the extracted data is combined and presented in a structured manner for formulating the problem model [183].

Selecting which data and determining the weight (importance) of each selected data for formulating the problem model are two critical issues in data fusion, which directly affect whether the model can accurately describe the optimization problem in the real world. EC algorithms are promising methods to address these two issues in data fusion. There are two potential solution frameworks: offline and online. In the offline framework, EC algorithms use historical data for data fusion to generate a static problem model. The advantage of the offline framework is that the EC algorithms only need to execute once. However, because the generated model is static, the EC algorithms must generate a robust problem model that is capable in various situations. In the online framework, a rough problem model is formulated initially. Then, the dynamic transportation data collected from the environment are used by EC algorithms to tune the problem model. The advantage of the online framework is that it can adapt to various situations. However, it tends to yield overfitting of the problem model and requires a real-time response of the EC algorithms.

B. Higher-Accuracy EC

The optimization problems of intelligent transportation in smart cities will be more and more complex in the future. On the one hand, many complex features exist in the optimization problems, such as large-scale data, multiple optimal solutions, multiple optimization objectives, multiple constraints, dynamic environments, and expensive evaluations. On the other hand, an optimization problem is usually with several complex features simultaneously. For example, optimization problems in traffic management will involve large-scale data and dynamic environments simultaneously.

Therefore, besides the traditional EC algorithms, the recently-proposed EC algorithms that have shown great performance in solving complex optimization problems like large-scale optimization problems, multimodal optimization problems, multi-/many-objective optimization problems, and in solving more complex problems like large-scale multiobjective optimization problems [184]–[186] and large-scale multimodal multiobjective optimization problems [187] are of great potential to be applied to solve the optimization problems of intelligent transportation in smart cities. Moreover, designing efficient EC algorithms that can deal with complex features and generate a high-accuracy solution is a meaningful research direction. There are three guidelines for the design of such efficient EC algorithms. Firstly, prior knowledge of the optimization problems should be utilized to provide search guidance in EC algorithms. Secondly, specific search strategies or evolutionary operators that adapt to the problem features and maintain sufficient search diversity for avoiding premature convergence can be designed. Thirdly, hybrid algorithms that benefit from the advantage of different EC algorithms are also a promising approach to enhance the algorithm performance.

C. Real-Time EC

Many optimization problems in smart cities require rapid response. For example, traffic flow is highly dynamic, and only real-time decision-making can achieve good results. As another example, when an emergency occurs, such as a chemical plant explosion, the response must be determined quickly to reduce casualties and to prevent the situation from deteriorating. However, the large-scale data in the optimization problems presents challenges for the design of EC algorithms to achieve a real-time response.

The combination of EC algorithms and distributed computing technology is a potential solution [188]. In EC algorithms, each individual in a population can evolve in parallel. Thus, deploying EC algorithms on distributed computing platforms, particularly cloud platforms, can greatly enhance time efficiency [189]. However, the communication (information sharing) among individuals of EC algorithms in distributed computing scenario is time-consuming. Researchers can focus on optimizing the population topology of EC algorithms to reduce communication among individuals while maintaining search efficiency. In addition, resource allocation is another research topic. The charging of cloud computing resources follows the "pay-as-you-go" principle that calculates charges based on resource usage. Thus, time and cost efficiency should be considered simultaneously. Researchers can focus on the formulation of resource allocation schemes for efficiently utilizing computing resources (e.g., maximizing algorithm performance while minimizing computing resources). Moreover, the latest and modern matrix-based EC [190], generation-level parallel EC [191], scale-adaptive fitness evaluation EC [75], and resource-aware distributed EC [192] have great potential to reduce execution time in achieving real-time response.

D. Data-Driven EC Algorithms

When designing EC algorithms to solve the optimization problems of intelligent transportation in smart cities, the related data can be analyzed to generate search guidance or knowledge for driving the evolution of EC algorithms. Machine learning (ML) techniques such as the artificial neural network and support vector machine are promising approaches for data analysis, which have been widely researched in recent years and have shown great performance. Therefore, the incorporation of ML techniques for designing an efficient data-driven EC algorithm is a promising research direction.

There are two types of related data that can be utilized. One is the problem data (i.e., the data in the optimization problems of intelligent transportation in smart cities). For example, when solving expensive optimization problems, the evaluation of a candidate solution involves massive computational tasks and thus usually takes a very long time or very high cost. ML techniques can analyze the existing evaluation results of some candidate solutions, and obtain a surrogate model to evaluate the new candidate solutions for saving time and cost [193], [194]. The other type of related data is the algorithm data, i.e., the data generated by the EC algorithms. For example, when solving dynamic optimization problems, the transfer learning technique can be used to analyze the algorithm data in the current and the past environments for generating useful knowledge that can help EC algorithms adapt to the next environment and enhance the search efficiency [195]. Moreover, the transfer learning technique can also be used when using EC algorithms to solve several instances of the same optimization problem. In detail, the search experience of EC algorithms on solved instances can be analyzed by the transfer learning technique for generating useful knowledge to drive the EC algorithms more efficiently when solving a new instance.

E. EC-Optimized Cloud-Edge Collaboration Framework

Intelligent transportation in smart cities relies on massive IoT devices. These devices generate a large amount of data to be processed. Sending all these data to the data center (e.g., cloud server) will result in unacceptable response time due to limited network bandwidth. With the development of edge computing, the cloud-edge collaboration framework is a promising approach to address this problem. In the cloud-edge collaboration framework, simple computational tasks can be processed at the edge of the network, which can reduce the amount of data required to be sent to the cloud server. The cloud server, which has a high computational capacity, will manage complex computational tasks. Thus, the cloud-edge collaboration framework can reduce the pressure of network transmission, reduce the network bandwidth requirement, and enhance the computational efficiency to achieve a shorter response time.

However, the configuration of the cloud-edge collaboration framework is a challenging optimization problem. The key issue is determining which tasks to be processed at the edge of the network, which data to be sent to the cloud server, and which tasks to be processed in the cloud server. This optimization problem involves a large amount of data and complex features, and EC algorithms have great potential to solve this problem efficiently.

F. Broader Application Scenes

The construction of smart cities is now in its infancy. An increasing number of optimization problems will emerge with the construction of smart cities. First, the three transportation modes (land, air, and sea) are interrelated. EC algorithms can be used to optimize the configuration of an integrated transportation management system that incorporates two or three transportation modes. Second, the integration of intelligent transportation and other applications in smart cities will yield many new optimization problems, where EC algorithms can be promising solvers. Indeed, many applications in smart cities rely on the support of intelligent transportation, such as intelligent logistics and supply chain systems. Third, self-driving technology has developed rapidly in recent years, and many self-driving vehicles may be put into use in the future. EC algorithms can be used to solve traffic optimization problems in the self-driving vehicle scenario.

VII. Conclusion

In this paper, a comprehensive survey of the application of EC for intelligent transportation in smart cities is conducted. Related studies are classified by a two-layer taxonomy. The first layer includes three categories (i.e., land, air, and sea transportation), which are based on the application scene of the optimization problem. In the second layer, related studies from the perspectives of government, business, and citizens based on the objective of the optimization problem are further classified. The related studies in each category are discussed in detail, showing that EC algorithms are efficient for solving the optimization problems of intelligent transportation in smart cities. Several future research directions and open issues are also presented. This paper hopes to provide researchers with a comprehensive overview of EC for intelligent transportation in smart cities and inspire researchers' future work.

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