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Optimizing Energy Consumption in Smart Cities' Mobility: Electric Vehicles, Algorithms, and Collaborative Economy

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Abstract: Mobility and transportation activities in smart cities require an increasing amount of energy. With the frequent energy crises arising worldwide and the need for a more sustainable and environmental friendly economy, optimizing energy consumption in these growing activities becomes a must. This work reviews the latest works in this matter and discusses several challenges that emerge from the aforementioned social and industrial demands. The paper analyzes how collaborative concepts and the increasing use of electric vehicles can contribute to reduce energy consumption practices, as well as intelligent x-heuristic algorithms that can be employed to achieve this fundamental goal. In addition, the paper analyzes computational results from previous works on mobility and transportation in smart cities applying x-heuristics algorithms. Finally, a novel computational experiment, involving a ridesharing example, is carried out to illustrate the benefits that can be obtained by employing these algorithms.

Keywords: energy consumption; mobility; transportation; smart cities; optimization; x-heuristics

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1. Introduction

In the emerging world of cutting-edge technologies, smart city is a term used to describe cities that offer the possibility of collecting various data. These data might support decision-making in different decision levels and sectors. One of these decisions is optimal energy utilization or "smart energy" [1]. Thus, researchers have investigated various approaches to reduce the energy consumption in smart cities (Figure 1). A total of 574 articles were found in the Scopus database when searching for "energy consumption" and "smart cities". In these articles, either "algorithm", "electric vehicle", or "collaborative economy" are studied. These articles investigate approaches to recommend solutions that allow us to reduce energy consumption in smart cities. Some of the most frequent topics are carpooling [2] and electric vehicles [3].

Different concepts have been defined to decrease the consumption of energy, such as the 2000-watt society [4]. This concept forces society to reduce its power consumption to 2000 W. The consumption of energy associated with transportation, personal activities, households, and other activities is divided by the population to determine the society's consumption. It is assumed that 2000 W per person is a sustainable value and environmentally friendly. However, this target is hardly achieved due to several factors, such as consumption habits. Hence, regulations need to be set to enforce efficient energy consumption. This has become a topic in various sectors, from cloud computing to the mobility sector, due to its reflection on the environment. The efficient utilization of cloud computing and networking resources decreases CO_2 emissions [5]. The trend in the building and housing industry forces cities to deal with different factors affecting the industry, e.g., overpopulation and urbanization [6]. However, this trend has its reflections on the environment, such as on household energy use and carbon emission [7]. It is thought that the service sector consumes less energy than other sectors [8]. However, most energy consumption in the service sector is consumed as mobility involved in providing or asking for the service [8]. Mobility refers to customer transportation to get a service and the travel of service providers. Various factors affect energy consumption in the mobility and transportation sector, such as air temperature and traffic delays [9]. Bartłomiejczyk and Kołacz [9] mentioned that traffic delays could be responsible for increasing the energy consumption by 60% in electric buses. Auxiliaries in the buses contribute to this consumption. The dynamic changes in the world, e.g., changes in fuel prices, force the search for renewable energy sources. Since the transportation and mobility sector heavily utilizes fossil fuel, these dynamic changes affect the operational costs and force improving sustainable fuel technologies [10,11]. In addition, changes resulting from the COVID-19 pandemic influenced the habits of society and the practices of citizens worldwide, and gave rise to new opportunities related to energy consumption [12].

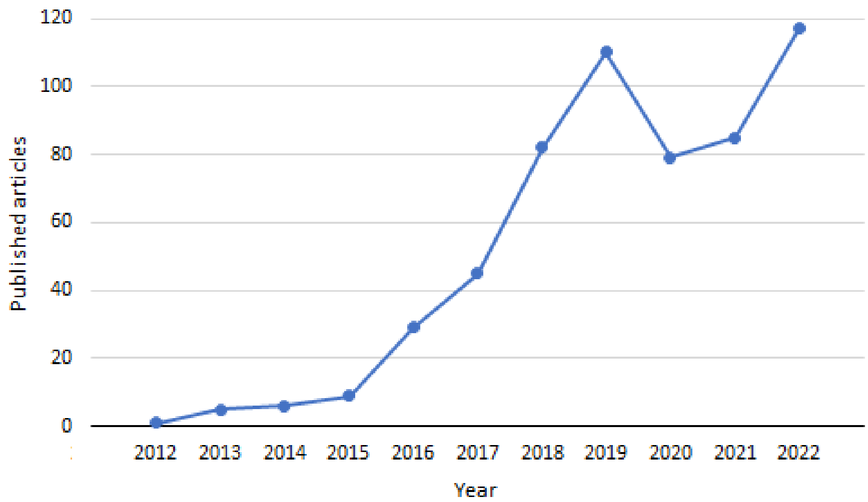


Figure 1. The number of Scopus papers published after searching in the title, abstract, and keywords for "energy consumption" and "smart cities" when either "electric vehicle", "algorithms", or "collaborative economy" was mentioned.

Thus, minimizing the consumption of energy in order to reach sustainable development has become a must all around the world. Frequent energy crises, such as that following Russia's invasion of Ukraine in early 2022, tend to affect global energy markets, increase inflationary pressures, and slow economic growth. In this international context of increasing awareness about environmental issues and instability in the world, institutions such as the European Commission and the United Nations (UN) set their objectives and plans to provide an energy-saving scheme [13,14]. In light of the increased awareness, our paper tries to consider the literature by studying and proposing strategies that can effectively contribute to energy consumption optimization in the transportation and mobility sector. Hence, the first contribution of this work is the analysis of relevant trends in the context of energy consumption optimization in this sector. Another contribution is the identification of the challenges faced in the sector, as well as strategies that can effectively contribute to the aforementioned challenges. These strategies rely on concepts and technologies such as: (i) collaborative economy—which helps to achieve the sustainable development goals proposed by the UN [15]; (ii) electric vehicles—which are expected to provide 30% of the passenger fleets all around the world by 2032 [16]; and (iii) intelligent algorithms (e.g., x-heuristics)—which may provide better solutions for transportation in the context of optimization. Additionally, the paper reviews some related problems and computational results previously published in the literature. Finally, we also illustrate some of the previous concepts with a computational experiment regarding ridesharing mobility.

The rest of this research is organized as follows: Section 2 discusses energy utilization in transportation and mobility in smart cities, while Section 3 refers to the optimization of energy consumption. The challenges faced in the transportation and mobility sector are described in Section 4. Afterwards, some strategies that contribute to these challenges are introduced in Sections 5–7; these strategies rely on collaborative economy, electric vehicles, and x-heuristic algorithms, respectively, and aim to optimize energy consumption. Some computational results obtained in previous studies are analyzed in Section 8. Section 9 provides a computational experiment, related to ridesharing mobility, to illustrate how intelligent algorithms can contribute to reduce energy consumption. Finally, Section 10 summarizes the conclusions.

2. Energy Consumption in Smart Cities' Mobility

The aspect of mobility is only one of many characteristics that ultimately define a city's aspiration to eventually become smart [17]. In a smart city, mobility is continuously advanced through technologies that are already transforming the urban landscape: automated driving in both citizen and goods transportation, connected vehicles, and usage of communicating sensors form a foundation for further innovation [18,19]. Mobility is set to shift from fossil-fueled, ownership-driven modes of transport toward mobility as a service using an exceedingly electrified fleet [20]. To provide sustainable value, smart city mobility must aim to decrease pollution and traffic jams. Both of these goals can be met by optimizing urban traffic and using an electric-powered mobility grid [21]. From a top-level view, Chen et al. [22] argue that the key enablers for the successful implementation of energy-saving mobility systems are the users themselves, who can change the way they perceive and use transportation means. In their article, Butler et al. [23] derived four main levers to reduce energy consumption in smart cities context: First, connected vehicle networks can improve traffic flow and reduce overall energy wasted in congestion. Secondly, automatic vehicles can improve driving efficiency. Thirdly, the use of non-combustion engines could also improve traffic flow. Lastly, they note that sustainable transport should exploit efficiencies created through flexible transportation services. Such services increase traffic performance by providing flexibility regarding means, timing, routing, and payment of and for transportation [24]. Referring to this concept as "mobility-as-a-service" (MaaS), Mulley et al. [25] state that a flexible mobility service might include an on-demand mix of different means of transportation that can be booked as needed. In the rest of this section, the energy consumption in transportation and smart cities' mobility are discussed in more detail.

2.1. Energy Consumption in Transportation

A significant part of energy consumption is associated with the required energy in the transportation sector. The United States recorded that 28% of energy consumption in 2021 was used in transporting people and goods [26]. Petroleum products, bio-fuels, natural gas, and electricity are the major types of energy used for transportation. In particular, petroleum contributed around 90% of the total energy consumed in 2021. Comprehensively, a trend that began emerging in the 1950s shows that the transportation sector is responsible for a growing share in the world's total oil consumption. Around 62% of all oil used in a year, and also 29% of the world's energy demand, is associated with the transportation sector, including concepts such as: (i) vehicles manufacturing, maintenance, and disposal; (ii) vehicles operations; and (iii) infrastructure construction and maintenance. As pointed out by Rodrigue [27], a vast amount of energy is consumed on land (around 85% of the total), maritime, and air transportation modes.

2.2. Sustainability and Smart Urban Mobility

Sustainable urban mobility can be defined as "an affordable access by traveling to one's destination with the minimum impact on the environment" [28]. In addition, affordability and accessibility can be extended by changing some factors such as technology advances, supportive economic policies, behavior change, and improving urban designs. The concept of sustainability in transportation is accepted by most governments in the world, and the countries' authorities consider it as an ultimate goal and a critical point in their environmental plans [27]. Transportation is among the fastest-growing sources of pollution produced in the world, and accounts for 17% of global greenhouse gas (GHG) emissions, as well as for 20% of global CO_2 emissions [29]. The COVID-19 pandemic in 2020 gave rise to a significant decrease in GHG emissions as a result of the reduction in transportation used during the lockdown. Despite this massive drop, emissions rebounded in 2021 [29]. Under the IEA's sustainable development Scenario, the emission from all types of transportation should be decreased over the future years. One aspect that can contribute to this effect is the development of an EV battery market. Projections forecast a market increase by a growth rate of 14% between 2019 and 2030 [29].

Sustainability in city logistics is also promoted by using state-of-the-art advances in carsharing and ridesharing systems. The raise of carsharing services can decrease the number of private cars and change travel behaviors toward sustainability [30]. As a matter of fact, carsharing users can take advantage of using private cars without the responsibility and cost associated with car ownership [31]. At first, city managers considered carsharing and ridesharing as affordable systems for low-income people such as students. However, more and more citizens in developed countries show a preference for using carsharing and ridesharing options for commutes and trips [32]. In the case of using EVs in carsharing, in addition to relocation and route scheduling, the area of the charging stations and charging scheduling are some of the current subjects of the new research in the field of carsharing [33].

3. Energy Optimization in Transportation

Energy consumption optimization is an essential aspect of improving energy efficiency worldwide. Studies show an opposite relation between energy consumption and urban density. On the one hand, cities and countries with a lower urban density, such as USA and Canada, have a higher energy consumption. On the other hand, more densely-populated countries such as Japan and China have less energy consumption [33]. Two fundamental reasons justify this reverse relation. Firstly, in sparsely populated countries, the average distances in the cities are higher. Commuting these distances requires higher energy consumption by vehicles. Secondly, in dense cities, using public and non-motorized transportation is common [27].

Reducing the use of energy in transportation and minimizing travel time are among the most repeated goals in energy-consumption optimization problems. Likewise, multi-objective models are applied to sustainable transportation systems. In most problems, the environmental impacts (e.g., greenhouse gas emission, energy consumption, and pollution) as well as social impacts (e.g., accessibility, reliability, and health) are considered [34]. Machine learning and metaheuristics constitute two solution mechanisms to achieve high-quality solutions in the energy optimization field [35]. While exact methods are able to find the optimal solutions in most of the times, the computational time required tends to be prohibitive. Thus, their use for large-sized problems is not efficient [36]. In contrast, metaheuristics are capable of providing feasible and high-quality solutions and, in comparison with machine learning algorithms, they usually generate solutions of a higher quality [37].

Due to the population growth and the development of smart cities, the need for energy optimization has increased. In the last decade, a huge number of publications regarding energy optimization has been published. Among them, many researchers have discussed the energy consumption associated with traffic issues, EVs, roads conditions, and so on. Table 1 presents representative and recent works on energy consumption problems.

Table 1. The latest works on the energy consumption problem.

Authors	Problem Addressed	Solving Approach	Remarks
Du et al. [38]	A nonlinear route optimization model for ship fuel oil consumption.	Particle swarm optimization (PSO) algorithm.	The model improves the energy efficiency, increases the benefits, and reduces the pollutant emissions.
Zhou et al. [39]	Optimization of schedule and train circulation plan to reduce the energy consumption in urban rail train.	PSO algorithm.	The model decreases the total costs of trains in a case study of Guangzhou Metro in China.
Lin et al. [40]	Energy consumption optimization of dual-motor EVs.	Non-dominated sorting genetic algorithm-II.	This method considers a real-time optimization of energy and shift shocks
Naldini et al. [41]	A real-time energy consumption optimization of rail traffic management problem.	Ant colony optimization algorithm.	The objective function minimizes the energy consumption and total delays in railways.
Xing et al. [42]	Energy optimization of tramway operation.	Competition mechanism-based PSO.	The model aims to reduce the operational cost of tramways. A case study based on the Guangzhou Haizhu tramway is presented.
Dai et al. [43]	An energy consumption model for autonomous taxi ridesharing system.	Unified optimization model.	All the possible paths of vehicles are represented in order to build an energy-efficient carsharing model.
Wang et al. [44]	Optimization energy consumption of the ship industry in order to reduce the CO_2 emissions.	A model predictive control strategy of the sailing parameters and PSO algorithm.	To build a nonlinear dynamic model, the spatial and temporal distribution characteristics are firstly analyzed.
Fan et al. [45]	Energy-efficient model of sea-rail inter-modal transportation.	Performance-driven multi-algorithm selection strategy.	A learning-forgetting algorithm is proposed to improve the selection probability of the methods from a pool of differential evolution algorithm variants.
Zhao et al. [46]	Efficiency optimization of extended-range EV.	A combination of artificial neural network (ANN) and genetic algorithm.	Results show that a higher maximum efficiency of the range-extender engine can be fulfilled.
Chuang et al. [47]	Coasting speed optimization for a mass rapid transit system to minimize the energy consumption and travel times.	ANN.	The data of travel times and energy consumption has been built by simulation. In addition, a case study in China is selected to validate the approach.

4. Challenges in Mobility Energy Consumption

Transportation, as one of the biggest consumer sectors, is responsible 30% of the total energy consumption [4]. In addition, it is included and forms a basis for other sectors, such as the service sector. Thus, the transportation and mobility sector greatly influences energy consumption. Accordingly, this sector is affected by the energy crisis and various energy and environmental regulations. For example, the war between Russia and Ukraine raised the energy crisis worldwide. This crisis impacts energy policies and strategic plans, thus raising energy costs worldwide. Concepts and regulations were set to force a decrease in energy consumption, such as the European Commission call for a neutral climate by 2025 [48]. These regulations demand changing the efficiency of energy consumption and usage. In addition, these environmental regulations force a reduction of the carbon impact. The required changes by these regulations demand investments dedicated to research and development [10]. New approaches should be developed to realize the defined concepts and satisfy the set regulations. The research and development phase includes the investigation of new technologies capable of energy-efficient strategies. In addition, predictive models are required to forecast dynamic changes and energy demands [49]. Better models enable the practical planning and utilization of energy resources and, hence, a reliable supply of energy. These models could be used to plan vehicle routing while reducing travel distance and, hence, energy consumption in general. However, various factors contribute to energy consumption, such as traffic delays, weather conditions, and vehicles' kinetic characteristics [9,49]. These factors are difficult model [49], increasing the difficulty of building an accurate prediction model.

In addition, the prediction and optimization models benefit from the global positioning system (GPS) and different distance-based metrics [50]. Changes in the transportation and mobility sector are affected by culture. Using private cars for mobility influences the energy consumption in this sector [4]. Sustainable mobility demands changing habits and replacing them with a sustainable alternative. According to Ref. Scarinci et al. [4], the acceptability of the required changes should be investigated. With increased awareness in societies, the available infrastructure constrains the transition toward sustainable mobility. For example, sustainable alternatives require appropriate infrastructures presented, such as public transportation, walking and cycling paths, carsharing and ridesharing possibilities, etc. The current trends in transportation and mobility involve the benefits of automobile advancement. EVs have begun to replace traditional fuel vehicles. This new vehicle type has created a new concern related to the traveled distance and battery technology [51]. In addition, personal mobility has become one of the new solutions [52].

5. Collaborative Economy

According to Petropoulos [53], a collaborative economy refers to establishing a connection between people with the goal to share assets and services via the internet. Platforms may help to match potential providers and consumers based on their preferences and characteristics. These platforms may allow more efficient transactions by removing barriers to information sharing. Airbnb and Uber are popular examples of such platforms. Botsman [54] proposed five criteria for a collaborative economy platform: (i) "the core business idea involves unlocking the value of unused or under-utilized assets"; (ii) "the company should have a clear values-driven mission and be built on meaningful principles including transparency and authenticity"; (iii) "the providers should be valued, respected and empowered, and the companies behind the platforms should be committed to making the lives of these providers economically and socially better"; (iv) "the customers should benefit from being able to access goods and services in more efficient ways, with payment for access instead of ownership"; and (v) "the business should be built on distributed marketplaces or decentralized networks that create a sense of community, collective accountability and mutual benefit". The four sectors in which a collaborative economy has a higher relevance are accommodation, transportation, online labor markets (e.g., Amazon Mechanical Tusk), and finance (e.g., the crow-funding platform Kickstarter).

Focusing on transportation, we find platforms facilitating the sharing of vehicles such as cars, motorbikes, bicycles, and motorized scooter (e.g., ZipCar, EasyCar, and car2go) as well as platforms that enables their users to offer services as well as their assets to be rented (e.g., BlaBlaCar, Sidecar, and Uber). Gordon-Harris [55] refers to carsharing as a sustainable urban mobility solution to facilitate a population mobility demand. The author states that the success of individual carsharing schemes depends on the availability of (i) a effective public transport system that complements the carsharing schema; (ii) a proper pricing structure; (iii) a diverse and large urban population; (iv) adequate charging infrastructure; (v) allocated spaces for stations and on-street parking; and (vi) a support from public authorities. Wadhwani and Saha [56] reveals that carsharing market size surpassed $2 billion in 2020. This market is expected to grow in 20% from 2021 to 2027. Some experts also forecast that technology will continue revolutionizing and disrupting the carsharing market [57]. The developments in EVs and autonomous driving as well as route optimization influences the ways in which cars are utilized. However, there are significant barriers to carsharing demand and use. For instance, Hazée et al. [58] highlight the main challenges as service complexity (in terms of its understanding, perceived access, and usage); reliability of the service and related technology; perceived contamination and access of vehicles by different users; responsibility (user being accountable for their own and others' usage); limited availability of cars or waiting time [59]; low public awareness and lack of prior experiences with similar services [60]; non-monetary costs (e.g., the inconvenience of having to reserve a car [61]; as well as comfort and independence limitations [62].

Carsharing can reduce the number of cars on roads, using this smaller fleet more intensively [63]. Shaheen et al. [64] summarize the next generally-accepted effects of carsharing: (i) decrease in vehicle purchases; (ii) increased use of other transportation alternatives, e.g., walking, biking, etc.; (iii) reduced vehicles traveled distances; (iv) increase the percentage of formerly carless households; (v) reduced energy consumption and greenhouse gas emissions; and (vi) increased environmental awareness. However, as expected, there are several factors that affect the magnitude of these effects, such as region, population density, public transit accessibility, and carsharing service and business model, among many others. Esfandabadi et al. [65] utilized system dynamics and casual-loop diagrams to study the correlation between carsharing services and their environmental effects. The subsystems considered are: population, transportation, car manufacturers, environment, and regulations and administration. The authors propose the following managerial strategies: expanding carsharing offered services while controlling the number of fleets, using environmental-friendly vehicles, and using renewable energy sources for the generation of electricity for EVs. Indeed, the flexibility of charging EVs makes both grid balancing and the integration of renewable energy sources possible [66].

6. Electric Vehicles

Electric mobility, and especially EVs, plays a crucial role not only in the context of sustainability in smart cities, but also in the trans-national politics of countries to achieve an economy with low carbon emissions [67]. Usage of EVs in both people and goods transportation promises to ameliorate fossil fuel consumption and resulting emissions, enabling city ecosystems to reduce their carbon footprint. Indeed, in a 2018 meta-analysis of 4734 studies, Requia et al. [68] found that EVs generally reduce greenhouse gas emissions and other critical pollutants. This effect is emphasized in cities, since the actual place of emission is shifted away from the combustion engine on a road to a power-generating plant typically in the countryside. Especially in wealthy countries, the market share of EVs and the corresponding charging infrastructure are steadily growing, increasing in momentum through governmental policies [16]. A crucial success factor in maintaining this momentum is consumers' willingness to switch from a combustion engine to an EV. Li et al. [69] argue that, apart from demographic factors, the intention to buy an EV is mostly influenced by technical and psychological features such as the driving experience or the cost of ownership. The impact of a mobility transformation in smart cities is clear: air quality can be significantly improved when citizens use EVs for transportation [70]. This positive effect can be accredited to the nature of emissions for EVs; since the vehicle runs on an electric battery, it does not produce local emissions [71]. However, the benefits of EV usage strongly depend on how the energy they use is produced: the cleaner the energy production, the greater the positive impact of electric mobility in comparison to fuel-powered vehicles [72].

Despite a global trend towards sustainable energy, non-renewable sources still represent the majority of worldwide energy production [73]. Therefore, policy makers should both increase EV acceptance and usage while simultaneously advocating for a more sustainable energy mix. However, it is not sufficient to only invest in a transition toward EVs. To reap the benefits of electric mobility to their fullest, smart cities should minimize the energy consumption of vehicles. In an urban environment, EV energy consumption is influenced by external factors such as traffic conditions and travel duration as well as internal factors such as the respective driver's style of driving [74,75]. However, it is not only the origin of the energy used by electric vehicles that is a concern for smart cities. Nour et al. [76] warn that EV charging, when not controlled, can increase peak electricity demands in a city grid, potentially overwhelming the grid infrastructure and risking power outages and disruptions. The research to prevent such scenarios is well-established. For example, Gan et al. [77] have formulated an algorithm to mitigate imbalances in charging scheduling by allowing communication between electric vehicles and charging providers.

Energy Optimization Using Electric Vehicles

As mentioned in Section 3, energy optimization in transportation has received increasingly more attention in the last decade. For instance, Corlu et al. [78] review studies on the optimization of energy consumption in transportation, specifically, road freight, passenger rail, maritime, and air transportation modes. According to Corlu et al. [78], the main strategies used to optimize energy consumption in road freight are the following: First, modifying the objective function of the vehicle routing problem (VRP) and its variants to consider energy aspects. Li et al. [79] present an illustrative example, which addresses the routing problem of EVs, including their constraints of battery life and battery swapping stations. Their problem aims to minimize the total costs, energy consumption, and travel time of EVs. Secondly, they aim to reduce the load factors while maintaining the traditional distance-based objective function (e.g., by considering back-hauling or including pick-up and delivery applications). In this context, Nolz et al. [80] describe a consistent VRP for the delivery of parcels with EVs, which is addressed by implementing a template-based adaptive large neighborhood search. Finally, they design horizontal cooperation practices to promote sustainable policies and optimize energy consumption. Muñoz-Villamizar et al. [81] study the utilization of fleet of EVs, working in urban goods distribution, in the context of a horizontal collaboration between carriers. A multi-objective function is defined based on delivery and environmental costs.

Designing routes considering EVs constitutes a task that has been explored by many authors. These works either considered energy consumption as an objective function (such as total consumed energy, recharging time, and number of used charging stations or EVs) or energy-related constraints. For instance, the use of electric batteries typically present driving-range limitations and long re-charging times. Martins et al. [82] present a review on EV routing. The paper describes a current trend in the literature of integrating real-life characteristics such as partial recharging, battery swapping, allocation of charging stations, horizontal cooperation strategies, backhauling practices, hybrid gas and electric fleets, and battery durability.

In addition, the authors discuss the need of developing prediction models for battery charge status according to multiple factors, such as weather conditions, speed, weight of the vehicle, and road condition. Another review is presented by Kucukoglu et al. [83], in which the authors study more than 130 articles on the routing of battery EVs. The authors highlight the extended use of metaheuristics to solve the related problems, mainly large neighborhood search, tabu search, and variable neighborhood search, and call for more realistic and complex benchmark instances and parallel solving approaches to obtain solutions in computational times that are acceptable in practice.

Regarding the management of carsharing systems with EVs, a wide range of optimization problems arise at strategic, tactical, and operational levels [84]. Table 2 lists the most relevant decision-making processes in this context and introduce a recent work for each of them.

Table 2. Recent works on the management of carsharing systems with electric vehicles.

Authors	Problem Addressed	Solving Approach	Remarks
Brandstätter et al. [85]	Location of stations and station capacity	A two-stage stochastic integer linear programming formulation and a heuristic for medium and big instances.	Aim: determine optimal locations for charging stations and number of EVs. Computational experiments based on real world instances from Vienna are presented.
Huang et al. [86]	Fleet sizing	A mixed integer non-linear program model. A rolling horizon method, a golden section line search method, and a shadow price algorithm.	Aim: select the fleet size and the station capacity, as well as the required relocation operations. A large-scale case study is carried out for the Suzhou industrial park in China.

Table 2. *Cont.*

Authors	Problem Addressed	Solving Approach	Remarks
Huo et al. [87]	Allocation/relocation of vehicles to existing stations	Combination of a probability expectation model and a linear programming model.	The authors study historical order data from a company to characterize the dynamics of vehicles and the behavioral features of the users. An instance with real data is solved.
Vosooghi et al. [88]	Battery swap	Combination of a probability expectation model and a linear programming model.	In the context of shared autonomous EVs, the authors study the impacts of station placement, charging type, and vehicle range onto service efficiency and customer experience. An agent-based simulation based on the Rouen Normandie metropolitan area in France is carried out.

An interesting and recent line of research in this field is the use of renewable energy sources in carsharing systems with EVs. Indeed, carsharing contributes to the electrification of the transport sector and, hence, makes transportation less polluting. However, the usage of EVs increases the electricity demand in the electricity supply system, which could lead to a shortage. The electricity suppliers, electric power systems, have significant environmental impacts, such as CO_2 emission. Both problems can be addressed by relying on renewable energy sources for EV charging. However, renewable energy sources may be difficult to predict. Arranging EV charging based on renewable resources and generation constitutes a challenging optimization problem. Smart charging EVs may contribute to compensate power fluctuations in the electric grid. Thus, researchers have investigated integrating renewable energy sources such as wind and solar energies in the smart grid environment [66]. Iacobucci et al. [89] minimize the total costs of a fleet of shared autonomous EVs by scheduling their charging and discharge. In their problem, the EVs could be charged through a virtual power plant or microgrid.

The topic of carsharing systems providing autonomous connected EV is still in its infancy. As described in Ref. Miao et al. [90], autonomous vehicle technology presents many advantages: eliminates users walk towards available vehicles, allows for automatic relocation of vehicles, and reduces energy consumption as a consequence of a more efficient driving. Connected vehicle technology may provide a more efficient carsharing system management thanks to the use of real-time data when making decisions. Miao et al. [90] present a two-stage multi-objective optimization model. In the first stage, the approach optimizes the geographical service area. The second stage of the model optimizes the distribution of charging infrastructure. In another study, Ma et al. [91] optimize the allocation of stations that play the role as a depot and charging stations for autonomous EVs used in carsharing. Several mixed-integer nonlinear models are formulated and separately solved using GAMS and a genetic algorithm. Computational experiments are used to test the approaches.

7. Intelligent x-Heuristic Algorithms

Mobility and transportation optimization problems in smart cities are composed of many variables (e.g., customers, products, facilities, etc.), as well as a set of rich and soft constraints, making them NP-hard problems. Considering these characteristics, exact optimization methods show limited capabilities to solve these problems. Thus, heuristics and their extensions are needed. These extensions combine heuristics with other methods, and are called x-heuristics [92]. They constitute excellent alternatives to generate high-quality solutions in reasonable computing times. Hence, heuristics and metaheuristics can be hybridized using exact methods (matheuristics) [93], which allows us to find solutions of higher quality in relatively short computational times. However, mobility and transportation problems are challenging not only because of their size but also because their variables can be subject to uncertain and dynamic conditions.

Simulation-based optimization approaches are required to deal with random events and consider the variables' stochasticity. In these approaches, optimization algorithms and simulation methods are combined. The simulation method might be Monte Carlo simulation, discrete-event simulation, agent-based simulation, etc. The optimization algorithm could be heuristics or metaheuristics. For example, biased-randomized heuristics and simheuristics combine simulation and a heuristic or metaheuristic algorithm. Using biased-randomized heuristics [94], a deterministic constructive method becomes a stochastic one. Thus, different solutions are defined at each execution of the method. These solutions are of 'good' quality and are found in extremely short computing times. In biased-randomized heuristic, a "light" randomness is introduced to the procedure, without modifying the original logic behind the heuristic. One way to introduce this randomness is by selecting the next step in the procedure based on a skewed probability distribution. Thus, a candidate list of building steps is ordered based on a criteria, such as the shortest travel distance. The candidate list can be used during the solution-building process, where each building step gets a probability of being selected based on its order in the candidate list. The probability distribution is skewed; thus, the building steps at the top of the list get a higher selection probability compared to the steps at the bottom of the list. The building steps are selected one after another by employing Monte Carlo Simulation. Thus, relatively, some deviation to the deterministic selection of building steps is achieved. This deviation is controlled through a parameter. At each execution of the biased-randomized heuristic, a different solution is constructed. Running this heuristic several times generates several solution alternatives based on the main selection logic. Notice that biased-randomized heuristics can be combined with parallel programming techniques to run several instances of the heuristic in parallel, without increasing the wall-clock time.

In contrast, simheuristics [95] refers to a particular type of simulation-based optimization, which combines metaheuristics with any type of simulation. Simheuristics aims to solve optimization problems with the stochastic nature. In that way, metaheuristics and simulation exchange information while exploring the search space of a stochastic problem. In the simheuristic solution approach, it is assumed that when solving the deterministic version of a problem, it could be a high-quality solution to the stochastic version of the problem. This assumption is valid for stochastic problems of moderate degree of variability. Although simheuristics allows one to deal with scenarios with uncertainty, due to the complexity of smart cities, other extensions of metaheuristics need to be considered. For instance, some mobility activities such as carsharing or ridesharing systems present dynamic behavior—e.g., delays and travel times can be influenced by traffic conjunctions, customers can appear and disappear dynamically in the system, etc. This dynamic nature might be solved by combining metaheuristics and machine learning methods (learnheuristics) [96]. This combination enables handling the dynamic (non-static) problem input. The main idea behind the learnheuristics is that some problem inputs are influenced by specific configurations of the built solution (e.g., defining a vehicle route might influence the travel times and delays of other vehicles). Although these influences and dependencies between variables could be identified, it is difficult to formulate them. They might depend on other factors (e.g., the system status at any given time) or follow a complex pattern, forming a 'black box' that influence the consequences of taken decisions. The optimization of problems with dynamic inputs demands building predictive models to emulate the dependencies and predict the consequences of making decisions within a solution.

8. Review of Computational Results

Researchers have defined some NP-Hard optimization problems in mobility and transportation problems in smart cities. We have selected some publications related to these problems in which the solution approach is based on the intelligent x-heuristic algorithms. Specifically, we have focused on solution approaches that use biased-randomized heuristics, because they can solve large-scale optimization problems, providing 'good' quality solutions in reasonable computing times. Table 3 lists the eight selected optimization problems, their acronyms, and the publications in which the problems were solved. In addition, Table 4 documents the solution values found for the problems in Table 4. The solution values are tabulated as (i) the problem best-known solution (BKS); (ii) the solution reported by the authors (OBS) of the selected publication; and (iii) the percentage gap between the BKS and the OBS with respect to the BKS. Figure 2 depicts a summary of the tabulated results for the problems; the vertical axis represents the calculated percentage gap. According to the results, algorithms based on biased-randomized heuristics provide a competitive performance for all the selected problems, improving the BKS by about −0.44% on average, varying from about 0.41% for the LRP up to −2.55% for the VRPMDR. In particular, to solve the former problem,the authors use a simple but effective constructive biased-randomized heuristic.

Table 3. Selected optimization problems.

Problem	Acronym	Reference
Multidepot Vehicle Routing Problem	MDVRP-1	[97]
Multidepot Vehicle Routing Problem	MDVRP-2	[98]
Vehicle Routing Problem with Multiple Driving Ranges	VRPMDR	[99]
Fleet Mixed Vehicle Routing Problem with Backhauls	FSMVRPB	[100]
Vehicle Routing Problem with Multiple Driving Ranges and Loading Capacities	HeVRPMD	[101]
Sustainable Vehicle Routing Problem	SU-VRP	[102]
Location Routing Problem	LRP	[103]
Location Routing Problem with a Constrained Distance	LRPCD	[104]

Table 4. Summary of the results of the different optimization problems.

Reference	Problem	BKS (1)	OBS (2)	GAP (1)–(2)
[97]	MDVRP-1	1879.42	1885.54	0.33%
[98]	MDVRP-2	2662.42	2673.35	0.41%
[99]	VRPMDR	1047.42	1020.68	−2.55%
[100]	FSMVRPB	3086.86	3067.89	−0.61%
[101]	HeVRPMD	1016.26	1013.62	−0.26%
[102]	SU-VRP	750.46	741.27	−1.22%
[103]	LRP	196.77	197.47	0.36%
[104]	LRPCD	891.24	891.62	0.04%

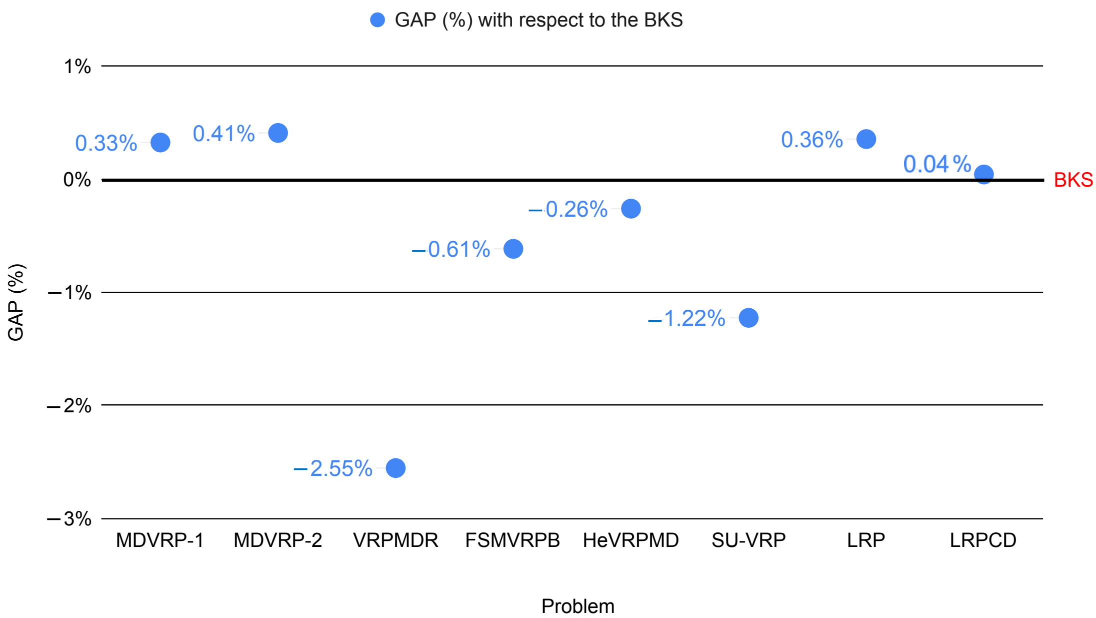


Figure 2. Gaps between OBS and best BKS (baseline 0% gap).

9. A Case Study Regarding Ridesharing Mobility

This section illustrates the benefits that can be achieved by expanding ridesharing practices in urban areas. We consider a typical scenario in which citizens departing from multiple origins wish to reach certain common destinations by a target time. Thus, Figure 3 shows a simple example of such a scenario, where a vehicle departs from each source node (circles i, j, k, etc.) and has to be in its associated destination (D1, D2, or D3). In addition, we will assume that each route cannot exceed a maximum travel time $t > 0$.

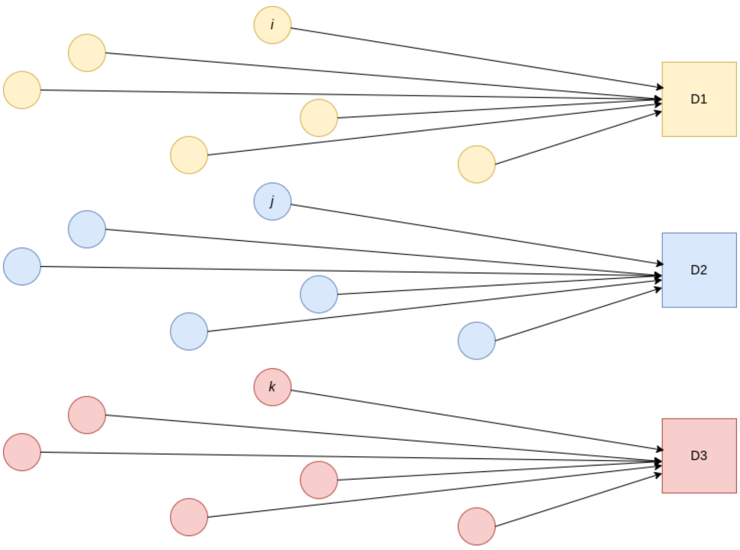


Figure 3. A multi-origin multi-destination mobility scenario.

Clearly, a ridesharing practice such as the one illustrated in Figure 4 would require less vehicles, cover shorter distances, and consume less energy.

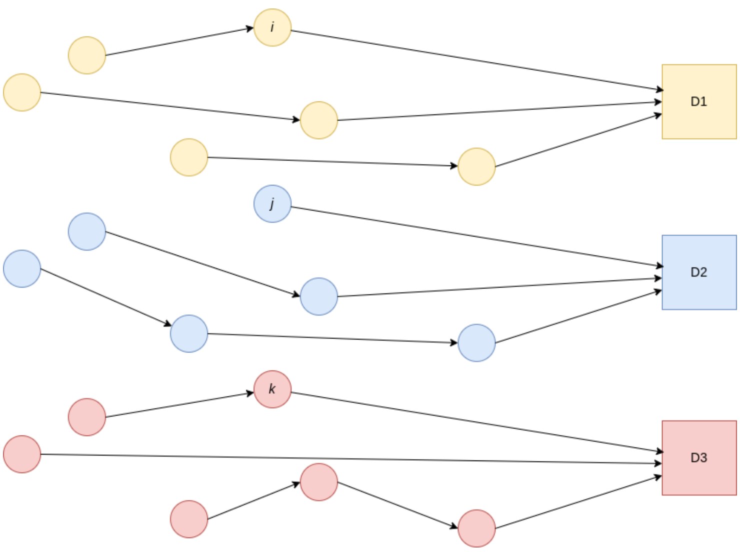


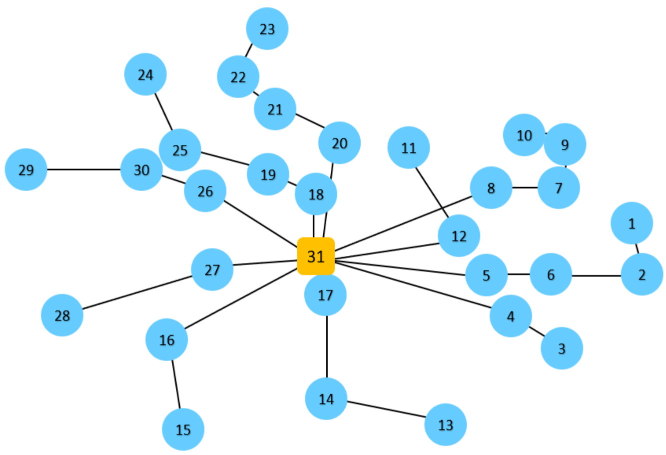
Figure 4. A carsharing strategy for the multi-source multi-destination scenario.

The questions are then: how many vehicles are really necessary to provide the same mobility service? What is the reduction in distance (and, hence, in energy consumption) that can be obtained if the operations are optimized? In order to illustrate how intelligent algorithms can contribute to answer the aforementioned questions, a case study regarding multiple sources and three different destinations is considered and solved using an adapted variant of the algorithm proposed in the study by Panadero et al. [105] for the deterministic version of the team orienteering problem. The algorithm was adapted to take into account that there is a maximum occupancy level per vehicle and the fact that the final solution has to cover all nodes while still respecting the maximum traveling time per route. Python 3.9 was used to implement and run the proposed algorithm, and we run experiments on a workstation with an Intel(R) Xeon(R) processor at 3.2 GHz with 64 GB of RAM memory. In our experiment, we used three small instances from the well-known team orienteering problem benchmarks proposed by Chao et al. [106]. These benchmarks consist of 320 instances, belonging to 7 different subsets. An instance name follows the nomenclature 'pa.b.c', where 'a', 'b', and 'c' refer to the subset number, the number of available vehicles, and the specific instance under study, respectively. In this work we have selected the instances *p1.4.k* (subproblem 1), *p2.4.k* (subproblem 2), and *p3.4.k* (subproblem 3) to illustrate the benefits of ridesharing strategies. Notice that the aggregation of these three instances (subproblems) lead to a multi-source and multi-destination team orienteering problem, thus emulating the scenario represented in Figure 3. In fact, the aforementioned scenario is obtained when the single origin in each subproblem is connected with each of the circular nodes in the subproblem and the traveling times of these connections are set to 0. In our computational experiments, we have assumed that the capacity of each vehicle is 4 passengers. Table 5 shows the parameters assumed in each sub-problem and the final results obtained for both the individual and the ridesharing mobility strategies. The total time-based costs (total time traveled) obtained for the ridesharing (collaborative) strategy are 95.21, 31.73, and 90.42, respectively. In the individual (non-collaborative) strategy, the total costs obtained are 195.03, 67.94, and 181.46, respectively. As the percentage gap column shows, even in a small-sized instance such as the one considered, the gains can be noticeable.

Table 5. Parameters and final results obtained for each mobility strategy.

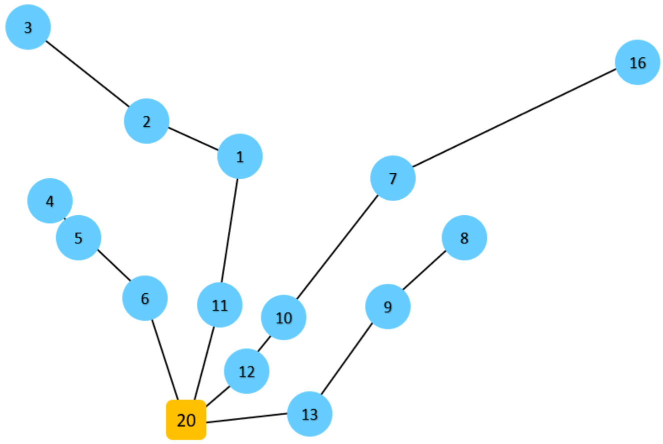
Sub-Problem	No. of Customers	Maximum Traveling Time per Route	Maximum Occupancy per Vehicle	Final Cost Individual (1)	Final Cost Ridesharing (2)	Gap (%) (1)–(2)
1	31	13.8	4	195.03	95.21	−51.18%
2	20	11.2	4	67.94	31.73	−53.29%
3	32	16.2	4	181.46	90.42	−50.17%

Figure 5 illustrates the ridesharing solution proposed by the algorithm for each of the tested subproblems. Notice that, in the ridesharing strategy, most passengers in a sub-problem are serviced by shared vehicles unless they are far away from other source nodes and this makes it impossible to include them into an already existing route without violating either the occupancy capacity or the maximum traveling time constraint.

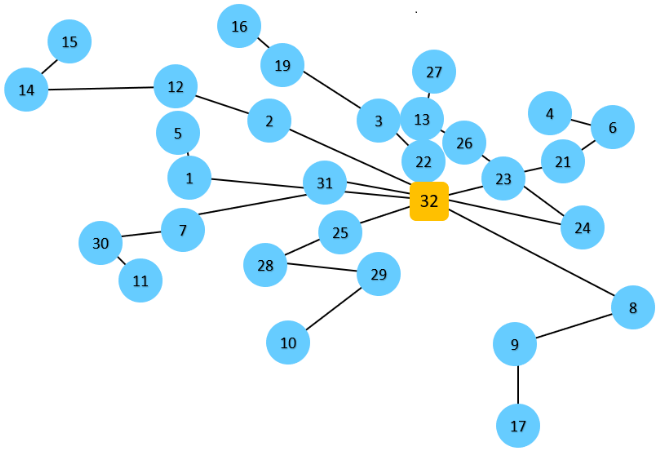


(**a**) Sub-problem 1

Figure 5. *Cont.*



(**b**) Sub-problem 2



(**c**) Sub-problem 3

Figure 5. Optimized ridesharing strategy for each subproblem.

10. Conclusions

This paper focuses on studies related to energy consumption in the transportation and mobility sector. This sector, as well as other sectors, is affected by the global crisis and by a shortage in energy sources. In addition, energy consumption contributes to gas emission, and regulations have been set to reduce both energy consumption and gas emission. Studies are examining efficient energy resource utilization and strategies to reduce energy consumption. Current trends are raised in the form of EVs and collaborative economy. EVs could replace traditional vehicles and their usage is spread, despite some challenges associated with them in the form of charging time and battery life. The spread of carsharing and ridesharing indicates the impact of the collaborative economy in the transportation and mobility sector. New optimization problems arise in this context. The new problems include additional constraints or objective functions related to EVs, carsharing, or ridesharing concepts. These problems tend to be real-world optimization problems under uncertainty, dynamic, and synchronization scenarios. Thus, advanced x-heuristic approaches are needed in order to efficiently solve them. The potential benefits of these algorithms are discussed by employing computational results that refer to different transportation problems. Our analysis shows that the use of x-heuristics based on biased-randomization techniques have been able to provide highly competitive results for many different transportation and mobility problems, with average gaps (with respect to the best-known solution) ranging from −2.55% to 0.41%. In addition, a novel computational experiment is introduced to show the potential benefits of employing ridesharing (collaborative) strategies over utilizing individual (non-collaborative) ones. As expected, the results indicate that a noticeable reduction in time-based total costs can be achieved. In particular, for each considered subproblem, a reduction larger than 50% in these costs has been obtained. Obviously, such a significant reduction in time-based costs impact other dimensions such as energy consumption and sustainability of the transportation system. Regarding future work, we plan to employ different x-heuristics to analyze the impact of intelligent strategies on carsharing and ridesharing mobility practices.

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