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On the Use of Agile Optimization for Efficient Energy Consumption in Smart Cities's Transportation and Mobility

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Abstract: Urban logistics consumes a large portion of energy resources worldwide. Thus, optimization algorithms are used to define mobility modes, vehicle fleets, routing plans, and last-mile delivery operations to reduce energy consumption such as metaheuristics. With the emergence of smart cities, new opportunities were defined, such as carsharing and ridesharing. In addition to last-mile delivery, these opportunities form a challenging problem because of the dynamism they possess. New orders or ride requests could be placed or canceled at any time. Further, transportation times might evolve due to traffic conditions. These dynamic changes challenge traditional optimization methods to propose solutions in real-time to large-scale energy-optimization problems. Thus, a more 'agile optimization' approach is required to provide fast solutions to optimization problems when these changes occur. Agile optimization combines biased randomization and parallelism. It provides 'good' solutions compared to solutions found by traditional optimization methods, such as in-team orienteering problems. Additionally, these solutions are found in short wall clock, real-time.

Keywords: smart cities; carsharing; ridesharing; last-mile delivery; efficient energy consumption; sustainability

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1. Introduction

Energy is one of the vital resources in our daily life. In addition, it is the driving factor for different sectors, such as industry and transportation, because of its role, its consumption increases. As depicted in Figure 1, energy consumption increased by 50.9% between 2000 and 2021 worldwide. Ahmad and Zhang [1] expect that energy consumption will continue to rise. High energy demand triggers oil, gas, and coal prices to rise. In the past years, gasoline prices increased by 127% between 2000 and 2021 on the west coast of the United States (https://data.bts.gov/stories/s/5bfv-z8ek (accessed on 13 October 2022)). These prices are influenced by increased demand, climate policies, etc. [2].

The transportation sector, with its air, train, marine, and road modes, offers various services involving transporting people or goods between different locations. Despite the contribution of this sector to society, it uses around 29% of the global energy consumed [3]. Because of the expected increase in energy demand, energy consumption and CO_2 emission by the transportation sector will also increase. Accordingly, actions should be taken to define policies to reduce energy consumption as well as CO_2 emissions. Sustainability awareness is increasing, and recent research trends study the optimization of energy consumption and reducing the emission of greenhouse gases. Figure 2 displays an exponential increase in the number of publications after the financial crisis in 2008. Researchers have investigated several approaches to increase energy efficiency [4,5] and studied energy optimization in the transportation sector [6,7]. Several reviews have been published about energy consumption in road transportation [6] and maritime transportation [8], just to mention some. In addition, researchers have focused on transportation advancements such as hybrid and electric cars [9,10]. Approaches such as machine learning, mathematical programming, simulation, and metaheuristics have been used intensively in optimizing the transportation sector [11].

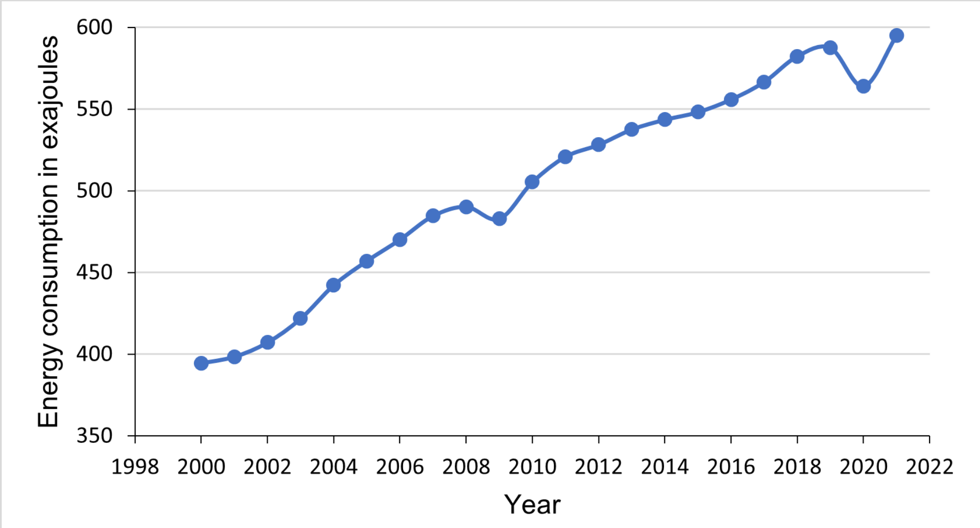

Figure 1. Energy consumption worldwide from 2000 to 2021 (source: https://www.statista.com/statistics/265598/consumption-of-primary-energy-worldwide (accessed on 13 October 2022)).

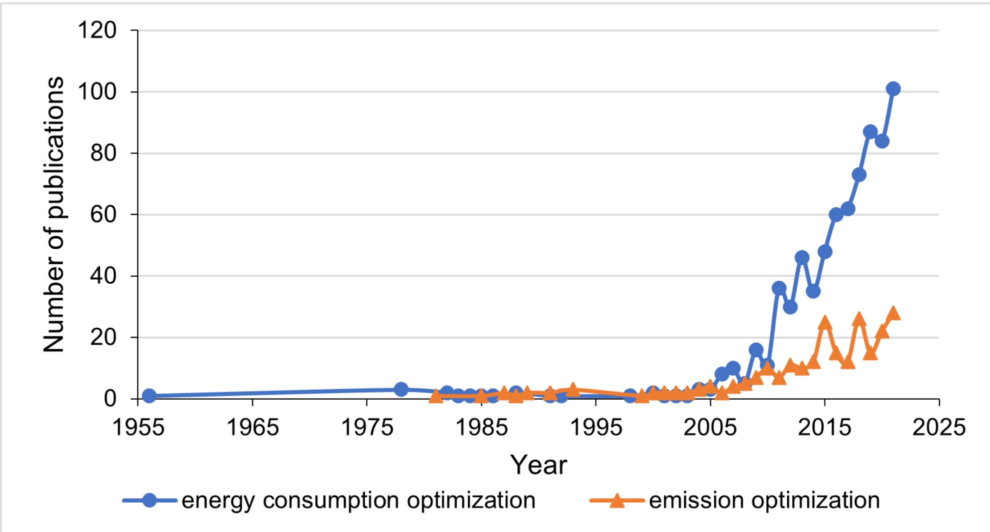

Figure 2. Evolution of Scopus-indexed articles for energy consumption and emission optimization problems.

Public transportation is a critical infrastructure used by citizens. Smart cities were defined by advancements in information and communication technologies and big data. In this context, new transportation solutions, such as carsharing and ridesharing, evolved. Thus, passengers are no longer confined to using only public transportation; they might arrange their flexible travel with the evolved solutions. Another advantage of utilizing information and communication technology is the possibility of reducing CO_2 emissions in the transportation sector [12]. In addition, current purchasing trends involve shopping and placing orders online, which require planning last-mile delivery services.

In this paper, we investigate problems raised in smart cities in the context of energy consumption. We focus our study on problems related to transport and mobility in smart cities, such as carsharing, ridesharing, and last-mile delivery. The study aims to identify problems in smart cities and the optimization methods used to recommend solutions considering energy requirements and their efficient consumption. Transportation problems are mostly NP-hard and large-scale. Therefore, the efficiency of exact optimization methods is limited. As a consequence, modern optimization approaches are usually required to solve these problems. These approaches could be machine learning, heuristics, or hybrid approaches combining several methods. In any case, they should handle complex and dynamic problems. Real-time problems in smart cities involve a large number of passengers and customers. Hence, they are complex in terms of the problem size. In addition, these problems are dynamic in terms of data updates, such as added orders and canceled trips. Upon such changes, the problem parameters change and, accordingly, recommended solutions that optimize energy consumption should be updated to reflect these changes. This dynamic characteristic adds to the complexity of the defined problems in smart cities, and because of its nature, it requires a quick update of solutions. Approaches, such as metaheuristics, cannot provide fast solutions upon request in real-time. Thus, optimization approaches should become agile in solving problems. Agile optimization (AO) algorithms solve a given problem in short wall clock time and are candidates to solve raised problems in smart cities.

The rest of the paper is arranged as follows. Section 2 illustrates energy consumption and resources in cities. Next, Sections 3 and 4 discuss optimization problems related to mobility in smart cities and last-mile delivery, respectively. The AO dedicated to optimizing dynamic problems is presented in Section 5. Section 6 presents some dynamic problems that are solved using agile AO.

2. Energy Requirements in Urban Logistics

This section presents a literature review on energy requirements in urban logistics. The logistics industry is one of the fundamental and supportive sectors in any developed economy, and it is highly correlated with energy consumption [13]. Specifically, urban logistics needs energy resources for transportation, and using state-of-the-art technologies in urban logistics leads to more optimal exploitation of energy resources.

As shown in Figure 3, we can consider four main factors that influence the selection of transportation energy sources. The factors can be grouped into technology, economic, infrastructure, and urban form [14]. Technology is an impressive factor that can improve the vehicles' efficiency and also change the type of fuel in use. Pan et al. [15] present a review of energy harvesting technologies for different applications in land transportation. In another work, Jin et al. [16] discuss the development of intelligent transportation systems and the role of technology in the advancement of this sector. In this work, the nanogenerator is discussed as a new energy technology for self-powered intelligent transportation systems. Further, economic factors such as fuel prices and incomes play an essential role in selecting the economical type of fuel and vehicles. In this regard, Schislyaeva et al. [17] discuss the economic condition of gas resources for the transportation sector. This article analyzes the relationship of Russia with Turkey and the EU from the point of view of trilateral economic relations. The infrastructure factor of each city consists of different modes, and the level of services is the other main factor that influences the selection of transportation energy. In this regard, Wang et al. [18] discuss the impact of transportation infrastructure on energy efficiency. In this research, the relationship between transportation infrastructure and industrial energy efficiency is evaluated. Finally, the urban form of each city, such as density and residential centrality, also determines the type of transportation fuel. Kaza [19] analyze the effectiveness of urban form on energy consumption in the transportation sector. In this work, demographic, economic, and landscape characteristics of the cities are analyzed to evaluate the consumption of energy in transportation.

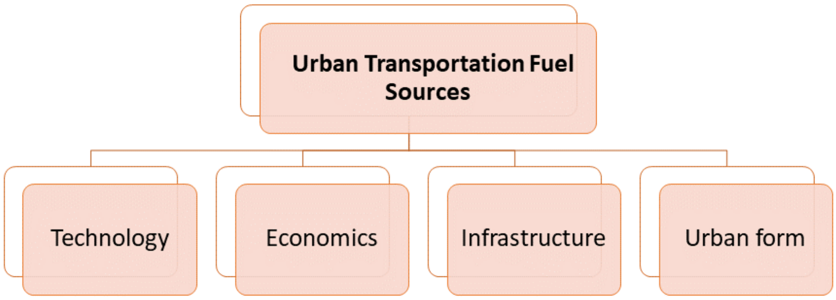

Figure 3. Decisive factors in the type of urban transportation fuel sources.

Figure 4 shows the relationship between urban density and transport-related energy consumption [14].

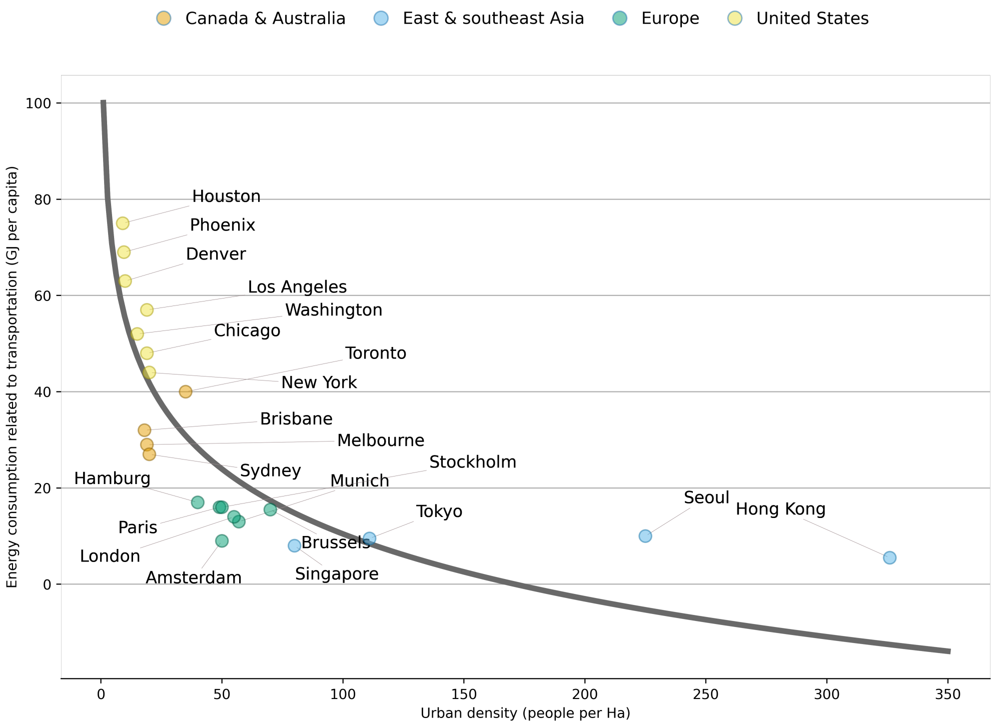

Figure 4. Urban density and energy consumption.

Among different countries worldwide, the USA and Canada consume the most energy in transportation. On the other side, Asian countries such as China and Japan use less energy despite high population density. There may be two important reasons for this opposite relationship between transportation energy consumption and urban density. First, in non-dense countries, the average commuting distance increases, which explains the higher energy consumption related to transportation. Second, shifting from a public and non-motorized form of transportation to private automobile use is probably the other reason for higher energy consumption in non-dense countries [20].

Recent analysis shows that transportation is responsible for 37% of CO_2 emissions, which is the highest reliance on fossil fuels of any other sector. Even during the COVID-19 crisis, the demand for transportation increased extensively, and it was one of the sectors that were affected by the pandemic intensively [21]. The prediction models prove that by increasing transportation demand, the Net Zero Emissions scenario requires transportation emissions to fall by 20% by 2030. Achieving this drop requires implementing new policies emphasizing the use of the least carbon-intensive travel methods and applying new operational models to expand energy-efficient behaviors [21]. Using alternative fuels for urban transportation, such as Biofuels, natural gas, hydrogen, electricity, and hybrid vehicles, helps reduce CO_2 emissions. However, these fuels have lower efficiency in comparison with gasoline, and thus we need more of them. Generally, not only does producing these fuels require notable capital investments, but also they need a more complicated storage system in vehicles [20]. In the United States, petroleum products accounted for about 90% of the total energy used in the logistics sector [22]. Gasoline is used in cars, motorcycles, trucks, boats, and airplanes. Further, distillate fuels are mainly used by trucks, buses, trains, and ships. Jet fuel is also used in airplanes and some types of helicopters [22].

In the last decade, research has been carried out on the energy requirements for logistics. Recently, due to the expansion of cities and the advancement of technology, the importance of urban logistics has increased, and many researchers have discussed the role of energy in urban logistics. Gorcun [23] discusses the energy costs in urban logistics. This study has shown that the energy costs in road transportation are related to different factors such as distance, the type of vehicles, traffic flow rate, etc. Further, there is an opposite relationship between the marginal energy costs of vehicles and the traffic flow rate, which means that more traffic flow rates may reduce marginal energy costs. Further, the speed of the vehicles is another factor that plays an important role in the total energy costs. This study argues that defining the minimum speed for the roads, such as the maximum speed, can control traffic congestion in order to have an optimum rate of traffic considering the energy costs rate. In another work, Wu et al. [24] develop convex programming to optimize the energy costs and component sizing of the plug-in fuel cell urban logistics vehicle while satisfying vehicle power and battery health requirements. In this paper, four different drive cycles are considered in order to achieve the optimal energy cost, battery power, and energy capacity. Further, they investigated the power distribution to analyze the different hydrogen prices and their impacts on plug-in fuel cell urban logistics vehicles' fuel economy. Malladi et al. [25] optimize the size and the mix of the mixed fleet of electric vehicles. Since the uncertain requests of the customers are revealed at the beginning of each operational period, different models associated with each operational period for the energy consumption of vehicles are considered. Two case studies show the functionality of the proposed solution approach. In these studies, the total cost of ownership of a mixed fleet with electric vehicles is calculated.

Recently, many publications have focused on environmental policies to reduce energy consumption in urban logistics. For instance, Xu and Xu [26] have assessed the role of environmental regulations in improving energy efficiency. This work applies a quantile regression to analyze incentive and mandatory environmental regulations and their impacts on energy efficiency and CO_2 emissions in urban logistics. The researchers investigate different cities in China to obtain results and provide information for the government to apply various environmental policies in different cities. In another work, Jones et al. [27] discuss freight transportation and using hydrogen vehicles instead of diesel-powered vehicles by addressing the sustainability concerns in urban logistics. In this work, a comprehensive analysis of the total costs of ownership and some other related policies are presented. The results show that some kinds of diesel vehicles are still the most competitive options.

Based on the Paris agreement, global warming should be held below 2 degrees Celsius to avoid harmful environmental consequences, such as biodiversity, food security, and so on. Furthermore, according to the agreement, countries should diminish the production of harmful pollutants in all sectors, such as logistics [28]. Thus, sustainability is another hot topic related to energy requirements in urban logistics. Magazzino et al. [29] discuss a methodology that helps to achieve a sustainable path in the European area. In this work, the performance of logistics operations is evaluated by considering fossil fuels and their pollution effects in the transportation sector. They use a macro-level time-series dataset from 27 European countries from 2007 until 2018. An artificial neural network algorithm is adapted to investigate the dynamic interactions between different logistics performance indexes. Based on the results, they recommend new policies that help governments improve the logistics sector to a more sustainable path.

In another work, Wang et al. [30] discuss energy efficiency in logistics. In this work, a sample of 216 prefecture-level cities for the period 2009–2017 in China is evaluated. They use a stochastic frontier analysis based on the translog production function. They find that digitalization, environmental regulations, and education positively correlate with energy efficiency in different cities, while government intervention and road density correlate negatively. Turoń et al. [31] discuss the environmental aspects of energy consumption in the logistics industry. In this work, they determine the factors that affect energy consumption in carsharing system vehicles and develop recommendations for carsharing users to optimize the energy consumption of electric vehicles. According to the results, the most critical factors in consuming energy are travel time, distance, and external temperature.

3. Energy Consumption Optimization Problems in Smart Cities

This section introduces the concept of a smart city, reviews of the most recent works in energy consumption optimization, and ends by focusing on sustainability and smart transportation projects. A smart city should be seen as the union of a smart economy, smart people, smart governance, smart environment, smart living, and smart urban mobility [32]. However, some papers agree on a certain weakness: the lack of consensus and low interoperability between the different parts [33]. The definition of smart cities has changed according to different actors and commentators with differing priorities and goals [34]. It goes beyond being a technology-centric concept, including people and community needs as well as sustainability concepts.

3.1. Energy Consumption Optimization Problems

Energy is an indispensable element in cities. It supports transport, industrial and commercial activities, water distribution, food production, as well as buildings and infrastructure. Energy consumption increases with population growth and an increased number of industrial activities. Therefore, cities need to manage their energy efficiency to reduce energy consumption and meet sustainability goals.

Researchers have optimized energy consumption in cities in their work. For example, in the context of Vehicle Routing Problem with Backhauls (VRPB), in which the customer set is divided into those who require deliveries and those who require pickups, Koç and Laporte [35] provide a comprehensive review of the existing literature, focusing on the solutions, methods, and models that have been developed. Santos et al. [36] aim to complement the work by Koç and Laporte [35] by analyzing the sustainable impacts on the VRPB. Although it is usually modeled as a cost minimization problem, they show that some studies include environmental objectives in the equation, such as the minimization of CO_2 emissions and energy consumption. An example of this can be found in Chávez et al. [37], in which a multi-depot VRPB is proposed where the objectives are the minimization of the travel distance, travel time, and total energy consumption. It is solved by means of a multiobjective algorithm based on an Ant Colony System. In Lin et al. [38], a review of the state-of-the-art of Green Vehicle Routing Problems (GVRP) is provided, in which they distinguish between the GVRP, Pollution Routing Problem (PRP), and VRP in Reverse Logistics, offering a complete vision of the trends and future directions for GVRP.

Energy consumption optimization problems do not remain only in the field of transportation. There are many other areas in which energy optimization must be applied in smart cities. Shah et al. [39] provide a comprehensive review of energy optimization techniques and scheduling in smart homes, evaluating factors such as thermal comfort, visual comfort, and air quality, concluding that genetic algorithms have performed generally better than other options. Yang et al. [40] present a web-based parallel genetic algorithm (GA) optimization framework that aims to reduce the computational time of simulation-based building energy optimization problems. They carried out some experiments on a testing building in Spain, where the objective was minimizing energy consumption. In fact, results show a reduction of about 15%, where the parallel GA took significantly less computational time than a single GA. By performing further analysis, they also show that the correlation between south window shading of a solar radiation set point and building energy consumption is positive. Solar radiation increases cooling energy consumption in summer, while solar gain entering south-facing windows can reduce heating energy consumption in winter. In the context of mobile terminal devices, Li et al. [41] aim to balance energy consumption and delay, adopting a trade-off strategy that can realize optimal energy consumption with a delay threshold. They model a three-layer fog-cloud cooperation system by describing energy and delay functions with queue theory. González-Briones et al. [42] provide state-of-the-art developments in Multi-Agent Systems and their application to energy optimization problems. They recognize that this approach is commonly used due to its robustness when assigning different tasks to agents and its capacity for the communication, cooperation, and coordination of agents. In their case study with an Intelligent Building, an average reduction of energy consumption of 20.58% was obtained. In the same line of building energy consumption, Papastamatiou et al. [43] present a decision support framework for the assessment and optimization of energy use in buildings, as well as reducing CO_2 emissions and energy costs.

Ejaz et al. [44] cover various directions to investigate energy-efficient solutions and energy harvesting for IoT devices in smart cities. Two case studies to illustrate the significance of energy management have been presented. The first case study uses a heuristic for solving appliance scheduling optimization in smart home networks, which aims to reduce electricity costs. The second case study covers the efficient scheduling of dedicated energy sources for IoT devices in smart cities, utilizing a branch and bound algorithm. Lu et al. [45] propose an architectural design of green wireless sensor networks for smart cities, exploiting the collaborative energy and information transfer protocol and illustrating the challenging issues in this design. Optimization techniques are used to support decision-making, such as the work performed by Carli et al. [46]. They provide a decision-making tool based on a quadratic integer programming formulation that aims to support the selection of the optimal energy retrofit interventions on an existing street lighting system, reducing energy consumption, and ensuring an optimal allocation.

The reviewed papers that cover an optimization technique implementation are summarized in Table 1. This analysis aims to show the wide variety of areas in which energy optimization can be applied, along with different methods.

Table 1. Summary of optimization techniques used in different fields.

Paper	Context	Technique	Objective	Advantages
Chávez et al. [37]	Multi-depot VRPB.	Ant Colony System.	Minimization of the travel distance, travel time, and total energy consumption.	The proposed algorithm is a novel metaheuristic approach that obtains good results within short computing times.
Yang et al. [40]	Building energy optimization.	Parallel Genetic Algorithm.	Reduce computational time of simulation-based building optimization problems.	Lower computational times compared to single GA.
Li et al. [41]	Mobile terminal devices.	Fog-cloud cooperation system, Nonlinear programming, SPML.	Balance energy consumption and delay.	Trade-off strategy that can realize optimal energy consumption with a delay threshold.
González-Briones et al. [42]	Intelligent Buildings.	Multi-Agent Systems.	Energy consumption optimization.	MASs are going through constant evolution and thanks to their multiple characteristics, they are a very suitable approach to modeling systems in the field of energy optimization.
Ejaz et al. [44]	IoT devices in smart cities.	Heuristic, Branch-and-Bound.	Reduce electricity costs, scheduling of dedicated energy sources for IoT device.	Heuristics are efficient algorithms to solve the NP-hard integer programming problem. Branch-and-Bound offer similar results compared to exhaustive search but with less complexity.
Lu et al. [45]	Wireless sensor networks.	Dual decomposition, subgradient-based methods.	Maximizing transmission rate performance.	Decomposes the problem into smaller problems.

Table 1. *Cont.*

Paper	Context	Technique	Objective	Advantages
Carli et al. [46]	Street lighting systems.	Quadratic Integer Programming.	Select optimal energy retrofit interventions.	Allows simultaneously reducing energy consumption while ensuring an optimal allocation of the retrofit actions among the various street lighting subsystems.

3.2. Sustainability and Smart Urban Mobility

The World Health Organization (WHO) data shows that almost all of the global population (99%) breathe air that exceeds WHO guideline limits and contains high levels of pollutants, with low and middle-income countries suffering from the highest exposures (https://www.who.int/health-topics/air-pollution#tab=tab_1 (accessed on 13 October 2022)). In Europe, road transport constitutes the highest proportion of overall transport emissions. In 2019, it emitted 72% of all domestic and international transport greenhouse gas emissions. For these reasons, sustainability and smart urban mobility are topics that should be taken into account in our cities. Smart urban mobility is defined by Lyons [34] as: 'connectivity in towns and cities that is affordable, effective, attractive and sustainable'. In this subsection, we will review some recent works on these concepts. As part of the solutions proposed in the existing smart mobility literature, concepts such as carsharing and last-mile delivery are becoming very popular.

In the context of urban mobility, Calvet et al. [47] interviewed 16 entities from different sectors, such as food distribution, construction, transportation, hospitality, and public administrations, to gain insights into the main concerns about logistics in cities. They conclude that e-commerce growth has multiplied the number of destinations and reduced the average size of the parcels and time window restrictions for entering cities. At the end of their study, they propose an agile optimization approach to handle the current raised problems and converge to sustainable smart cities. In another work, Peyman et al. [48] review the state-of-the-art of IoT in intelligent transportation systems and identify challenges posed by cloud, fog, and edge computing in ITS. They develop a methodology based on agile optimization algorithms for solving a dynamic ridesharing problem (DRSP) in the context of edge/fog computing. A numerical example considering a DRSP is provided, in which the potential of employing edge/fog computing, open data, and agile algorithms is illustrated. Martins et al. [49] provide a review of recent works on optimization problems related to ridesharing and carpooling, classifying them according to the employed solving methodology, then identifying the main challenges and tackling the need for agile optimization techniques.

A particular service belonging to smart urban mobility is carsharing. This service allows users to pick up a car, use it, and bring it back to a parking lot, paying just for the usage. The service reduces vehicle ownership, urban congestion and polluting emissions (gas and noise), and offers cheaper mobility options for the population while freeing up parking spaces. Shared cars might be electric or non-electric. Some of the most mentioned challenges include the relocation of the vehicles and route scheduling. Further, in the case of electric cars, the location of charging stations and charging scheduling. In addition, electricity consumption is affected by driving and environmental conditions. Therefore, electricity consumption should be modeled to estimate the actual charge status of the cars during the day.

The number of works related to carsharing services has rapidly increased over the last few years (Figure 5). Some of the most recent works on carsharing optimization are described next. Bruglieri et al. [50] address a three-objective relocation problem in the context of one-way electric carsharing. One-way refers to users being able to return a car to a station different from its original one. The objectives include: maximizing the number of relocation requests served, minimizing the duration of the workers' longest route when relocating the cars among stations, and minimizing the number of workers. They solve it by applying mixed integer linear programming (MILP). Lai et al. [51] propose an optimization model based on MILP for optimal routing and charging scheduling of electric vehicles in a carsharing service, considering a multi-temporal and multi-task operation. The proposed model formulates the decision-making process for various electric vehicle states (i.e., charging, parking, transporting), as well as additional constraints representing state transitions, working hour requirements, and neutral energy position of batteries. In another work, Lu et al. [52] investigate the vehicle relocation problem with operation teams encountered by a carsharing company in China. A mathematical model is first built to describe the problem. An adaptive large neighborhood search (ALNS) algorithm is applied to efficiently find the relocation pairs of stations and the visiting routes of operation vehicles. In the context of shared autonomous electric vehicles, Ma et al. [53] propose a combined optimization problem to simultaneously locate charging stations and optimize the fleet size and routes to minimize total costs. They formulate a mixed-integer nonlinear model and find a solution using a genetic algorithm. Chang et al. [54] tackle the real-time vehicle relocation and staff rebalancing problem in the one-way carsharing system, employing a new deep learning algorithm. They predict the inflows and outflows at each station and solve a two-phase integer programming model using an ALNS-based heuristic to optimize the process of vehicle relocation and staff rebalancing with cooperative relocation strategies. They show, for a specific case in China, that the profit of four carsharing companies can be increased by 25.49%. An interesting discussion on how people perceive carsharing is provided by Hartl et al. [55], where they show that interviews with users indicate that the sustainable impact of carsharing is perceived as a positive side effect rather than the main argument for carsharing. Consumers are more concerned about the price of the service, the easiness to use, and flexibility, so this should be taken into account by policy-makers and marketers in order to promote carsharing services because of sustainable benefits.

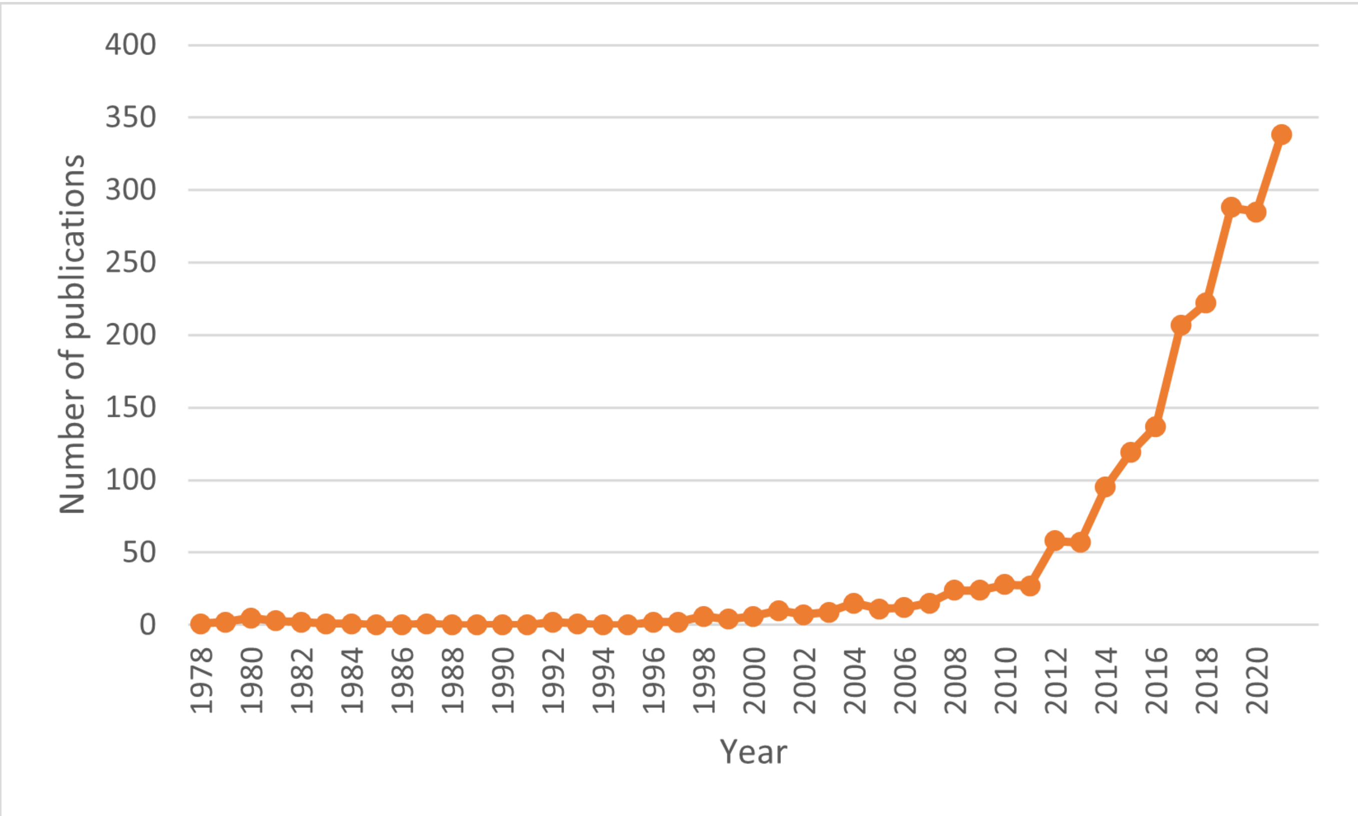

Figure 5. Evolution of Scopus-indexed articles for carsharing or car-sharing.

Table 2 summarizes the main targeted objectives in the context of carsharing along with the methodology used in the reviewed papers.

Table 2. Main targeted objectives in the reviewed carsharing papers.

Paper	Context	Technique	Objective
Bruglieri et al. [50]	One-way electric carsharing	Mixed Integer Linear Programming	Three-objective relocation problem
Lai et al. [51]	Electric carsharing	Mixed Integer Linear Programming	Optimal routing and charging scheduling
Lu et al. [52]	Carsharing	Adaptive Large-Neighborhood Search	Vehicle relocation with operation teams
Ma et al. [53]	Shared autonomous electric vehicles	Mixed Integer Nonlinear model, Genetic Algorithm	Locating charging stations, optimizing fleet size and routes
Chang et al. [54]	One-way carsharing	Heuristic, Deep learning algorithm	Vehicle relocation and staff rebalancing

4. Energy Consumption in Last-Mile Delivery

Last-mile delivery is the most expensive and least efficient portion of a supply chain. It accounts for more than 70% of the energy consumption in a distribution channel [56]. The concern about delivering parcels to a specific address increased during the COVID-19 pandemic leading to the raised importance of last-mile deliveries. Therefore, researchers have studied energy efficiency and its consumption in cities. Some models were built to estimate energy efficiency [57] and gas emissions [58], and the number of publications increased, as depicted in Figure 6. Analysis based on collected data showed that energy efficiency is reduced in city centers compared to other parts of the cities because of traffic jams, traffic lights, and crossing pedestrians [59]. As a result, different optimization problems were defined in the context of last-mile delivery in cities, such as capacitated pollution-routing problems with pickup and delivery [58]. Several studies have recommended replacing the use of diesel cars in last-mile delivery with more environmental and sustainable solutions [59]. In addition, increased city traffic triggered studies to analyze traffic, energy consumption, and gas emissions in cities.

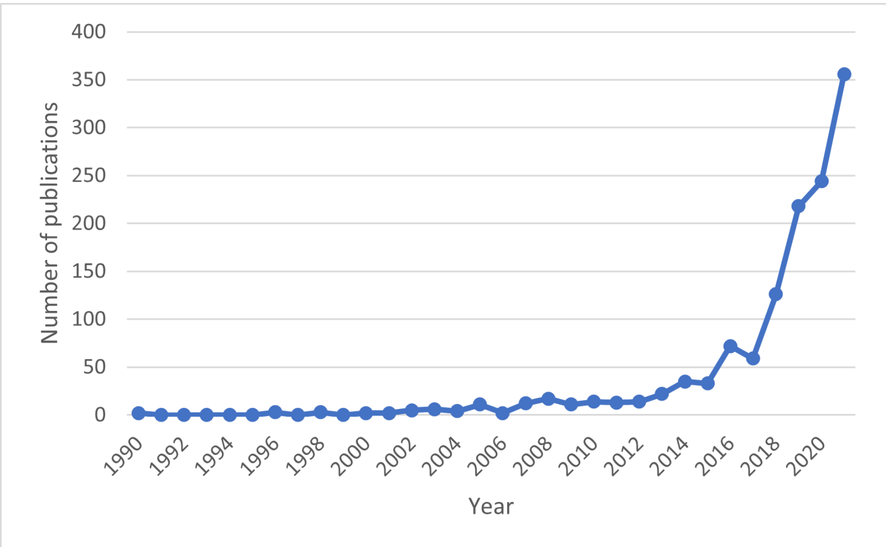

Figure 6. Evolution of Scopus-indexed articles for last-mile delivery.

One of the recommendations is to replace traditional vehicles with electric vehicles [60]. The utilization of electric vehicles aims to reduce emissions in urban areas [61]. However, they possess new types of challenges, such as short driving range, limited battery capacity, and required charging infrastructure. Thus, an analysis of these challenges and the effect of electric vehicles on energy consumption in last-mile delivery has been investigated [62]. For example, Napoli et al. [63] investigated the location of charging stations to reduce energy usage. In the study, the considered recharging stations were based on renewable energy. Iwan et al. [61] studied the effect of the specificity of a delivering area on the energy consumption of a specific electric vehicle. Another work has considered integrating electric vehicles with the grid net [64]. In this work, electric vehicles could be charged or recharged and used as energy storage. The problem was modeled as a vehicle routing with a time window and time-variant price. These different analyses prove the suitability of electric vehicles for urban last-mile deliveries.

Electric vehicles could be unmanned aerial vehicles (UAVs) or drones. These vehicles do not face traffic jams in urban cities and could be used to deliver parcels to customers. Although UAVs are flexible, they have several drawbacks, such as low battery capacity and limited delivery distances and times. Therefore, the costs and energy consumption associated with UAVs become topics to be studied [65]. Energy consumption is related to different environmental conditions and flight patterns [66] and is affected by the battery weight and the weight of the carried parcel [67]. In addition, studies show that the carbon footprint is reduced by using UAVs in last-mile delivery [68]. Problems involving UAVs are formulated as VRPs [67,68]. Real-world problems are characterized by uncertainty and dynamicity. Thus, these characteristics should be considered in problem formulation and an approach used to solve it [69].

In order to handle limited battery capacity, approaches combining UAVs and other vehicles have been proposed, including crowdsourced vehicles [70,71]. UAVs are carried by electric vehicles, trucks [71], or even buses [72]. The vehicles travel along their route, and a UAV leaves the vehicle near its destination to deliver parcels. The vehicles could play a role in charging UAVs and, hence, help to increase the delivery distance and time that UAVs cover. In this approach, energy consumption is reduced. It is affected by the carried weight and the environmental conditions [71,72], and the delivery capacity presented by delivery time and distance increase. In the end, the UAVs could return to the vehicles to be recharged. This cooperation between vehicles and UAVs could be extended to utilize public transportation (buses), raising synchronization issues in such problems [73].

Instead of UAVs, autonomous delivery robots might deliver parcels for the last mile [74,75], e.g.: delivery at a university campus. Autonomous delivery robots reduce energy consumption and CO_2 emissions [74]. Further, in a hybrid system of vehicles and autonomous delivery robots, the vehicles could be used to recharge the autonomous delivery robots or replace their batteries [75].

Bicycles and tricycles are another means of sustainable last-mile delivery [60], and most researchers recommend using bicycles or tricycles [76]. de Mello Bandeira et al. [77] suggested using electric tricycles for delivery in urban areas, which has an advantage over electric or small size vehicles concerning sustainable dimensions such as CO_2 emissions.

Solutions to handle last-mile delivery in urban areas are not limited to vehicles or autonomous-driven vehicles. Instead, parcel lockers become a suggested solution to reduce energy consumption and CO_2 emission for parcel delivery [56,78]. Increased utilization of parcel lockers was noticed during the COVID-19 pandemic [56]. One of the challenges associated with this problem is to plan the locations of these lockers to satisfy the expected demand [79].

5. Agile Optimization

The next generation of transportation and logistics systems of smart cities requires using on-demand economy and e-commerce, big data, the internet of things, and zero-emission vehicles in ridesharing and carsharing modes [80]. Since most smart cities' problems are large-scale, NP-hard, and dynamic that require making decisions in a rapid computational time, using the exact methods or even metaheuristics does not fulfill the requirement and is not a good option. Thus, we need methods that find near-optimal solutions and solve the problem in a very short computational time. Smart cities' mobility problems demand real-time optimization as well as re-optimization every few seconds because of frequent changes in data regarding traffic jams, parking lots, and other facilities.

As a solving methodology, AO is a tool for dynamic and real-time optimization problems [80] and is based on Biased-Randomization (BR) and parallel runs. BR is a solution approach that uses randomization in a heuristics procedure [81]. This approach changes the deterministic environment of a heuristic into a probabilistic one. In a heuristic used to solve an optimization problem, a list of solution candidate elements is defined and sorted according to the constructive heuristic logic. This logic could be the shortest travel distance or travel time, depending on the considered problem. Then, a greedy solution is constructed by selecting the first element from the candidate list in each heuristic iteration. The first element is the best candidate with respect to the considered logic aiming to optimize the solution. Hence, the constructed solution is greedy and remains the same each time the heuristic is applied. This greedy solution represents a solution for the considered problem, but there is no guarantee that it is an optimal solution. This solution might be a good solution, but the combination of the candidates might not form the best solution.

In order to construct different variants of the greedy solution, BR assigns a selection probability to each candidate element in the list. In such a way, the elements on the top of the list have the highest probability of being selected compared to the other elements in the list (Figure 7). Thus, BR uses the logic behind the heuristics based on randomization and probabilities. The selection probability can follow different probability distributions, such as a geometric distribution. The geometric distribution has one parameter, p, that refers to the selection probability of the first element in the candidate list. The second element is assigned a lower selection probability, as shown in Figure 7. Since the selection of elements in BR is based on probabilities, different variants of the greedy solution are constructed in each run of the biased-randomized heuristic. For example, one solution could start with element e_1 and another with e_3 from Figure 7.

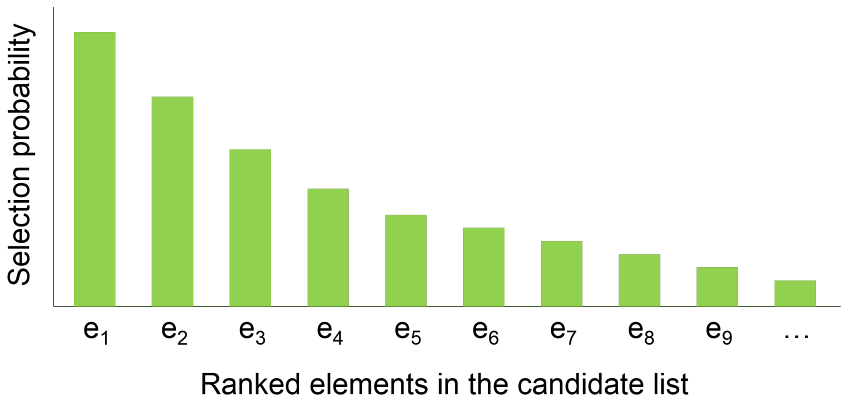

Figure 7. The selection probability of elements in the list of candidates.

The construction of solutions by the heuristic or the biased randomized heuristic is fast. Elements in the list are ranked and assigned selection probabilities, and an element is selected randomly according to its selection probabilities. Thus, running several executions of the biased randomized heuristic in parallel (utilizing multi-threads) constructs several solution variants during the same clock time; thousands of solutions could be generated from the BR algorithm execution if thousands of executions are run in parallel. Multi-threads or parallel processors could be utilized to run the executions. These variants differ from the greedy solution because of the biased randomized selection of elements, but they are constructed according to the same heuristic logic. The solution that outperforms the others will be selected among the generated solution variants. Combining the biased randomized approach and the parallel execution forms AO illustrated in Figure 8. It is noted that the execution time of all threads in Figure 8 is instantaneous. Thus, a large number of variants of the greedy solution are constructed in an extremely short time.

Flexibility, high capability of parallelization (easy to execute in parallel), and ability to generate solutions for dynamic problems in a short computational time are some advantages of applying AO to transportation mobility in smart cities' problems. These problems are dynamic in nature. In addition, AO does not need many intensive parameters, which makes it an effective and high-quality solution approach [49]. If the geometric distribution is selected for the biased randomized behavior, then one parameter, p, should be defined.

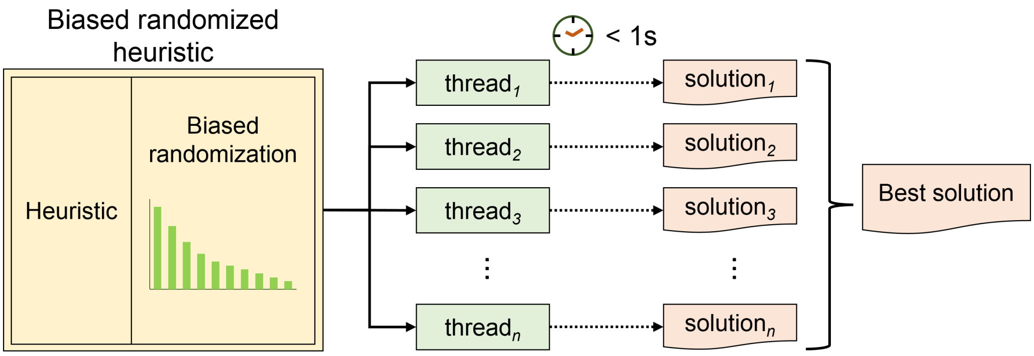

Figure 8. Schematic illustration of an agile algorithm.

6. Problems Solved Using Agile Optimization

After describing problems related to carsharing, ridesharing, and last-mile delivery in cities with respect to energy, this section presents some of the problems solved using AO algorithms. Table 3 lists articles and the solved problems considered in this section. These articles define an optimization problem and use an AO algorithm to solve it. A comparison between the best-found solutions (BFS) and the solutions obtained by an AO algorithm (AOS) are tabulated in Table 3. The BFS could be the best-known solution in the literature or the best-found solution determined using an optimization algorithm other than AO. For example, for the team orienteering problem presented in Panadero et al. [82], the average best-known solution for the solved instances is 126, and the average of solutions found by an AO algorithm is 124.69 for the same instances. Panadero et al. [82] studied instantaneously solving team orienteering problems. The team orienteering problem definition could be used to define UAV routing that is related to smart city mobility. The percentage differences between BFS and AOS (gaps) are plotted in Figure 9.

Table 3. Selected problems solved using an AO algorithm.

Reference	Problem	Acronym	BFS	AOS
Panadero et al. [82]	Team Orienteering Problem, set 1, maximization	TOP	126	124.69
Almouhanna et al. [83]	Location Routing Problem with a Constrained Distance, Barreto's set, minimization	LRPCD	3637.84	3655.15
Martins et al. [84]	Two-echelon Vehicle Routing Problem with Pickup and Delivery, tight inventory, minimization	2E-VRP	2023.43	2450.44
Martins et al. [80]	Uncapacitated Facility Location Problem, minimization	UFLP	1,200,339	1,236,828

According to Figure 9, BFSs outperform solutions found by the AO algorithm for the selected problems. However, BFSs usually require extremely long computational times to find optimal or near-optimal solutions since they perform an intensive search and exploration of the solution space. The computational time depends on the size of problem instances (size of solution space) and the stopping criteria of the used optimization methods. In addition, for large-size problem instances, the optimal solution is not guaranteed. On the contrary, AO algorithms follow a fast heuristic behavior in constructing a solution and possess a biased randomized behavior to construct variant solutions of the heuristic solution. Because of the BR and parallelism utilization, AO algorithms construct many solutions in a short wall clock time that could be less than a second. Thus, these algorithms logically explore the solution space for feasible and promising solutions with respect to the objective function of the considered optimization problem.

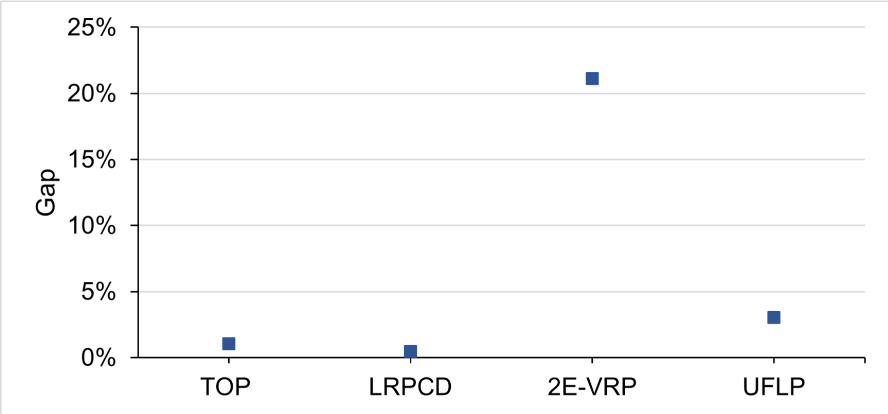

Figure 9. Absolute gap difference between BFS and AOS for the selected problems with respect to the BFS.

Furthermore, referring to Figure 9, the gap between the BFS and AOS is relatively small. A trade-off between both approaches exists; 'good' solutions are found in an extremely short time using AO algorithms, and better solutions might be found using traditional optimization methods over a long computation time. Given that the AO algorithms found these solutions in a short search time, the relatively small gap between solutions could be negligible in cases requiring fast, promising solution recommendations, such as solving real-world optimization problems that require instantaneous solutions to changed inputs. Thus, the AO algorithm characteristics enable solving real-time optimization problems. As mentioned previously, these characteristics described raised mobility and energy problems in smart cities.

7. Conclusions

Problems demanding real-time solutions (dynamic problems) are challenging to solve. These problems emerge because of dynamic changes in problem inputs. In the context of city mobility, these changes might be new orders, cancellation of trips or orders. The dynamic characteristic in optimization problems becomes evident in real-world problems triggered by advancements in information and communication technology. Thus, the concept of smart cities raises the need to handle problems related to optimizing routing time and distance and, hence, reducing energy consumption and gas emission. Carsharing and last-mile delivery are examples of such problems.

The agile optimization presented in the manuscript is based on biased randomization behavior and parallel execution of a heuristic. Thus, in a short wall clock time, many solutions are constructed according to heuristic logic, and the best solution among them can be identified. Adapting this approach enables defining a promising solution to optimization problems that require instantaneous solutions. An example of a successful implementation of this approach is found in Tordecilla et al. [85].

Various optimization problems in the context of smart cities are defined, and the AO can propose solutions to these problems in real-time. The defined initiatives to reduce energy consumption are a candidate to be solved using AO. In addition, other problem characteristics in the real world could be considered, such as stochastic and fuzzy uncertainty of travel times. Further studies should consider the reliability of shared cars and their impact on energy consumption and related decisions.

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References

1. Ahmad, T.; Zhang, D. A critical review of comparative global historical energy consumption and future demand: The story told so far. *Energy Rep.* **2020**, *6*, 1973–1991. [CrossRef]
2. Guo, J.; Long, S.; Luo, W. Nonlinear effects of climate policy uncertainty and financial speculation on the global prices of oil and gas. *Int. Rev. Financ. Anal.* **2022**, *83*, 102286. [CrossRef]
3. Chen, G.; Wu, X.; Guo, J.; Meng, J.; Li, C. Global overview for energy use of the world economy: Household-consumption-based accounting based on the world input-output database (WIOD). *Energy Econ.* **2019**, *81*, 835–847. [CrossRef]
4. Jayaprakash, S.; Nagarajan, M.D.; Prado, R.P.d.; Subramanian, S.; Divakarachari, P.B. A Systematic Review of Energy Management Strategies for Resource Allocation in the Cloud: Clustering, Optimization and Machine Learning. *Energies* **2021**, *14*, 5322. [CrossRef]
5. Bhatt, A.N.; Shrivastava, N. Application of Artificial Neural Network for Internal Combustion Engines: A State of the Art Review. *Arch. Comput. Methods Eng.* **2022**, *29*, 897–919. [CrossRef]
6. Bektaş, T.; Ehmke, J.F.; Psaraftis, H.N.; Puchinger, J. The role of operational research in green freight transportation. *Eur. J. Oper. Res.* **2019**, *274*, 807–823. [CrossRef]
7. Corlu, C.G.; de la Torre, R.; Serrano-Hernandez, A.; Juan, A.A.; Faulin, J. Optimizing Energy Consumption in Transportation: Literature Review, Insights, and Research Opportunities. *Energies* **2020**, *13*, 1115. [CrossRef]
8. Psaraftis, H.N.; Kontovas, C.A. Speed models for energy-efficient maritime transportation: A taxonomy and survey. *Transp. Res. Part C Emerg. Technol.* **2013**, *26*, 331–351. [CrossRef]
9. Casella, V.; Fernandez Valderrama, D.; Ferro, G.; Minciardi, R.; Paolucci, M.; Parodi, L.; Robba, M. Towards the Integration of Sustainable Transportation and Smart Grids: A Review on Electric Vehicles' Management. *Energies* **2022**, *15*, 4020. [CrossRef]
10. Wang, N.; Tang, G. A Review on Environmental Efficiency Evaluation of New Energy Vehicles Using Life Cycle Analysis. *Sustainability* **2022**, *14*, 3371. [CrossRef]
11. Faulin, J.; Grasman, S.E.; Juan, A.A.; Hirsch, P. Sustainable Transportation: Concepts and Current Practices. In *Sustainable Transportation and Smart Logistics*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 3–23.
12. Chatti, W. Moving towards environmental sustainability: Information and communication technology (ICT), freight transport, and CO_2 emissions. *Heliyon* **2021**, *7*, 08190. [CrossRef] [PubMed]
13. Rashidi, K.; Cullinane, K. Evaluating the sustainability of national logistics performance using Data Envelopment Analysis. *Transp. Policy* **2019**, *74*, 35–46. [CrossRef]
14. Newman, P.; Kenworthy, J. *Sustainability and Cities: Overcoming Automobile Dependence*; Island Press: New York, NY, USA, 1999; pp. 69–72.
15. Pan, H.; Qi, L.; Zhang, Z.; Yan, J. Kinetic energy harvesting technologies for applications in land transportation: A comprehensive review. *Appl. Energy* **2021**, *286*, 116518. [CrossRef]
16. Jin, L.; Zhang, B.; Zhang, L.; Yang, W. Nanogenerator as new energy technology for self-powered intelligent transportation system. *Nano Energy* **2019**, *66*, 104086. [CrossRef]
17. Schislyaeva, E.; Evgrafova, I.; Butakova, N.; Mishalchenko, Y. The EU–Russia–Turkey energy triangle: Legal and economic conditions of gas transportation via the TurkStream pipeline. *Transp. Res. Procedia* **2022**, *63*, 1984–1990. [CrossRef]
18. Wang, N.; Zhu, Y.; Yang, T. The impact of transportation infrastructure and industrial agglomeration on energy efficiency: Evidence from China's industrial sectors. *J. Clean. Prod.* **2020**, *244*, 118708. [CrossRef]
19. Kaza, N. Urban form and transportation energy consumption. *Energy Policy* **2020**, *136*, 111049. [CrossRef]
20. Rodrigue, J.P. *The Geography of Transport Systems*, 5th ed.; Routledge: New York, NY, USA, 2020; pp. 285–330.
21. IEA. *Transportation: Improving the Sustainability of Passenger and Freight Transport*; International Energy Egency: Paris, France, 2012. Available online: https://www.iea.org/ (accessed on 13 October 2022).
22. U.S. Energy Information Administration (EIA). Energy Use for Transportation. 2022. Available online: https://www.eia.gov/ (accessed on 13 October 2022).
23. Gorcun, O.F. Reduction of Energy Costs and Traffic Flow Rate in Urban Logistics Process. *Energy Procedia* **2017**, *113*, 82–89. [CrossRef]
24. Wu, X.; Hu, X.; Yin, X.; Li, L.; Zeng, Z.; Pickert, V. Convex programming energy management and components sizing of a plug-in fuel cell urban logistics vehicle. *J. Power Sources* **2019**, *423*, 358–366. [CrossRef]

25. Malladi, S.S.; Christensen, J.M.; Ramírez, D.; Larsen, A.; Pacino, D. Stochastic fleet mix optimization: Evaluating electromobility in urban logistics. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *158*, 102554. [CrossRef]
26. Xu, B.; Xu, R. Assessing the role of environmental regulations in improving energy efficiency and reducing CO_2 emissions: Evidence from the logistics industry. *Environ. Impact Assess. Rev.* **2022**, *96*, 106831. [CrossRef]
27. Jones, J.; Genovese, A.; Tob-Ogu, A. Hydrogen vehicles in urban logistics: A total cost of ownership analysis and some policy implications. *Renew. Sustain. Energy Rev.* **2020**, *119*, 109595. [CrossRef]
28. Rogelj, J.; Den Elzen, M.; Höhne, N.; Fransen, T.; Fekete, H.; Winkler, H.; Schaeffer, R.; Sha, F.; Riahi, K.; Meinshausen, M. Paris agreement climate proposals need a boost to keep warming well below 2 °C. *Nature* **2016**, *534*, 631–639. [CrossRef]
29. Magazzino, C.; Mele, M.; Schneider, N. A new artificial neural networks algorithm to analyze the nexus among logistics performance, energy demand, and environmental degradation. *Struct. Chang. Econ. Dyn.* **2022**, *60*, 315–328. [CrossRef]
30. Wang, D.; Li, J.; Tarasov, A. Technical and energy efficiency of urban logistics in China: Empirical analysis of 216 prefecture-level cities. *Math. Probl. Eng.* **2021**, *2021*, 6671890. [CrossRef]
31. Turoń, K.; Kubik, A.; Chen, F. Operational aspects of electric vehicles from car-sharing systems. *Energies* **2019**, *12*, 4614. [CrossRef]
32. Giffinger, R.; Fertner, C.; Kramar, H.; Meijers, E. City-ranking of European medium-sized cities. *Cent. Reg. Sci. Vienna UT* **2007**, *9*, 1–12.
33. Komninos, N.; Kakderi, C.; Mora, L.; Panori, A.; Sefertzi, E. Towards high impact smart cities: A universal architecture based on connected intelligence spaces. *J. Knowl. Econ.* **2022**, *13*, 1169–1197. [CrossRef]
34. Lyons, G. Getting smart about urban mobility—Aligning the paradigms of smart and sustainable. *Transp. Res. Part A Policy Pract.* **2018**, *115*, 4–14. [CrossRef]
35. Koç, Ç.; Laporte, G. Vehicle routing with backhauls: Review and research perspectives. *Comput. Oper. Res.* **2018**, *91*, 79–91. [CrossRef]
36. Santos, M.J.; Amorim, P.; Marques, A.; Carvalho, A.; Póvoa, A. The vehicle routing problem with backhauls towards a sustainability perspective: A review. *Top* **2020**, *28*, 358–401. [CrossRef]
37. Chávez, J.; Escobar, J.; Echeverri, M. A multi-objective Pareto ant colony algorithm for the Multi-Depot Vehicle Routing problem with Backhauls. *Int. J. Ind. Eng. Comput.* **2016**, *7*, 35–48. [CrossRef]
38. Lin, C.; Choy, K.L.; Ho, G.T.; Chung, S.H.; Lam, H. Survey of green vehicle routing problem: Past and future trends. *Expert Syst. Appl.* **2014**, *41*, 1118–1138. [CrossRef]
39. Shah, A.S.; Nasir, H.; Fayaz, M.; Lajis, A.; Shah, A. A Review on Energy Consumption Optimization Techniques in IoT Based Smart Building Environments. *Information* **2019**, *10*, 108. [CrossRef]
40. Yang, C.; Li, H.; Rezgui, Y.; Petri, I.; Yuce, B.; Chen, B.; Jayan, B. High throughput computing based distributed genetic algorithm for building energy consumption optimization. *Energy Build.* **2014**, *76*, 92–101. [CrossRef]
41. Li, G.; Yan, J.; Chen, L.; Wu, J.; Lin, Q.; Zhang, Y. Energy Consumption Optimization With a Delay Threshold in Cloud-Fog Cooperation Computing. *IEEE Access* **2019**, *7*, 159688–159697. [CrossRef]
42. González-Briones, A.; De La Prieta, F.; Mohamad, M.S.; Omatu, S.; Corchado, J.M. Multi-Agent Systems Applications in Energy Optimization Problems: A State-of-the-Art Review. *Energies* **2018**, *11*, 1928. [CrossRef]
43. Papastamatiou, I.; Marinakis, V.; Doukas, H.; Psarras, J. A Decision Support Framework for Smart Cities Energy Assessment and Optimization. *Energy Procedia* **2017**, *111*, 800–809. [CrossRef]
44. Ejaz, W.; Naeem, M.; Shahid, A.; Anpalagan, A.; Jo, M. Efficient Energy Management for the Internet of Things in Smart Cities. *IEEE Commun. Mag.* **2017**, *55*, 84–91. [CrossRef]
45. Lu, W.; Gong, Y.; Liu, X.; Wu, J.; Peng, H. Collaborative Energy and Information Transfer in Green Wireless Sensor Networks for Smart Cities. *IEEE Trans. Ind. Inform.* **2018**, *14*, 1585–1593. [CrossRef]
46. Carli, R.; Dotoli, M.; Cianci, E. An optimization tool for energy efficiency of street lighting systems in smart cities. *IFAC-PapersOnLine* **2017**, *50*, 14460–14464. [CrossRef]
47. Calvet, L.; Alvarez-Palau, E.J.; Viu, M.; Castillo, C.; Copado, P.; Juan, A.A. Promoting Sustainable and Intelligent Freight Transportation Systems in the Barcelona Metropolitan Area. *Transp. Res. Procedia* **2021**, *58*, 408–415. j.trpro.2021.11.055. [CrossRef]
48. Peyman, M.; Copado, P.J.; Tordecilla, R.D.; Martins, L.d.C.; Xhafa, F.; Juan, A.A. Edge Computing and IoT Analytics for Agile Optimization in Intelligent Transportation Systems. *Energies* **2021**, *14*, 6309. [CrossRef]
49. Martins, L.d.C.; de la Torre, R.; Corlu, C.G.; Juan, A.A.; Masmoudi, M.A. Optimizing ride-sharing operations in smart sustainable cities: Challenges and the need for agile algorithms. *Comput. Ind. Eng.* **2021**, *153*, 107080. [CrossRef]
50. Bruglieri, M.; Pezzella, F.; Pisacane, O. A two-phase optimization method for a multiobjective vehicle relocation problem in electric carsharing systems. *J. Comb. Optim.* **2018**, *36*, 162–193. [CrossRef]
51. Lai, K.; Chen, T.; Natarajan, B. Optimal scheduling of electric vehicles car-sharing service with multi-temporal and multi-task operation. *Energy* **2020**, *204*, 117929. [CrossRef]
52. Lu, Y.; Wang, K.; Yuan, B. The vehicle relocation problem with operation teams in one-way carsharing systems. *Int. J. Prod. Res.* **2022**, *60*, 3829–3843. [CrossRef]
53. Ma, B.; Hu, D.; Wu, X. The location routing problem of the car-sharing system with autonomous electric vehicles. *KSCE J. Civ. Eng.* **2021**, *25*, 3107–3120. [CrossRef]

54. Chang, X.; Wu, J.; de Almeida Correia, G.H.; Sun, H.; Feng, Z. A cooperative strategy for optimizing vehicle relocations and staff movements in cities where several carsharing companies operate simultaneously. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *161*, 102711. [CrossRef]
55. Hartl, B.; Sabitzer, T.; Hofmann, E.; Penz, E. "Sustainability is a nice bonus" the role of sustainability in carsharing from a consumer perspective. *J. Clean. Prod.* **2018**, *202*, 88–100. [CrossRef]
56. Milewski, D.; Milewska, B. The Energy Efficiency of the Last Mile in the E-Commerce Distribution in the Context the COVID-19 Pandemic. *Energies* **2021**, *14*, 7863. [CrossRef]
57. Bányai, T. Real-time decision making in first mile and last mile logistics: How smart scheduling affects energy efficiency of hyperconnected supply chain solutions. *Energies* **2018**, *11*, 1833. [CrossRef]
58. Tan, Y.; Deng, L.; Li, L.; Yuan, F. The capacitated pollution routing problem with pickup and delivery in the last mile. *Asia Pac. J. Mark. Logist.* **2019**, *31*, 1193–1215. [CrossRef]
59. Boggio-Marzet, A.; Monzón, A.; Luque-Rodríguez, P.; Álvarez-Mántaras, D. Comparative Analysis of the Environmental Performance of Delivery Routes in the City Center and Peri-Urban Area of Madrid. *Atmosphere* **2021**, *12*, 1233. [CrossRef]
60. Oliveira, C.M.d.; Albergaria De Mello Bandeira, R.; Vasconcelos Goes, G.; Schmitz Gonçalves, D.N.; D'Agosto, M.D.A. Sustainable vehicles-based alternatives in last mile distribution of urban freight transport: A systematic literature review. *Sustainability* **2017**, *9*, 1324. [CrossRef]
61. Iwan, S.; Nürnberg, M.; Jedliński, M.; Kijewska, K. Efficiency of light electric vehicles in last mile deliveries–Szczecin case study. *Sustain. Cities Soc.* **2021**, *74*, 103167. [CrossRef]
62. Fiori, C.; Marzano, V. Modelling energy consumption of electric freight vehicles in urban pickup/delivery operations: Analysis and estimation on a real-world dataset. *Transp. Res. Part D Transp. Environ.* **2018**, *65*, 658–673. [CrossRef]
63. Napoli, G.; Micari, S.; Dispenza, G.; Andaloro, L.; Antonucci, V.; Polimeni, A. Freight distribution with electric vehicles: A case study in Sicily. RES, infrastructures and vehicle routing. *Transp. Eng.* **2021**, *3*, 100047. [CrossRef]
64. Lin, B.; Ghaddar, B.; Nathwani, J. Electric vehicle routing with charging/discharging under time-variant electricity prices. *Transp. Res. Part C Emerg. Technol.* **2021**, *130*, 103285. [CrossRef]
65. She, R.; Ouyang, Y. Efficiency of UAV-based last-mile delivery under congestion in low-altitude air. *Transp. Res. Part C Emerg. Technol.* **2021**, *122*, 102878. [CrossRef]
66. Kirschstein, T. Comparison of energy demands of drone-based and ground-based parcel delivery services. *Transp. Res. Part D Transp. Environ.* **2020**, *78*, 102209. [CrossRef]
67. Dorling, K.; Heinrichs, J.; Messier, G.G.; Magierowski, S. Vehicle routing problems for drone delivery. *IEEE Trans. Syst. Man Cybern. Syst.* **2016**, *47*, 70–85. [CrossRef]
68. Chiang, W.C.; Li, Y.; Shang, J.; Urban, T.L. Impact of drone delivery on sustainability and cost: Realizing the UAV potential through vehicle routing optimization. *Appl. Energy* **2019**, *242*, 1164–1175. [CrossRef]
69. Radzki, G.; Nielsen, I.; Golińska-Dawson, P.; Bocewicz, G.; Banaszak, Z. Reactive UAV fleet's mission planning in highly dynamic and unpredictable environments. *Sustainability* **2021**, *13*, 5228. [CrossRef]
70. Guo, X.; Jaramillo, Y.J.L.; Bloemhof-Ruwaard, J.; Claassen, G. On integrating crowdsourced delivery in last-mile logistics: A simulation study to quantify its feasibility. *J. Clean. Prod.* **2019**, *241*, 118365. [CrossRef]
71. Di Puglia Pugliese, L.; Guerriero, F.; Scutellá, M.G. The last-mile delivery process with trucks and drones under uncertain energy consumption. *J. Optim. Theory Appl.* **2021**, *191*, 31–67. [CrossRef]
72. Pan, Y.; Li, S.; Chen, Q.; Zhang, N.; Cheng, T.; Li, Z.; Guo, B.; Han, Q.; Zhu, T. Efficient Schedule of Energy-Constrained UAV Using Crowdsourced Buses in Last-Mile Parcel Delivery. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2021**, *5*, 1–23. [CrossRef]
73. Moadab, A.; Farajzadeh, F.; Fatahi Valilai, O. Drone routing problem model for last-mile delivery using the public transportation capacity as moving charging stations. *Sci. Rep.* **2022**, *12*, 6361. [CrossRef]
74. Figliozzi, M.; Jennings, D. Autonomous delivery robots and their potential impacts on urban freight energy consumption and emissions. *Transp. Res. Procedia* **2020**, *46*, 21–28. [CrossRef]
75. Yu, S.; Puchinger, J.; Sun, S. Van-based robot hybrid pickup and delivery routing problem. *Eur. J. Oper. Res.* **2022**, *298*, 894–914. [CrossRef]
76. Goes, G.V.; Schmitz, D.N.; de Mello Bandeira, R.A.; de Oliveira, C.M.; Márcio de Almeida, D. Sustentabilidade na última milha do transporte urbano de carga: O papel da eficiência energética do veículo. *Sustain. Debate* **2018**, *9*, 134–144. [CrossRef]
77. de Mello Bandeira, R.A.; Goes, G.V.; Gonçalves, D.N.S.; Márcio de Almeida, D.; de Oliveira, C.M. Electric vehicles in the last mile of urban freight transportation: A sustainability assessment of postal deliveries in Rio de Janeiro-Brazil. *Transp. Res. Part D Transp. Environ.* **2019**, *67*, 491–502. [CrossRef]
78. Moore, A.M. Innovative scenarios for modeling intra-city freight delivery. *Transp. Res. Interdiscip. Perspect.* **2019**, *3*, 100024. [CrossRef]
79. Rabe, M.; Gonzalez-Feliu, J.; Chicaiza-Vaca, J.; Tordecilla, R.D. Simulation-optimization approach for multi-period facility location problems with forecasted and random demands in a last-mile logistics application. *Algorithms* **2021**, *14*, 41. [CrossRef]
80. Martins, L.; Tarchi, D.; Juan, A.; Fusco, A. Agile Optimization for Real-Time Facility Location Problem in Internet of Vehicle Scenarios. *Networks* **2022**, *79*, 501–514. [CrossRef]

81. Juan, A.; Faulin, J.; Ferrer, A.; Lourenço, H.; Barrios, B. MIRHA: Multi-start biased randomization of heuristics with adaptive local search for solving non-smooth routing problems. *TOP* **2013**, *21*, 109–132. [CrossRef]
82. Panadero, J.; Ammouriova, M.; Juan, A.A.; Agustin, A.; Nogal, M.; Serrat, C. Combining parallel computing and biased randomization for solving the team orienteering problem in real-time. *Appl. Sci.* **2021**, *11*, 12092. [CrossRef]
83. Almouhanna, A.; Quintero-Araujo, C.L.; Panadero, J.; Juan, A.A.; Khosravi, B.; Ouelhadj, D. The location routing problem using electric vehicles with constrained distance. *Comput. Oper. Res.* **2020**, *115*, 104864. [CrossRef]
84. Martins, L.d.C.; Hirsch, P.; Juan, A.A. Agile optimization of a two-echelon vehicle routing problem with pickup and delivery. *Int. Trans. Oper. Res.* **2021**, *28*, 201–221. [CrossRef]
85. Tordecilla, R.D.; Martins, L.d.C.; Saiz, M.; Copado-Mendez, P.J.; Panadero, J.; Juan, A.A. Agile computational intelligence for supporting hospital logistics during the COVID-19 crisis. In *Computational Management*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 383–407.