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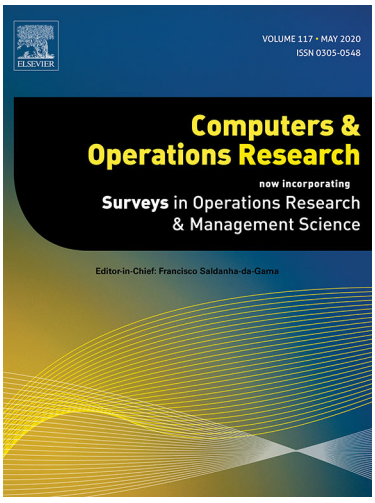

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Environmental and social implications of incorporating carpooling service on a customized bus system

Abstract

This study addresses one of the most challenging issues in designing a sustainable and efficient ride-sharing service. This paper uses an extensive computational study to quantify the behavior of carpooling in customized bus routing problems. This mechanism allows organizations to draw on the potential of their employees' private cars to provide convenient alternative rides for other employees, thereby reducing air pollution and greenhouse gas emissions as well as increasing overall satisfaction with the transportation system offered. The objective functions minimize: (*i*) total transportation costs and incentives paid to drivers of private cars, (*ii*) dissatisfaction as determined by staff walking distance, travel time, and delays in arriving at work, and (*iii*) total carbon emissions generated by commuting. We propose a resolution algorithm based on Pareto Strength Ant Colony Optimization (PSACO) as an effective meta-heuristic method for solving the multi-objective mathematical model and compare it with the results obtained by an exact method. The effectiveness and applicability of the proposed problem have been evaluated by performing computational experiments on a real case study in Paris using a number of comparative metrics with appropriate assumptions. Different parameters affecting the performance of the algorithm are also investigated. The concluding section presents a comparison of the results achieved. The test outcomes confirm that the formulation and the solution methods can be useful references for practice. The insights obtained from the research could provide the basis for designing incentive schemes and information campaigns aimed at making ride-sharing systems more successful and improving their performance.

Keywords: Ride-sharing system; Customized buses; Vehicle routing problem; Sustainable transportation; Pareto strength ant colony optimization

1. Introduction

People around the world usually drive their own cars to work, most often with no one else in the car. Large companies and organizations require thousands of individuals to be present at work every day, significantly increasing car use. The high number of commuter trips during peak hours and low vehicle occupancy rates often lead to severe traffic congestion in cities. These commuting practices lead to numerous problems, including noise pollution, high greenhouse gas emissions, and the scarcity of parking spots (Asghari and Mirzapour Al-e-Hashem, 2020b, 2021). The resulting air pollution and stress can negatively affect health.

While public transportation systems can almost entirely alleviate the problem, more often than not, they are essentially ignored by the many people who prefer not to use them (Bruck et al., 2017). This is

due to the fact that public transportation cannot serve all requests cost-effectively or provide a level of comfort and convenience anywhere near that of private vehicles. If there is no nearby bus station, people may find themselves stranded and forced to wait a long time or walk long distances. In such conditions, they may not be interested in using the bus service for future trips.

In light of these considerations, customized carpooling has been proposed as an economically efficient and innovative solution for organizations to offer non-stop door-to-door ride services, a sustainable option that has drawn increasing attention in recent years as public awareness of environmental issues has grown (Caulfield, 2009; Delhomme and Gheorghiu, 2016; Bruck et al., 2017; Javid et al., 2017). Carpooling is a ride-sharing practice in which one of a group of people picks up and drops off the other group members in their private car on their way to and from work (Caulfield, 2009). To reduce the number of personal vehicles traveling to and from the workplace, a large company that organizes a carpooling program can provide incentives to encourage its employees to participate in the program and pick up colleagues on their commute (Baldacci et al., 2004). The benefits of this type of program are particularly relevant in terms of the decrease in both personal vehicle use and the amount of parking space needed.

To inform the adoption of emerging transportation technologies such as carpooling systems and their net effects on sustainability, in competition with existing modes, a complete economic, environmental, and social analysis of these new modes and integrated form of them need further evaluation. This study is motivated by environmental problems caused by transportation and the corresponding need to deploy sustainable solutions. As one of those solutions, we deal with interoperating carpooling for bus routing problems and propose a different multi-objective model because of the bus and private car route planning simultaneously in the literature. We believe that this is the first work to attempt to use a multi-objective optimization model to consider carpooling behavior in Customized Bus (CB) service. The problem aims to develop an integrated configuration of the company's transportation service and employees' private cars to efficiently organize carpooling employees heading to a common destination on a daily basis. The developed formulation incorporates three objective functions, including the company's total loss, employee satisfaction, and total vehicle emissions.

The mathematical model is then linearized, which enables us to solve the suggested model more efficiently. To provide users with viable compromise solutions, a meta-heuristic algorithm based on Pareto Strength Ant Colony Optimization (PSACO) is embedded in the last multi-objective mathematical programming model. To carry out the effects of crucial parameters on the overall performance of the PSACO and find the most appropriate setting, we use parameter tuning, Iterated Racing for Automatic Algorithm Configuration (IRACE, López-Ibáñez et al., 2016). The results of the adapted meta-heuristic are compared with an exact method. In this paper, we use a real case at a service company to demonstrate the properties of the proposed model. The practical case results attest to great

potential for achieving cost savings while satisfying individuals and reducing emissions by using carpooling in the different scenarios.

The remainder of the paper is organized as follows. **Section 2** presents a brief review of the existing literature and highlights the gaps in it. In **Sections 3** and **4**, respectively the problem description, mathematical formulation, and solution framework are presented in detail. In **Section 5**, several numerical tests are executed and the efficiency of the model and its solution approaches are considered. Finally, conclusions and future research opportunities are discussed in **Section 6**.

2. Literature review

The increase in research into more sharable and sustainable systems of transportation reflects emerging challenges, such as growing environmental concerns, rising oil prices, and increasing traffic congestion. This section provides a brief overview of the main studies related to our paper in the field of customized bus problems, ride-sharing optimization models, and their solution techniques. This literature review sets out a summary report and describes the contribution of the study to the state-of-the-art.

2.1. Related work

The CB service design, in the field of operations research, is an optimization problem that involves the setting of vehicle timetables and routes serving the requests of known passengers. Chang and Schonfeld (1991) have undertaken one of the first studies of flexible bus service methods, which analytically compares the subscription feeder bus system with the conventional one. In recent years, several optimization models have addressed the operation-planning process of CB service design determining timetables, routes, stop locations, and passengers' assignment (Guo et al., 2019; Qiu et al., 2019; Dou et al., 2020; Ma et al., 2020; Sun et al., 2020; Cao and Wang, 2016).

A comprehensive examination of CB network design in China was presented by Liu and Ceder (2015). The authors analyzed the operation-planning process, including fare design and collection, real-time control, crew scheduling, vehicle scheduling, timetable development, network route design, and elements of online demand collection. Tong et al. (2017) proposed a mixed inter programming formulation for addressing practical challenges in CB service and used a Lagrangian decomposition-based algorithm to solve it. Lyu et al. (2019) jointly optimized routes, stops, timetables, and passengers' mode choices for a CB system. Huang et al. (2020) proposed a two-phase optimization model for the demand-responsive CB service. They formulated the interactive mechanism between passengers and the operator in an integrated decision-making framework. Shang et al. (2021) proposed a time-discretized dynamic programming-based school bus routing problem to design students commuting to different schools.

A data-driven approach for the arrangement and emission reduction of CB services is undertaken by Yu et al. (2020). Wang et al. (2020) proposed a multi-objective CB routing problem under stochastic

demands and employed a two-stage approach based on the NSGA-II algorithm to process static and dynamic ride requests. Chen et al. (2021) modeled a bi-objective optimization problem minimizing operating and passenger costs in the CB route design. To efficiently solve the proposed model, the authors used a heuristic algorithm with adaptive variable neighborhood search. Recently, Liu et al. (2021) investigated the operational strategy of CB considering passengers' changes in different stages.

Motivated by emerging transportation technologies, many studies have been devoted to innovative mobility ways, such as car-sharing and ride pooling systems, which have the potential to improve the efficiency and sustainability of transportation (Jorge et al., 2015; Ma et al., 2017). Carpooling, also known as ride-sharing, has attracted the attention of many researchers, leading to the existence of comprehensive literature. Readers who are interested in a more in-depth study can refer to Furuhata et al. (2013), where the authors presented a framework for identifying the main obstacles to carpooling and fostering the development of effective carpooling mechanisms. The authors in Chan and Shaheen (2012) focused on how the Internet, social media, and cell phone use are integrated into ride-sharing applications. A thorough survey of the relevant literature on ride-sharing problems was provided by Agatz et al. (2012).

In the carpooling problem literature, different objective functions have been used. Some studies aim to minimize the total fixed costs of vehicles as well as network travel costs (Yan and Chen, 2011; Mahmoudi and Zhou, 2016; Ou and Tang, 2018). Some focus on minimizing delays in carpooling services (Guo et al., 2013b). Other studies model the related problems by taking into account the penalty cost of unserved requests (Yan and Chen, 2011; Baldacci et al., 2004). While few studies focus on exact algorithms to solve the problem (Baldacci et al., 2004; Masoud and Jayakrishnan, 2017; Masoud et al., 2017; Xue et al., 2016; He et al., 2017), most previous studies introduced heuristic solution methods due to the NP-hard complexity of carpooling problems (Najmi et al., 2017; Xia et al., 2015). Some of the most important studies are discussed in detail below.

In one of the early attempts at the carpooling service problem, Agatz et al. (2011) applied an optimization model to minimize the total cost of matching riders and drivers. For the many-to-many carpooling problem developed by Yan and Chen (2011), a time-space network flow method with various kinds of vehicles was investigated and was finally solved using a Lagrangian relaxation technique. Another study performed by Bruglieri et al. (2011) introduced a carpooling problem on a carpooling service for the faculty, students, and employees of two universities with the goal of minimizing total route length while maximizing the number of users served. To solve the problem, the authors used a heuristic guided Monte-Carlo strategy. An optimization-based method for the real-time carpooling matching problem was presented by Ghoseiri (2012). In this study, a negotiating policy was supposed to match preference ride-sharing and a hierarchical temporal and spatial decomposition technique was developed to solve the problem. To handle the long-term carpooling problem, a multi-agent-based self-adaptive genetic algorithm was described by Guo et al. (2013a), who developed an ant colony-based resolution algorithm for a multi-destination version of the problem, (Guo et al., 2013b).

Yan et al. (2014) applied a heuristic technique based on a constraint relaxation algorithm to solve the carpooling problem with stochastic vehicle travel times. To minimize the transportation costs and ride distances, He et al. (2014) focused on mining Global Positioning System (GPS) trajectories in an urban ride-sharing system. Filcek and Gasior (2014) formulated a common route planning problem for carpoolers as a multi-objective optimization task and used an exact method to solve it. Hrncır et al. (2015) aimed to determine the appropriate pricing and incentive schemes to assess the potential services in the multiagent carpool routing problem. Pelzer et al. (2015) used a heuristic agent-based approach to solve a carpooling model. The objective function was to minimize detours due to picking up and dropping off additional passengers.

To provide appropriate ride matches for the carpooling service problem, Chou et al. (2016) developed a meta-heuristic algorithm of stochastic set-based particle swarm optimization based on local exploration. Zhang et al. (2016) presented a stochastic optimization-based approach; it aims to minimize the fleet size required to meet all transportation demand while maximizing the passengers served by the multi-vehicle carpooling problem. Najmi et al. (2017) employed a clustering heuristic to solve a new dynamic formulation of a real-time ride-sharing system based on trip spatial attributes. Bruck et al. (2017) aimed to minimize carbon dioxide emissions in a practical daily carpool service. They also developed two heuristic approaches to efficiently solve their proposed mathematical formulations and finally presented a prototype of the web application. To optimality solve a multi-hop peer-to-peer ride-matching problem, Masoud and Jayakrishnan (2017) applied a decomposition technique.

Different solution techniques have been developed to solve multi-objective problems. One of these is the PSACO algorithm, which has been proven to be effective for solving multi-objective optimization problems (Ariyasingha and Fernando, 2015). Ant Colony Optimization (ACO) is a meta-heuristic solution method that has recently emerged in the literature to solve complex combinatorial optimization problems (Alba and Dorronsoro, 2006; Stützle and Dorigo, 2003). The basic mechanism of such an algorithm is that a colony of artificial ants cooperates in finding good solutions for combinatorial optimization problems (see Dorigo and Di Caro, 1999). Ant System (AS) was the first attempt to use the algorithm to solve the traveling salesman problem (Colorni et al., 1992a, 1992b; Dorigo et al., 1991a, 1991b, 1996). Afterwards, various algorithms of ACO were developed as a result of further investigations done to enhance the algorithm's performance. They include Max-Min Ant System (MMAS) by Stützle and Hoos (1996, 1997), the rank-based ant system by Bullnheimer et al. (1999), ant colony combined with reinforcement learning technique (Ant-Q) by Gambardella and Dorigo (1995), and Acute Coronary Syndrome (ACS) by Gambardella and Dorigo (1996). Dorigo and Stützle (2019) published a comprehensive book on ACO algorithms.

Since the introduction of the AS by Dorigo et al. (1991a, 1991b, 1996) and Colorni et al. (1992a, 1992b), the algorithm has been employed in different NP-hard combinatorial optimization problems such as activity crashing in project management (Abdallah et al., 2009), the car sequencing problems (Moya et al., 2019; Sun and Fan, 2017), the vehicle routing problems (Kim and Park, 2018; Tan et al.,

2019; Liu et al., 2020), the job shop scheduling problems (Jong et al., 2020), resource allocation problems (Chaharsooghi and Kermani, 2008) and the travelling salesman problems (López-Ibáñez and Blum, 2010; Ebadinezhad, 2020). It has been shown ACO outperforms other heuristics like genetic algorithm and simulated annealing on a number of problems. To tackle mixed-variable optimization problems, Liao et al. (2014) extended the ACO algorithm for continuous optimization.

The ant colony optimization algorithm was initially used in single objective decision problems. Later, many studies tried to take a second objective and multiple objective functions into account (Stummer and Sun, 2005; Iredi et al., 2001; Doerner et al., 2004; McMullen 2001; Lopez-Ibanez and Stutzle, 2012). McMullen (2001) used a single combined pheromone matrix for a production sequencing problem with multiple objective functions. Stummer and Sun (2005) and Doerner et al. (2004, 2006, 2008) shown Pareto ant colony optimization using a scheme with multiple pheromone matrices, each corresponding to an objective, outperforms other meta-heuristics in solving multi-objective optimizations. In Pareto ACO, a subset of ants (within a population) updates pheromones to achieve the best and second-best solutions along with each respective objective on the current non-dominated fronts. However, in previous attempts, these updates on the constants were considered fixed and not related to their performance. To more information on various multi-objective ACO algorithms and their configurations, see Ariyasingha and Fernando (2015).

2.2. Research gaps and contribution

In **Table 1**, we summarize the most relevant studies on ride-sharing systems and carpooling services. The column headings represent the main features of these problems, including having several riders (R), considering vehicle capacity constraints (Ca), synchronization or coordinating different transportation units in terms of time and space (Syn), social impacts (Sc), environmental impacts (En), bus routing problem (BRP), multi-objective approach (MO), and the objectives and solution techniques employed to solve the problem. Considering synchronization constraints in carpooling problems can be another significant feature of these studies (Herbawi and Weber, 2012; Baldacci et al., 2004; Hosni et al., 2014; Lee and Savelsbergh, 2015; Stiglic et al., 2018; Żak et al., 2019). As shown in **Table 1**, very few ride-sharing papers have focused on participants' satisfaction with the service provided by the system (Masoud et al., 2017; Wang et al., 2018; Lu and Quadrifoglio, 2019; Żak et al., 2019) or greenhouse gas emissions (Stiglic et al., 2016; Javid et al., 2017) despite their importance in routing and scheduling realistic shared mobility systems like ride-sharing. We could not find any meaningful effort to consider the bus routing problem. Moreover, in the literature, multi-objective optimization is rarely studied, except by Żak et al. (2019) who used a combination of two multi-objective sub-problems, including the carpool matching problem and the vehicle routing problem, in a multiple criteria optimization problem, and Beed et al. (2020), who proposed a hierarchical approach of classifying objectives including the total distance traveled, individual passenger cost, and car utilization.

Table 1

An overview of the related papers.

Study authors (Year)	R	Ca	Syn	Sc	En	BRP	MO	Objective function	Solution method
Baldacci et al. (2004)	✓	✓	✓					Td, Pn	Column generation algorithm
Wolfler Calvo et al. (2004)	✓	✓						Tt	Heuristic
Herbawi and Weber (2012)	✓	✓	✓					Td, Tt, Pn	Genetic algorithm
Huang et al. (2013)								Oc	Branch-and-bound & integer programing algorithm
Kaan and Olinick (2013)	✓	✓						Oc	Heuristic
Hosni et al. (2014)	✓	✓	✓					Oc	Lagrangian decomposition
Lee and Savelsbergh (2015)			✓					Oc	Meta-heuristic
Santos and Xavier (2015)	✓	✓						Pn	Greedy randomized adaptive search procedure
Stiglic et al. (2015)	✓	✓						Td, Pn	Matching solution approach
Jung and Jayakrishnan (2016)	✓	✓						Tt, Oc	Hybrid-simulated annealing
Stiglic et al. (2016)	✓				✓			Pn	Simulation
Alonso-Mora et al. (2017)	✓	✓						Oc	Greedy assignment
Masoud et al. (2017)	✓	✓		✓				Pn	Exact method
Kalczynski and Miklas-Kalczynska (2018)	✓	✓						Td	Heuristic
Stiglic et al. (2018)	✓	✓	✓					Tt, Oc	Matching solution approach
Wang et al. (2018)		✓		✓				Td	Matching solution approach
Chen et al. (2019)	✓	✓						Tt, Oc, Dp	Constructive heuristic
Lu and Quadrifoglio (2019)		✓		✓				Td	Exact method
Tamannaei and Irandoost (2019)	✓	✓						Td, Fc, Dp	CPLEX
Żak et al. (2019)			✓	✓			✓	Td, Tt, Oc	NSGA-II
Beed et al. (2020)	✓	✓					✓	Td, Oc, Or	Genetic algorithm
Our study	✓	✓	✓	✓	✓	✓	✓	Td, Tt, Pn, Fc, Oc, E, Dp, Or	CPLEX & PSACO

Td: Travel distance, Tt: Travel time, Pn: Number of participants, Fc: Fix cost, Oc: Operational cost, E: Emissions, Dp: Delayed arrival penalty, Or: Occupancy rate.

This study seeks to bridge the gaps in the existing literature by developing a mixed-integer non-linear programming model to optimize carpooling behavior in a bus routing problem. This study's contribution to the state-of-the-art can be summarized as follows:

- To efficiently organize carpooling employees on a daily basis, this study develops an integrated configuration of the company's transportation service and employees' private cars in which the company is willing to provide incentives to employees who carpool to work.
- Unlike previous articles published in the context of ride-sharing systems and carpooling services, this study is the only research that designs and evaluates an integrated routing and scheduling

problem simultaneously exploring environmental and social implications of incorporating carpooling service into a customized bus system.

- The proposed problem extends the multi-vehicle carpooling problem to include: (*i*) transportation service costs and incentives intended to encourage staff to participate in the program, (*ii*) employee satisfaction resulting from door-to-door ride service and reduced commute times, and (*iii*) reducing traffic congestion, greenhouse gas emissions, individual employee commuting costs including fuel and tolls, and the stress of driving by having more employees use one vehicle.
- To guarantee the optimality of the larger-scale problems, this study proposes a resolution algorithm from a Pareto frontier based on the Pareto Strength Ant Colony Optimization algorithm. The results of the embedded meta-heuristic approach are compared with an exact method.

The proposed multi-objective mathematical model and the developed PSACO algorithm are expected to assist large companies in designing an integrated transit service and realizing the importance of tradeoffs among the conflicting route service components. We believe that if similar approaches, the combination of the existing modes with various novel transportation technologies and systems, are implemented in various state/private organizations, a significant reduction in the company costs and vehicle pollutants can be achieved. Furthermore, the social impact from this company-level customized ridesharing system looks noticeable to the society.

3. Problem definition

The research highlighted in the introduction is motivated by the environmental damage done by transportation and the corresponding need to deploy sustainable solutions. This study focuses on carpooling as one of those solutions and develops a multi-objective optimization model for the integrated carpooling and bus routing problem. As illustrated in **Fig. 1**, in this study we aim to design an integrated platform for carpooling groups and organize the company's bus system, which can be an effective tool in reducing transportation costs and directly cutting CO_2 emissions. This mechanism can provide an opportunity for decision-makers to make the company's transportation service more effective and individuals' participation more efficient. The insights acquired through this process can be used to establish a framework for designing incentive and pricing policies aimed at improving the ride-sharing system's performance.

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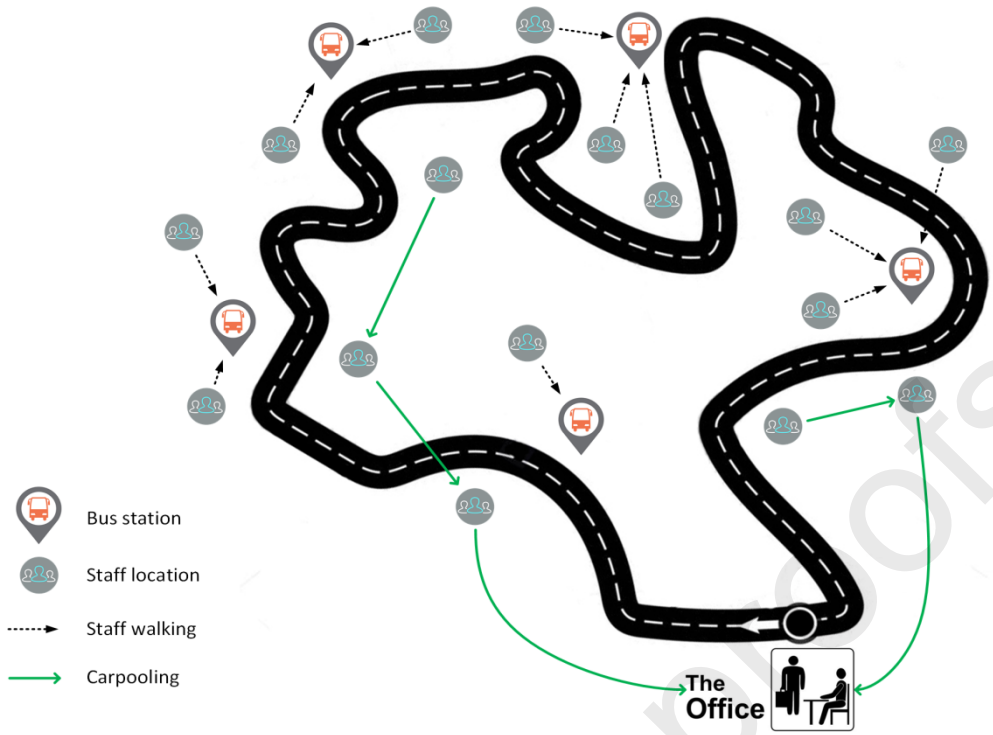

Fig. 1. The structure of the integrated network studied.

The model is intended to support the configuration of a company's transportation service for commuting, taking environmental and social impact into account. To this end, the objective functions minimize the company's bus operation and carpooling participation incentive costs, employees' dissatisfaction due to commuting, and the carbon emissions from transportation. In this problem, as in the real case, we assume that certain employees are expected to request to share trips with friends. The company or organization can rent an unlimited number of buses; the fixed and variable costs of using each one are considered in the objective function. Each bus used in the fleet must stop at a number of bus stops so that all stations are covered by buses. Each bus can pick up several passengers at each station as long as the capacity of the bus allows. Each of the buses will return to the organization at the end of the trip. In this case, we consider the satisfaction associated with traveling by bus to be different (probably less) than that associated with traveling by car.

The most important difference between the proposed approach and normal carpooling and CB/shuttle bus service is the more complexity of their simultaneous planning, which can be the result of the following:

- Integration of the two well-studied problems car-sharing and customized bus service problems that imposes more computational complexity on the system.
- The multi-objective framework of the proposed model to make a trade-off between the triple bottom line of sustainability.
- Private cars and buses visit different nodes.
- Not all nodes are visited by private cars nor all bus stops are visited by buses.

- The travel time required to traverse a specific distance is considered to be different for private cars and buses.
- Using each of the carpooling and company's shuttle bus service schemes has different carbon emissions and costs, and also creates different levels of satisfaction for travelers.
- The node from which each carpooling trip begins is one of the applicants' nodes designated by the model as the driver, the one to whom the incentive is paid.
- To encourage employees to participate in the carpooling program, incentives paid to drivers increase with the number of people using a shared car.
- Employees who want to take the bus will have to walk a certain distance from their homes to the nearest bus stop. On the other hand, employees who carpool or ride-share with colleagues do not need to walk, since they are picked up by a private car in front of their homes.

In this problem, we also consider the amount of emissions produced by private cars, which can vary depending on the distance each car travels, according to the standard rules proposed by Mirzapour Al-e-hashem et al. (2013).

Prior to describing the mathematical model, in the following subsections we provide the assumptions and notations pertaining to our framework for the reader's convenience.

3.1. Assumptions

- All parameters are considered to be deterministic.
- Private cars and buses are assumed to be heterogeneous, with different emission standards (e.g., Euro 5, Euro 6, etc.) and different CO_2 emission indices.
- All employee transportation demand is met.
- Each pickup point, including bus stations and staff locations, must be visited no more than once.
- For each private car, the whole penalty cost of delay is proportional to that vehicle's delay.
- If an employee registers as a passenger, he/she is not allowed to drive his/her car (for the home/office trip).
- Each bus has the same origin and destination.
- Compared to the operational costs of shuttle service, the implementation cost of this computer application is negligible; therefore, it is ignored.
- Compared to the operational costs of shuttle service, the subscription cost of this computer application is either negligible or could be added as fixed cost; therefore, it is ignored.

3.2. Constants

K:	Set of potential locations for bus stops. We consider 0 as the center (arrival and departure node).

L:	Set of all applicants' nodes. We consider 0 as the center (departure node).
N_j:	Set of applicants' nodes ($i \in L$) located at a distance less than a standard distance for covering (dl) from potential location j ($N_j = \{i \mid d_{ij} < dl\}, j \in K$).
B:	Set of all buses.
C:	Set of available private cars ($v \in V = \{B \cup C\}$), which its number is less than or equal to the number of employees ($\lvert C \rvert \leq \lvert L \rvert$). j_v indicates the applicant's node to which the car belongs ($j_v \in L, v \in C$).
st:	Starting time by which employees must be present at the office
d_{ij}:	Symmetrical distance between node i and node j (Km)
q_v:	Capacity of vehicle v
f_v:	Fixed costs of using bus v (USD)
c_{ijv}:	Variable costs of bus v traveled from location i to node j (USD/Km)
t_{ij}^B:	Travel time from node i to node j by bus (hour)
t_{ij}^C:	Travel time from node i to node j by private car (hour)
α:	Dissatisfaction comes along with the unit-time delay at the start of work
β:	Incentive paid for carpooling (USD)
δ_j:	Satisfaction (as a negative parameter) or dissatisfaction (as a positive parameter) for every 1 kilometer of walking by the person in node j
$\rho^C(\rho^B)$:	Dissatisfaction comes along with one unit of travel time by private car (bus)
t^w:	Average time required to walk one kilometer (hour)
ω_v:	CO_2 emitted by vehicle v (g/Km)
M:	An arbitrary large number

3.3. Decision variables

X_{ijv}:	1, if vehicle v visits node j immediately after node i; 0, otherwise
Y_{lj}:	1, if the person in node l needs to go to node j for using the bus; 0, otherwise
Z_v:	1, if bus v is used in the fleet; 0, otherwise
W_j:	Distance traveled by the person in node j to the nearest bus stop (Km)
T_j:	The bus/vehicle arrival time at node j

3.4. Mathematical model

Based on the descriptions and indices laid out above, a multi-objective mixed-integer non-linear programming model can be formulated as below:

$$\text{Min} \sum_{v \in B} f_v.Z_v + \sum_{i,j \in K} \sum_{v \in B} c_{ijv}.d_{ij}.X_{ijv} + \beta.\sum_{v \in C} Max\left\{\sum_{i,j \in L} X_{ijv} - 1,0\right\} \tag{1}$$

$$\text{Min} \sum_{i \in L} \delta_i.t^w.W_i + \sum_{i,j \in L} \sum_{v \in C} \rho^C.(st - T_j).X_{ijv} + \sum_{l \in N_j} \sum_{j \in K} \rho^B.(st - T_j + t^w.d_{lj}).Y_{lj} + \sum_{j \in L} \sum_{v \in C} \alpha.X_{j0v}.Max\{T_j + t_{j0}^C - st, 0\} \tag{2}$$

$$\text{Min} \sum_{i,j \in L} \sum_{v \in C} \omega_v.d_{ij}.X_{ijv} + \sum_{l \in L} \sum_{i,j \in K} \sum_{v \in B} \omega_v.d_{ij}.Y_{lj}.X_{ijv} \tag{3}$$

s.t.

$$\sum_{l \in N_j} Y_{lj} \leq M.\sum_{i \in K/j} \sum_{v \in B} X_{ijv}, \qquad \forall j \in K \tag{4}$$

$$\sum_{i \in K/j} \sum_{v \in B} X_{ijv} = 1, \qquad \forall j \in K/0 \tag{5}$$

$$\left\{\sum_{j \in K} X_{0jv}, \sum_{i \in K} X_{i0v}\right\} \leq 1, \qquad \forall v \in B \tag{6}$$

$$Y_{lj} + \sum_{i \in \{L \cup 0\}} \sum_{v \in C} X_{liv} = 1, \qquad \forall j \in K, \forall l \in N_j \tag{7}$$

$$\sum_{i,j \in K} X_{ijv} \leq M.Z_v, \qquad \forall v \in B \tag{8}$$

$$\sum_{i \in K/j} (X_{ijv} - X_{jiv}) = 0, \qquad \forall v \in B, \forall j \in K/0 \tag{9}$$

$$\sum_{i \in L/j} (X_{ijv} - X_{jiv}) = 0, \qquad \forall v \in C, \forall j \in L/\{j_v \cup 0\} \tag{10}$$

$$\sum_{i,j \in L} X_{ijv} \leq q_v, \qquad \forall v \in C \tag{11}$$

$$\sum_{l \in L} \sum_{i,j \in K} Y_{lj}.X_{ijv} \leq q_v, \qquad \forall v \in B \tag{12}$$

$$W_i = \sum_{j \in K} Y_{ij}.d_{ij}, \qquad \forall i \in L \tag{13}$$

$$T_i + t_{i0}^B \leq st + M\left(1 - \sum_{v \in B} X_{i0v}\right), \qquad \forall i \in K \tag{14}$$

$$T_i + t_{ij}^B \leq T_j + M\left(1 - \sum_{v \in B} X_{ijv}\right), \qquad \forall i,j \in K \tag{15}$$

$$T_i + t_{ij}^C \leq T_j + M\left(1 - \sum_{v \in C} X_{ijv}\right), \qquad \forall i,j \in L \tag{16}$$

$$T_j, W_j \in R^+, \qquad \forall j \in J \tag{17}$$

$$X_{ijv}, Y_{lj}, Z_v \in \{0,1\}, \qquad \forall i,j,l \in J, \forall v \in V \tag{18}$$

Three components of the first objective function (1) minimize, respectively, the fixed cost of using or renting buses, transportation-related costs modeled as a linear function of the distance traveled, and the incentive paid to the drivers of the private cars which depends on the number of people who share a car. The second objective function of the proposed mathematical model (2) measures the satisfaction or dissatisfaction resulting from the walk required to reach the nearest bus stop, travel time by private car and bus (since employees need to leave earlier to use the organization's bus service, there will usually be more dissatisfaction with the bus), and the penalty resulting from late arrival at work when employees use private cars. In calculating the late arrival time, we took into account the last applicant's node visited by car in the tour. The third objective function (3) aims to minimize the total amount of CO_2 emissions from vehicles used for commuting, which depends on the vehicle's occupation rate and the distance traveled. Constraint (4) ensures that if a person goes to a bus stop, that station must be served by a bus. Constraint (5) indicates that each bus stop is visited by a maximum of one bus.

Constraint (6) compels buses to begin from/return to the center. Constraint (7) ensures that each employee must be serviced either by a private car or by a bus. Constraint (8) forces the logical relationship between variables and ensures that nodes can only be assigned to buses used in the organization's fleet. Constraints (9) and (10) specify the flow conservation constraints for buses and private cars in turn. Constraints (11) and (12) prevent overuse of shared vehicles. Constraint (13) shows the distance a person must travel to reach the nearest bus stop. Constraints (14) – (16) guarantee that service to node *j* must be at least started after the service time to node *i*, plus the time needed to travel between two nodes, if the same vehicle serves node *i* immediately before node *j*. Eventually, constraint (17) forces the corresponding decision variables to be non-negative, and constraint (18) imposes the integrality restrictions on the binary values of decision variables.

Linearization technique

It is expedient for the proposed mathematical formula to be linearized because of the much lower computation time and the significant improvement in the efficiency of linear programming form compared to its non-linear form. Since this model is non-linear, which results from multiplying the variables in the second and third objective functions and constraint (12), we use a linearization method discussed in Asghari and Mirzapour Al-e-Hashem (2020a). To linearize two bilinear terms $T_j.X_{ijv}$ and $T_j.Y_{lj}$ in the second objective, we replace them with the following auxiliary variables:

$$T_j.X_{ijv} \rightarrow XT_{ijv}, \qquad \forall i, j \in L, \forall v \in C \tag{19}$$

$$T_j.Y_{lj} \rightarrow YT_{lj}, \qquad \forall l \in L, \forall j \in K \tag{20}$$

Using (19) and (20), the equations in the objective function would be rewritten as follows:

$$\sum_{j \in L} \sum_{v \in C} \alpha.\left(XT_{j0v} + X_{j0v}.t_{j0}^{C} - X_{j0v}.st\right) \tag{21}$$

$$\sum_{i,j \in L} \sum_{v \in C} \rho^{C}.\left(st.X_{ijv} - XT_{ijv}\right) + \sum_{l \in N} \sum_{j \in K} \rho^{B}.\left(st.Y_{lj} - YT_{lj} + t^{w}.d_{ij}.Y_{lj}\right) \tag{22}$$

So as to linearize two nonlinear expressions $Max\left\{\sum_{i,j \in J} X_{ijv} - 1, 0\right\}$ and $Max\left\{XT_{j0v} + X_{j0v}.t_{j0}^{C} - X_{j0v}.st, 0\right\}$ in the objective functions which are currently nonlinear due to the $maximum$ operators, we use the *maxl* function of IBM ILOG CPLEX. We also use the *minl* function by substituting the binary variables multiplication in the third objective function and constraint (12), $Y_{lj}.X_{ijv}$, with $minimum$ operator min $\{Y_{lj}, X_{ijv}\}$, respectively. Interested readers can investigate more about this linearization technique in Mohammadi et al. (2020). The model can be linearized by adding some new constraints as follows:

$$XT_{ijv} \leq \{T_j, M.X_{ijv}\}, \qquad \forall i, j \in J, \forall v \in V \tag{23}$$

$$XT_{ijv} \geq \{0, T_j + M.(X_{ijv} - 1)\}, \qquad \forall i, j \in J, \forall v \in V \tag{24}$$

$$YT_{lj} \leq \{T_j, M.Y_{lj}\}, \qquad \forall l \in L, \forall j \in J \tag{25}$$

$$YT_{lj} \geq \{0, T_j + M.(Y_{lj} - 1)\}, \qquad \forall l \in L, \forall j \in J \tag{26}$$

4. Solution procedures

There are several ways to solve combinatorial optimization problems with multiple and competing objectives, known as multi-objective programming. We utilize the IBM ILOG CPLEX solver to reach optimal solutions for the proposed linearized mathematical model in small-scale cases. However, the commercial solver cannot solve large-scale cases within a reasonable time, leading us to develop a meta-heuristic PSACO (Pareto Strength Ant Colony Optimization) algorithm.

ACO procedure is a widely used meta-heuristic to solve the combinatorial optimization problems concerning more than one objective (Sahraoui et al., 2018). However, early adaptations of multi-objective ACO applied equal or fixed weights for heuristic and/or pheromone trails in each objective, and then aggregated them based on a weighted sum or weighted product approach (Lopez-Ibanez and Stutzle, 2012). Thus, the solutions might be found only in a specific part of the Pareto front. The PSACO algorithms, which use the Pareto optimality and dominance concepts, have been proven to be very effective in the simultaneous optimization of any number of conflicting objectives and perform better when extended to deal with a discrete and combinatorial structure of large size multi-objective problems (Doerner et al., 2004).

Although the PSACO algorithm has previously been used for solving different multi-objective route planning (Pasia et al., 2007; Kuo et al., 2016), some changes are made to adapt this paradigm to our ride-sharing framework. For example, (i) how to update pheromone trails in which all ants from a population are contributed based on their performance, (ii) mutation operation that is perfectly designed for this problem, (iii) node clustering and its sequence codes, (iv) elitism procedure in which the concept of best non-dominated solutions is modified to promote diversity, and (v) the heuristic information value which represents a priori information of the problem and different objective functions. In the following, we detail the explanation of the algorithm adapted in this study.

4.1. Ant colony optimization algorithm

Ant System is the first ACO algorithm. It was developed by Dorigo et al. (1996) to solve stochastic combinatorial optimization problems. All the previously used pheromone trails are related to arcs which set to an initial given value of pheromone τ_0. The heuristic information η is equal to $1/d_{ij}$, where d_{ij} denotes the distance between nodes i and j. Initially, m ants are located in the randomly chosen nodes. Each ant k then changes position from node i to node j by employing the probabilistic formula,

$$P_{ij}^k = \begin{cases} \dfrac{(\tau_{ij})^\alpha (\eta_{ij})^\beta}{\sum_{u \in N_i^k} (\tau_{iu})^\alpha (\eta_{iu})^\beta}, & if\ j \in N_i^k \\ 0, & otherwise \end{cases} \tag{27}$$

where α and β are parameters that respectively represent the relative importance of the pheromone trail and the heuristic information. N_i^k is the feasible neighborhood of ant k in node i. At each construction step, every ant placed at node i probability selects the next node j as below:

$$j = \begin{cases} \arg\max\{(\tau_{iu})^{\alpha}(\eta_{iu})^{\beta}\}, & for\ u \notin tabu_k, if\ q \leq q_0 \\ S, & otherwise \end{cases} \tag{28}$$

where τ_{iu} denotes the pheromone value of the path between the current node i and the possible node u. The visibility on arc (i, u) is defined by η_{iu}, which is equal to the inverse of the distance between node i and node u, $\eta_{iu} = 1/d_{iu}$. Nodes that have already been visited by ant k are kept in the set $tabu_k$ and cannot be re-selected. q is a random variable that is uniformly distributed in [0, 1] and parameter q_0, $0 \leq q_0 \leq 1$, measures exploitation against the ants' exploration during the search process. S can be attained by the roulette wheel rule using the probabilistic formula given in equation (27).

Updating the pheromone trails is an essential part in ACO adaptive learning and improving the subsequent solutions. After n iterations when all the ants have completed their tour, the pheromone trails are deposited on the paths already visited by ants as follows:

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{29}$$

ρ ($0 \leq \rho < 1$) denotes the pheromone evaporation rate and $\Delta\tau_{ij}^{k}$ denotes the level of pheromones on arc (i, j) deposited by ant k. In AS, $\Delta\tau_{ij}^{k}$ is defined by the following equation:

$$\Delta\tau_{ij}^{k} = \frac{A}{L_k} \tag{30}$$

A is a constant and L_k denotes a fitness value of the tour completed by the kth ant. This fitness value is calculated as the sum of the objective functions (1)-(3).

To avoid premature convergence on a local optimum in the ACO algorithm and diversify the population, this study applies the mutation operation, which aims to change some assignments to generate new solutions to this algorithm. To explain the mutation operators, **Fig. 2** illustrates an example of a solution with 14 stations visited by 3 buses. As shown in **Fig. 3**, the mutation operation is executed on sequence codes transformed from the solution depicted in **Fig. 2** in which the depot and the employees who use the bus have been eliminated from the code.

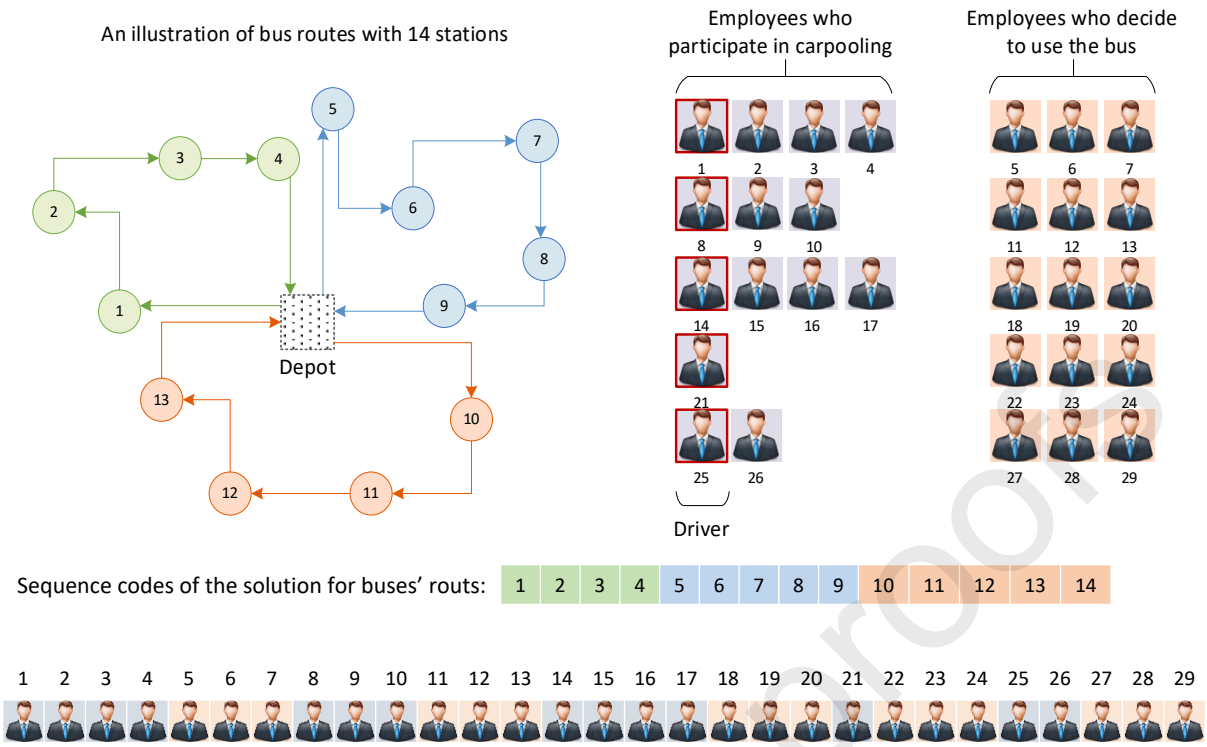

Fig. 2. Generic diagram of a typical solution and its sequence codes through a set of stations and carpool passengers.

In **Fig. 3**, carpooling participants who use a specific private car are divided by blank characters. These employees are classified into five different groups, {1, 2, 3, 4}, {8, 9, 10}, {14, 15, 16, 17}, {21}, and {25, 26}, in which the first numbers (i.e., 1, 8, 14, 21, and 25) show the car owners. The mutation operator randomly conducts node substitution without considering the restrictions on route times and vehicle capacity. The operator randomly selects several pairs of bus stations and travel applicants who registered for the carpooling program as passengers, e.g., 1 and 11, 3 and 6, 5 and 8 among the bus stops, and 2 and 8, 3 and 26, 10 and 21 among the employees who use carpooling. As shown in this figure, a new sequence code is obtained by replacing these pairs of nodes.

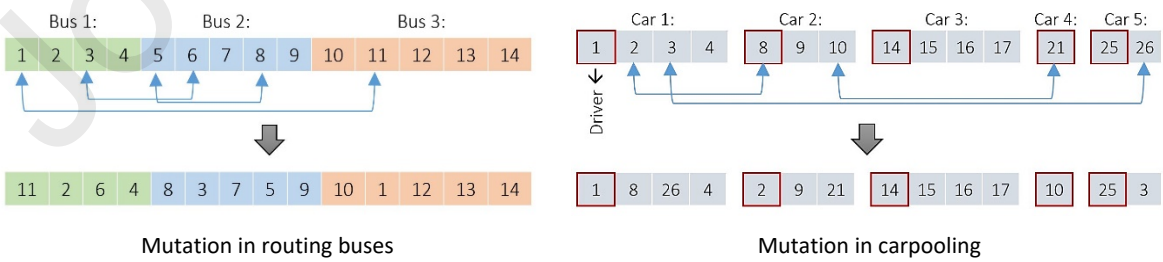

Fig. 3. Representation of the sequence obtained using the mutation operator.

Fig. 4 shows how to produce new solutions for carpooling using a random array. In this approach, the carpooling nodes are determined on the basis of values assigned to the nodes. Then, as shown in

Fig. 4, some points, e.g., 7, 16, 20, and 27, will be randomly selected and applicant clusters will be formed in the solution constructed by ant *l*. In producing solutions that fall on the current non-dominated fronts, all ants from a population are allowed to contribute in updating pheromones, the amounts of which depends on their performance. The solutions can be attained using Pseudo code 1.

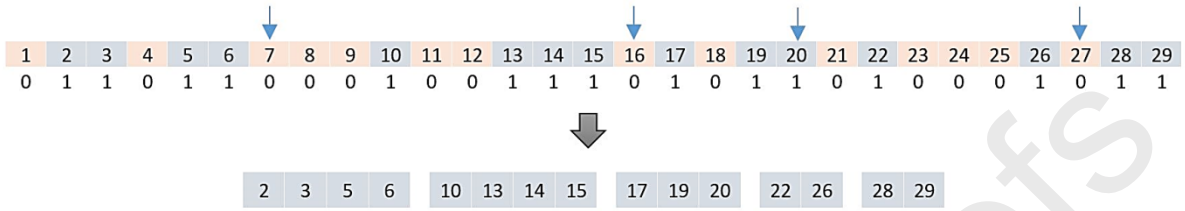

Fig. 4. New solution obtained using random array and clustering nodes.

Pseudo code 1. The ACO algorithm procedure for finding initial solutions.

Step 1.	Information:
-	*Input: the number of ants m,* $0 \le q_0 \le 1$*, the set of bus stops* (K) *and applicants' nodes* (L)*, the set of buses* (B) *and private cars* (C)*, maximum route time* r_i *and the limited capacity* q_i *for all* $i \in \{B \cup C\}$*.*
-	*Output: m initial solutions.*
Step 2.	Initialization:
-	*For* $k \in K$*, start ant k at the depot, for* $l \in L$*, start ant l at each applicant's node, and initialize the set of visited nodes* $tabu = \emptyset$*; candidate bus stops* $cnd_k = \{1, 2, \cdots, k\}$ *and applicants' nodes* $cnd_l = \{1, 2, \cdots, l\}$*.*
-	*Set* $k = 1$ *and* $l = 1$*.*
Step 3.	*For the given bus* $b \in B$ *and private car* $c \in C$*, make new solution for carpooling and set available capacity* $qq_i = q_i$*, and route time* $rr_i = r_i$*.*
Step 4.	Update the candidate list: *According to* $tabu$*,* qub_b*,* qq_c*,* rr_i*, constraint of allocating passengers to bus or private car* [*based on Eq.* (7)*, if the passenger is assigned to a bus, that applicant's node will be removed from the list of applicants' nodes* (cnd_l)]*, the capacity constraints* (11) *and* (12) *and route time constraints* (14)-(16)*, update* cnd_k and cnd_l *for ant k and l, respectively.*
Step 5.	Criterion of constructing another route:
-	*If* $cnd_k = \emptyset$*, then set* $k = k + 1$ *and return to Step 3 (the ant k recommences from the depot and constructs another route); otherwise, go to Step 6.*
-	*If* $cnd_l = \emptyset$*, then set* $l = l + 1$ *and return to Step 3 (the ant l recommences from the depot and constructs another route); otherwise, go to Step 6.*
Step 6.	Selecting the next node:
-	*If* $cnd_k \neq \emptyset$*, then select the next bus station to be visited j (*$j \notin tabu \wedge j \in cnd_k$*) according to Equations* (27) *and* (28)*.*
-	*If* $cnd_l \neq \emptyset$*, then select the next applicant's node to be visited j (*$j \notin tabu \wedge j \in cnd_l$*) according to Equations* (27) *and* (28)*.*
Step 7.	*Set* $tabu = tabu \cup \{j\}$*,* $rr_i = rr_i - t_{uj}$ *(u is the vertex visited before j by vehicle i) and* $qq_i = qq_i - 1$*, and go to Step 8.*

Step 8.	*If* $cnd_k = \emptyset$ *(then set* $k = k + 1$*) and* $cnd_l = \emptyset$ *(then set* $l = l + 1$*), go to Step 9; otherwise, go to Step 4.*
Step 9.	Stopping criterion*: If* $k > K \wedge l > L$*, then stop; otherwise, set* $k = 1$ *(if* $k \leq K$*)* or $l = 1$ *(if* $l \leq L$*) and go to Step 3.*

Suppose that the sum of the solutions is indicated by $S_1 + S_2$ where S_2 denotes offspring solutions attained by using the mutation operator and S_1 denotes the number of ants ($S_2 \leq S_1$). The $S_1 + S_2$ solutions are ranked based on the fitness value of ant l ($1 \leq l \leq S_1 + S_2$), which is evaluated by the objective values related to solution l. The first S_1 solutions are then applied to update the amount of pheromone on each arc defined in Eq. (30).

4.2. Pareto strength ant colony optimization algorithm

To obtain non-dominant solutions for the multi-objective mathematical model, this work develops a pareto strength version of the ACO algorithm. An AS-based PSACO algorithm was introduced by Thantulage (2009) for solving multi-objective optimization problems. The PSACO algorithm applies the same pheromone matrix for all the objective functions, while the pheromone trails are updated by applying the domination concept employed in SPEA-II (Zitzler et al., 2001). The ants use the random proposition rule as described in the AS algorithm, Eq. (27) while moving from one node to another. Although the PSACO algorithm has previously been used for solving different multi-objective routing problems, some changes must be made to adapt this algorithm to our framework.

The notable change in the PSACO algorithm is the pheromone update procedure. The algorithm keeps two sets of solutions in each iteration (t): population P_t and archive A_t. The population P_t contains solutions generated in the current iteration. The overall best non-dominated solutions are also stored in a fixed-number set, archive A_t. If the number of best non-dominated solutions is smaller than the archive size, the archive A_t will be completed with the current best dominated solutions. Note that, in SPEA, the concept of best non-dominated solutions is slightly modified to promote diversity. The number of solutions in the population P_t and the archive A_t dominated by a solution i assigns a strength value as follows:

$$S(i) = |\{j | j \in P_t \cup A_t \wedge i \succ j\}| \tag{31}$$

where $i \succ j$ represents that solution j is dominated by solution i and $|.|$ denotes the cardinality of a set. Based on this strength value, the raw fitness of each solution $R(i)$ can be determined. A form of proximity search, Nearest Neighbor Search, is also used to measure the density information $D(i)$. The quality of an individual solution $Q(i)$ can then be set using the following equation:

$$Q(i) = \frac{1}{R(i) + D(i)} \tag{32}$$

The value of $Q(i)$ used to update the pheromone in the PSACO algorithm follows the same procedure as that defined in Eq. (28) and Eq. (29) for AS. Consequently, a new archive is produced by copying all the non-dominated solutions in the population P_t and the archive A_t. If the number of non-dominated solutions exceeds the fixed size of the archive, some solutions will be removed from the archive. The heuristic information is calculated as follows:

$$\eta_{ij} = \theta \frac{1}{\rho \sum_{k \in K} w_k f_k} \tag{33}$$

where k denotes the number of objective functions and w_k is the weighting coefficient of each one. Moreover, the value of objective function k is denoted by f_k. θ and ρ are fixed parameters.

5. Computational results

To demonstrate the validity and effectiveness of the proposed mathematical model and the solution approaches, in this section, we implement them on numerical examples inspired by a real case. Sensitivity analyses are then performed to examine the results derived in prior sections and to survey the effects of the main parameters on the problem's behavior. To obtain optimum/near-optimum solutions, all experiments were coded using the CPLEX script accessed via IBM ILOG CPLEX Optimization Studio 12.8 and C# programming language on a machine with a 3-core 2.13 GHz processor and 4.0 GB of RAM.

5.1. Case study

To verify the effectiveness and applicability of the proposed problem, we provide real numerical evidence based on the collected data from a real employee transportation service in Paris and run the model on this case.

Input data description

As illustrated in **Fig. 5**, we consider a service network with 18 bus stops. The blue circle denotes the location of the office (arrival and departure node). The organization can rent an unlimited number of buses; the travel cost, the amount of generated greenhouse gas emissions, and the capacity of each of them are known. The stations must be visited by the company's buses include Rue des Pyrénées (S_1), Porte Maillot (S_2), Pont Cardinet (S_3), Javel (S_4), Vaugirard (S_5), Labrouste (S_6), Alesia (S_7), Observatoire (S_8), Université Paris VI (S_9), Daumesnil (S_{10}), Bercy Seine (S_{11}), Porte de Charenton (S_{12}), Avron (S_{13}), Rue Vieille du Temple (S_{14}), La Fayette (S_{15}), Stalingrad (S_{16}), Terminus Ligne (S_{17}), and George V (S_{18}). In this case, we examine 82 applicants where their approximate positions are shown in **Fig. 5** with gold circles.

Fig. 5. The employee transportation service network of the case study.

The symmetrical distance between each pair of bus stations is detailed in **Table 2** (0 is the index of office location). Travel times between the bus stations are determined by an average speed of around 22.81 km/h at which most public transport buses run on urban networks during rush hours. We have used an online tool, Google Maps for calculation distances between nodes. It should be noted that road congestion and travel time change during the day, thus the time traveled by private cars between each pair of nodes has been calculated using the same tool at 7:00 to 8:00 AM. The number of available private cars is assumed to be equal to three-quarters of the number of applicants. Besides, the capacity of private cars is 4 and the passenger seating capacity of buses ranges from 18 to 25 people. The fixed and variable cost of travel per unit of distance by each bus are assumed to be $200 and $0.65, respectively. We also estimated the emissions generated by different types of vehicles using the standard rules proposed by Mirzapour Al-e-hashem et al. (2013).

Table 2

Distance between each pair of nodes (kilometer).

Index	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}
0	6.2	9.1	8.2	6.8	5.5	4.3	2.9	1.7	1.9	2.4	2.5	5.3	4.4	4.2	5.7	7.1	5.8	6.8
S_1	0.0	10.3	8.4	18	16.2	14.1	7.4	6.2	4.3	3.4	7.2	3.7	1.6	4.1	5.2	4.8	6.4	8.6
S_2		000	3.2	8.7	9.8	10.7	12.2	7.5	7.9	9.4	9.5	17.6	14	8.2	6.6	9.4	4.6	2.7
S_3			0.0	6.8	7.0	7.3	7.5	6.3	6.6	8.6	8.7	18.4	14.9	6.5	4.4	4.4	2.4	3.2
S_4				0.0	2.1	3.2	5.6	5.0	7.4	9.7	9.3	11.9	16.5	8.4	8.2	8.9	6.2	3.8
S_5					0.0	1.1	3.5	2.9	4.8	6.8	6.9	10.3	8.8	6.0	6.7	7.8	6.0	4.1
S_6						0.0	3.1	3.1	5.1	7.7	7.1	9.6	13.3	7.0	7.0	8.1	6.4	4.8
S_7							0.0	2.3	4.9	6.2	5.5	7.3	11.0	6.3	7.0	8.1	7.6	6.7
S_8								0.0	2.6	4.6	4.7	7.5	6.7	4.0	4.7	5.8	4.8	5.2

Index	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}
S_9									0.0	1.9	2.4	5.2	4.0	2.3	4.2	5.2	4.3	5.7
S_{10}										0.0	2.3	2.3	2.1	2.2	4.2	5.0	5.3	7.6
S_{11}											0.0	3.2	3.6	3.4	5.9	6.2	6.0	7.4
S_{12}												0.0	2.7	5.5	7.5	7.3	8.7	10.1
S_{13}													0.0	3.7	4.9	4.5	6.1	9.4
S_{14}														0.0	2.6	3.5	3.4	6.3
S_{15}															0.0	5.5	3.2	1.4
S_{16}																0.0	4.1	6.4
S_{17}																	0.0	2.9

Table 3 lists the applicants covered by each bus station and their distance. We assume that employees whose residences locate more than 2 km away from the nearest bus stop would not use the organization's transportation service ($dl = 2$). The average speed of humans walking on crosswalks is assumed to be about 5 km/h. Therefore, the average time required to walk one kilometer is set to 0.2 hours. We also set dissatisfaction coefficient caused by delays, use of private cars, and buses between 2 and 9, and walking satisfaction/dissatisfaction between -10 and 10. The starting time by which employees must be present at the office is 8:00 AM. The company offers an incentive of about $10 to participate in the carpooling scheme and riding each passenger.

Table 3

Distance between applicants' locations and bus stations (kilometer).

Index	Covered applicants (N_j)	Distance
S_1	$\{a_{41},a_{42},a_{43},a_{44},a_{45},a_{46},a_{47}\}$	{1.919, 0.808, 1.746, 1.858, 1.573, 1.650, 1.903}
S_2	$\{a_{74},a_{75},a_{76},a_{78}\}$	{1.510, 1.069, 1.931, 1.784}
S_3	$\{a_{68},a_{69},a_{70},a_{72},a_{73}\}$	{1.755, 0.914, 1.403, 1.647, 1.912}
S_4	$\{a_2,a_4,a_5,a_6\}$	{1.741, 1.010, 0.918, 1.640}
S_5	$\{a_6,a_7,a_{11},a_{13}\}$	{1.908, 1.877, 1.286, 1.979}
S_6	$\{a_{10},a_{11},a_{13},a_{17}\}$	{1.205, 1.900, 0.754, 1.989}
S_7	$\{a_{14},a_{15},a_{16},a_{17},a_{18}\}$	{1.826, 1.579, 0.915, 1.163, 1.344}
S_8	$\{a_{20},a_{21}\}$	{1.308, 1.640}
S_9	$\{a_{22},a_{23}\}$	{1.029, 1.917}
S_{10}	$\{a_{26},a_{27},a_{28}\}$	{0.936, 1.180, 1.490}
S_{11}	$\{a_{28},a_{29},a_{30}\}$	{0.988, 1.451, 1.994}
S_{12}	$\{a_{29},a_{30},a_{31},a_{32},a_{33},a_{34},a_{35}\}$	{1.805, 0.795, 1.175, 1.837, 1.009, 1.953, 1.988}
S_{13}	$\{a_{36},a_{37},a_{38},a_{40}\}$	{1.095, 1.891, 1.969, 1.764}
S_{14}	$\{a_{22},a_{23},a_{24},a_{52}\}$	{1.929, 1.702, 1.814, 1.553}
S_{15}	$\{a_{53},a_{54},a_{61},a_{62}\}$	{0.978, 1.314, 1.702, 1.066}
S_{16}	$\{a_{54},a_{55},a_{56},a_{57},a_{59}\}$	{1.698, 1.811, 0.947, 1.990, 1.906}
S_{17}	$\{a_{63},a_{64},a_{65},a_{66}\}$	{1.399, 1.089, 1.460, 1.811}
S_{18}	$\{a_{76},a_{77}\}$	{1.177, 0.442}

Result analysis of the case

First, we transform the initial multi-objective optimization problem into an equivalent single-objective form and provides ideal compromise solutions. The detailed formulation, including a crisp goal programming (CGP) model as suggested by Abd El-Wahed and Lee (2006), can be summarized as below:

$$\max \sum_{h} \tau_h \alpha_h \tag{33}$$

s.t.

$$Z_h(x_i) \leq Z_h^{NIS} - \alpha_h\left(Z_h^{NIS} - Z_h^{PIS}\right), \qquad h, i \in \{1, 2, 3\} \tag{34}$$

$$\alpha_h \in [0, 1], \qquad h \in \{1, 2, 3\} \tag{35}$$

$$x \in F(x) \tag{36}$$

where τ_h is the importance factor of the hth objective function ($\sum_h \tau_h = 1$) confirmed by the decision-maker. $F(x)$ designates the feasible area associated with the constraints of the original model. This formulation aims to achieve the highest level of satisfaction, the α-value, in such a way that the constraints of the problem are satisfied. To determine the negative ideal solution (NIS) and the positive ideal solution (PIS) for each objective function, we first solve the initial mathematical model, the objective functions (1)-(3), separately to attain PISs, i.e., (Z_1^{PIS}, x_1^{PIS}), (Z_2^{PIS}, x_2^{PIS}) and (Z_3^{PIS}, x_3^{PIS}), following which the negative ideal solution for the objective functions is obtained as follows:

$$Z_1^{NIS} = Z_1\left(x_2^{PIS}\right) \; or \; Z_1\left(x_3^{PIS}\right) \tag{37}$$

$$Z_2^{NIS} = Z_2\left(x_1^{PIS}\right) \; or \; Z_2\left(x_3^{PIS}\right) \tag{38}$$

$$Z_3^{NIS} = Z_3\left(x_1^{PIS}\right) \; or \; Z_3\left(x_2^{PIS}\right) \tag{39}$$

Table 4 summarizes the results reported by the exact solution method on the case study. Columns 1-4 report the computational results obtained by CPLEX, including service routes, visited bus stops in the service route, arrival time to each bus stop, and picked up passengers from there, respectively. We use the same importance factors to choose the most preferable parameter values using the CGP approach. In this case, we had an execution time of about 285 minutes. It needs to be pointed out that the quality of the obtained solution depends on the importance factors and designated parameters, despite some vacillations, it is relatively acceptable.

Table 4

Statistics for the optimized service route schedule of the CBs.

Services	Bus stops	Arrival time	Boarded applicants
First bus	S_2	6:53:33 AM	$\{a_{75}, a_{76}\}$
	S_3	7:04:16 AM	$\{a_{68}, a_{69}, a_{70}, a_{72}\}$

Services	Bus stops	Arrival time	Boarded applicants
	S_{16}	7:19:23 AM	$\{a_{54},a_{55},a_{56},a_{57},a_{59}\}$
	S_{15}	7:37:07 AM	$\{a_{53},a_{54},a_{61},a_{62}\}$
	S_{14}	7:46:34 AM	$\{a_{22},a_{23},a_{24},a_{52}\}$
	S_9	7:54:01 AM	$\{a_{22},a_{23}\}$
Second bus	S_1	7:19:06 AM	$\{a_{42},a_{43},a_{44},a_{45},a_{46}\}$
	S_{13}	7:24:22 AM	$\{a_{36},a_{37},a_{38},a_{40}\}$
	S_{12}	7:33:09 AM	$\{a_{29},a_{30},a_{31},a_{32},a_{33},a_{34},a_{35}\}$
	S_{11}	7:44:47 AM	$\{a_{28},a_{29},a_{30}\}$
	S_{10}	7:52:19 AM	$\{a_{26},a_{27},a_{28}\}$
Third bus	S_{17}	7:02:34 AM	$\{a_{63},a_{64},a_{65}\}$
	S_{18}	7:12:01 AM	$\{a_{76},a_{77}\}$
	S_4	7:15:28 AM	$\{a_2,a_4,a_5,a_6\}$
	S_5	7:32:53 AM	$\{a_6,a_7,a_{11},a_{13}\}$
	S_6	7:36:17 AM	$\{a_{10},a_{11},a_{13},a_{17}\}$
	S_7	7:46:04 AM	$\{a_{14},a_{15},a_{16},a_{17},a_{18}\}$
	S_8	7:54:19 AM	$\{a_{20},a_{21}\}$

Fig. 6 illustrates a partial network of the case resulted by CPLEX. In this case, to catch up the best transportation service plan integrating the private cars and buses with minimum cost, dissatisfaction and emission, the company makes a schedule that employed three buses served 56 passengers, and the rest, 26 applicants, use car sharing service provided by 7 employees. Carpooling groups include $\{a_1,a_3,a_8,a_9\}$, $\{a_{81},a_{82},a_{12},a_{19}\}$, $\{a_{74},a_{78},a_{79},a_{80}\}$, $\{a_{66},a_{67},a_{71},a_{73}\}$, $\{a_{58},a_{60}\}$, $\{a_{47},a_{48},a_{49},a_{51}\}$, and $\{a_{25},a_{39},a_{41},a_{50}\}$. The total travel time by each of the buses was 67, 41 and 58 minutes, respectively. Also, the total incentive paid to private drivers that had participated in carpooling was equal to $190.

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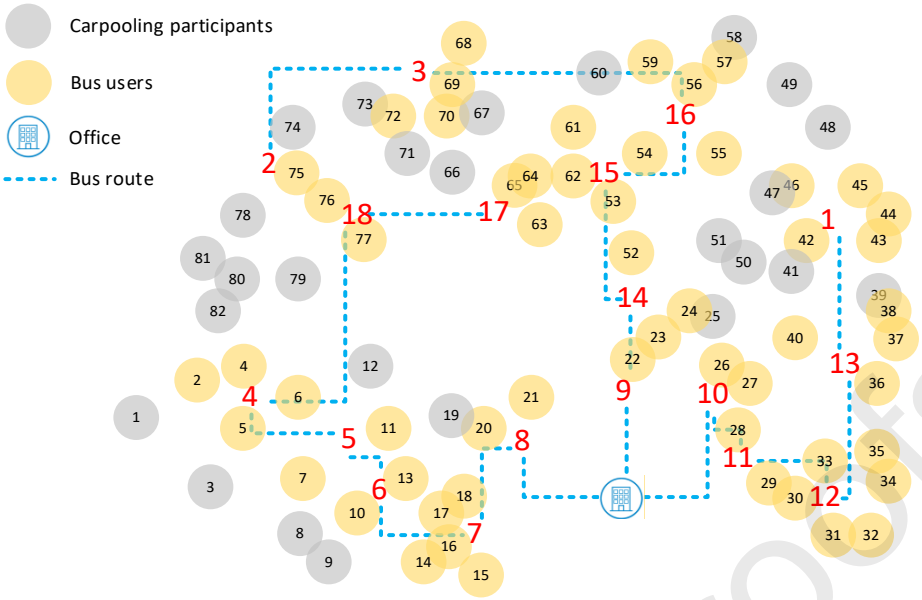


Fig. 6. Optimized service network for incorporating carpooling in the case.

To verify the utility and feasibility of the proposed model, we compare the optimal results of the case study with two manual solutions to the problem, including just the use of the company's buses and just the use of the carpooling system for staff transportation. The optimal results of the first to third objective functions of the case study obtained by CPLEX are \$834.51, \$471.03, and \$534.74, respectively. In a rough assessment, when the company uses only the bus shuttle service, the company needs to rent two more buses and its cost increases by 26.9 percent to \$1,059.02. The use of buses, while reducing emissions to a minimum of 361 grams, increases the employees' dissatisfaction due to commuting to 546.84, which is the result of increased dissatisfaction that comes along with walking and the travel time by buses.

In the second analysis, without using any bus, 23 drivers received a total of \$590 as an incentive to share their cars. Compared to the proposed solution, using the carpooling scheme reduces the second objective function, employee satisfaction, by about 50% to 246 and significantly increases emissions to 1,718 grams. Although the use of the bus shuttle service by all employees can minimize emissions, some of them in practice tend to use their own car instead of the company's buses. By paying incentives for sharing cars, the proposed solution not only saves costs and increases employee satisfaction, but also significantly reduces emissions compared to mere carpool or private car use.

5.2. Tuning of the PSACO parameters

Parameter setting is an important feature of the ACO algorithm and can control solution quality (Ghannadpour et al., 2014). Several studies have been conducted on parameter setting methodologies in different problem domains (Hutter et al., 2007; Ries and Beullens, 2015; López-Ibánez et al., 2011, 2016). In evolutionary computation, two common strategies are usually used to determine parameter

values: *parameter control* and *parameter tuning.* In parameter control, following the scheme proposed in Eiben and Smit (2011), the parameter values are specified while the algorithm is running. If this strategy is used, when the algorithm is started, the parameters are given an initial value and are modified during the execution of a given algorithm. With parameter tuning, the value of parameters is specified before executing a heuristic/meta-heuristic algorithm. If parameter tuning is used, the value of parameters is established in the initialization stage and remain unchanged during execution, for example Taguchi method (Roy, 1990; Gümüş et al., 2016; Sazvar et al., 2016), Response Surface Methodology (Montgomery, 2003; Myers et al., 2009), and IRACE (Dell'Amico et al., 2016; Samà et al., 2016).

This study determines the parameter settings for the PSACO algorithm by tuning them with the IRACE (López-Ibáñez et al., 2016) that automatically finds the most appropriate configurations through an iterated racing procedure. To select the best combination of the parameters, we applied the default IRACE Package settings on a dedicated set of examples, different from the one tested in subsection 5.1. We also set the stopping criterion to 3600 seconds of the processor with a maximum of 30,000 executions during the tuning. **Table 5** reports the settings tested for crucial parameters, including α, β, ρ, and the number of ants. In the study, the proposed PSACO is executed to solve the single-objective form of the problem with the implementation of equivalent CGP formulation. To choose the most preferable parameter values using the CGP approach, we use the same importance factors. According to the results listed in **Table 5**, the best α, β, ρ, and $nAnts$ obtained in our experiments were found to be equal to 1, 5, 0.05, and 150, respectively.

Table 5

Parameters used for computational tests.

Parameters	Meaning	Test interval	Selected value
α	The pheromone trail importance	1, 3, 5, 7, 9	1
β	The heuristic information importance	1, 3, 5, 7, 9	5
ρ	The pheromone evaporation rate	$uni[0.01,0.99]$	0.05
$nAnts$	The number of ants	100, 125, 150, 175, 200	150

5.3. Performance of the PSACO algorithm

In order to study the efficiency of the proposed PSACO algorithm, we generate 12 test problems with different dimensions. For this purpose, the parameters were randomly generated using a continuous uniform distribution. To carry out different illustrative examples, we will use the nominal data sources $f_v \sim uni[1000,3000]$, $c_{ijv} \sim uni[0.5,0.8]$, $d_{ij} \sim uni[0,12]$, $t_{ij}^B \sim \frac{d_{ij}}{uni[15,30]}$, $t_{ij}^C \sim \frac{d_{ij}}{uni[20,50]}$, $\alpha, \rho^C, \rho^B \sim uni[2,12]$, $\beta \sim uni[2,12]$, and $\delta_j \sim uni[-12,12]$ as fixed costs of using buses, variable costs of buses, the distance between each pair of nodes, travel time by bus, travel time by private car, dissatisfaction factors, incentive paid for carpooling, and walking satisfaction/dissatisfaction, respectively, where a and b in $uni[a,b]$ specifies the lower and upper bounds; the figures in the bracket indicate the range over which the probability is uniform within that range. In all the examples, the capacity of private cars

is assumed follows the uniform distribution between 3 to 5, and the passenger seating capacity of buses ranges from 20 to 40 people. The other parameters are generated using the data specified in subsection 5.1, *A case study*.

Table 6 summarizes the reported results for some non-dominated solutions in the Pareto set. As such, we solve all numerical examples first using CPLEX and then using PSACO. Columns 2-4 indicate the size of the test instances, respectively characterized by the number of bus stops, applicants, and available private cars. Columns 5-8 report the results obtained using CPLEX (Z_i^E) including economic (Z_1), satisfaction (Z_2) and environmental (Z_3) objectives and the number of iterations used, respectively. Columns 9-11 show the computational results obtained using PSACO (Z_i^H). In this study, ten independent runs of the algorithm were performed to solve the problem. In **Table 6**, the best-known results obtained using PSACO over 10 runs have been listed. The last three columns specify the gap between them determined by $\Delta_i = \frac{Z_i^H - Z_i^E}{\|Z_i^E\|}$ and can measure the relative efficiency of the proposed algorithm.

Table 6

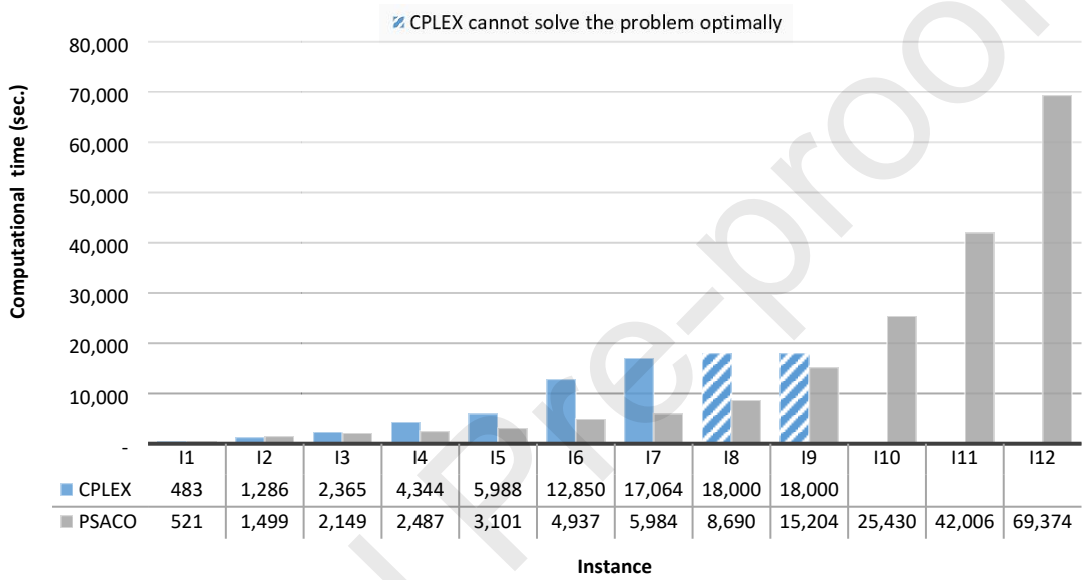
Solution approach performance on different examples.

Instance	Dimension			CPLEX			PSACO			Gap		
	K	L	C	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Δ_1	Δ_2	Δ_3
I_1	7	30	22	268.82	139.56	197.46	283.87	143.60	204.37	0.028	0.015	0.018
I_2	8	38	28	342.76	197.46	254.85	351.33	204.17	259.95	0.013	0.017	0.010
I_3	10	47	35	436.51	249.58	291.20	448.30	253.58	299.65	0.014	0.008	0.015
I_4	11	56	42	519.47	282.54	344.49	577.13	304.86	364.47	0.056	0.040	0.029
I_5	17	65	49	662.65	368.44	410.01	704.40	394.23	447.73	0.032	0.035	0.046
I_6	15	73	55	752.78	389.16	470.05	862.68	422.24	548.08	0.073	0.043	0.083
I_7	18	82	62	834.51	471.03	534.74	968.03	527.08	619.23	0.080	0.060	0.079
I_8	20	90	68	1,036.52*	502.83*	569.80*	1204.43	568.19	651.85	0.081	0.065	0.072
I_9	21	100	75	1,082.73*	593.69*	589.11*	1219.16	650.69	641.54	0.063	0.048	0.045
I_{10}	23	112	84	N/A	N/A	N/A	1393.53	698.72	693.68	-	-	-
I_{11}	26	125	91	N/A	N/A	N/A	1727.42	793.95	802.56	-	-	-
I_{12}	30	140	99	N/A	N/A	N/A	2155.82	908.28	934.82	-	-	-
Average										0.049	0.037	0.044

K: the number of bus stops, *L*: the number of applicants, *C*: available cars
* Lower bound

Table 6 shows that the PSACO algorithm consistently achieves reliable solutions, with an average gap of 4.3%. Note that CPLEX is unable to solve larger cases. Hence, to estimate the gaps for large-scale instances, we use the most trustworthy bounds of CPLEX attained after five hours reported in the *Engine* tab of the software. Therefore, the results obtained by the software for instances I_8 and I_9 are probably not optimal. In the last three test problems I_{10}-I_{12}, CPLEX was terminated as "out of memory" and did not reach a feasible solution by the reported time.

To give an idea of the execution time required by CPLEX and the best-known execution time of the PSACO algorithm, **Fig. 7** shows the computation time (in seconds) for all test problems. Since CPLEX was not able to solve the last example, the execution time is not shown in the figure. In instances I_8 and I_9, where we stopped the software after 5 hours, the time is shown as diagonal stripes. We note here that the execution time of the PSACO algorithm for medium and large-sized cases, is shorter than the exact method. Thus, our meta-heuristic algorithm has a more optimized execution time and virtually the only solution for large-sized problems compared with CPLEX, thereby validating its utility and feasibility in solving such problems.



	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
CPLEX	483	1,286	2,365	4,344	5,988	12,850	17,064	18,000	18,000			
PSACO	521	1,499	2,149	2,487	3,101	4,937	5,984	8,690	15,204	25,430	42,006	69,374

Fig. 7. Computation times for different examples.

5.4. Sensitivity analysis

Fig. 8 depicts the set of non-dominated solutions determined by running the PSACO algorithm on instance I_9. It should be underlined that in further iterations of the algorithm, the number of non-dominated solutions increased. However, in all cases, no significant improvement in the number and quality of non-dominated solutions appeared after 100 iterations. The last case has a larger solution space, which allowed the algorithm to produce several new feasible solutions, resulting in constant updating of the non-dominant set.

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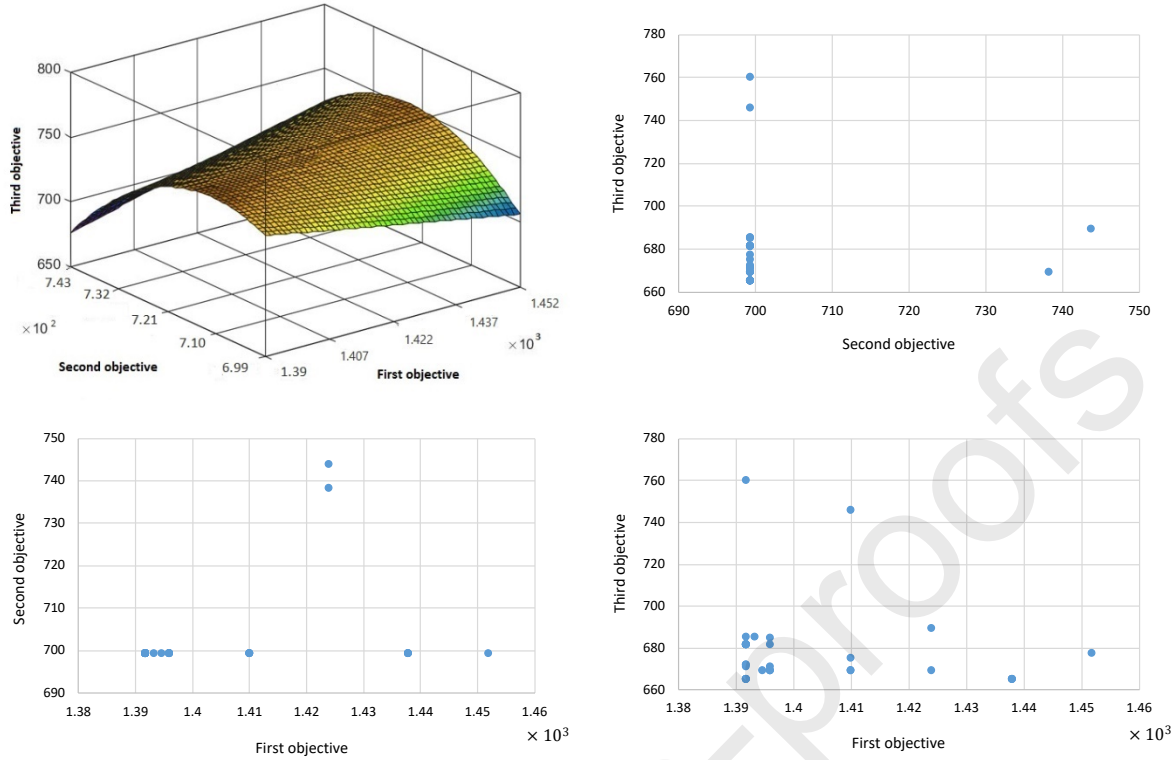

Fig. 8. Pareto fronts returned by PSACO algorithm for instance I_9.

Because of the probability nature of carpooling originated from an unknown rate of actual participation, **Fig. 9** depicts a sensitivity analysis on the participation rate (i.e. available cars). Therefore, we solve the instance $I_9$with 29 nodes for different participation rates to find the optimal size of the fleet, including both the buses used in the transportation service and the private cars involved in the carpooling program, over which this problem stays on a profitable role. **Fig. 9** confirms that increased individual participation not only considerably affects the organization's costs, staff satisfaction, and CO_2 emissions, but is also a convenient way for individual drivers who share their car to make money.

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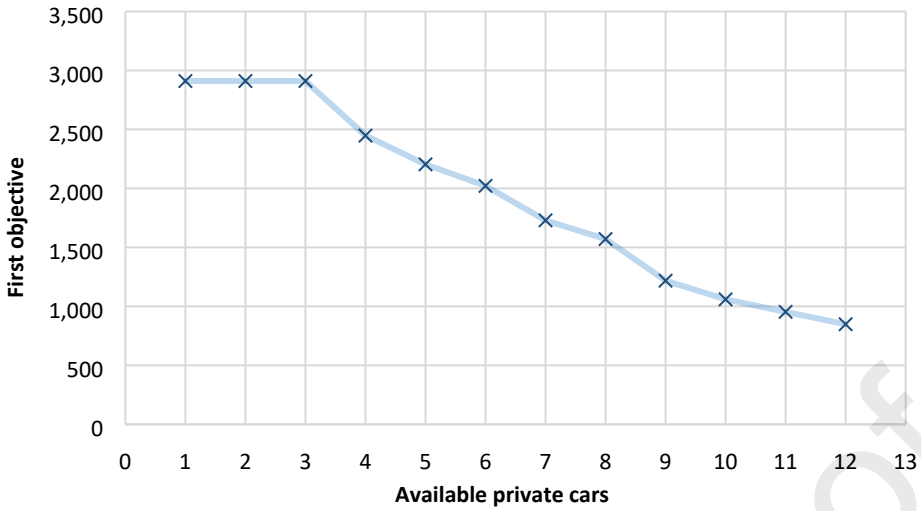
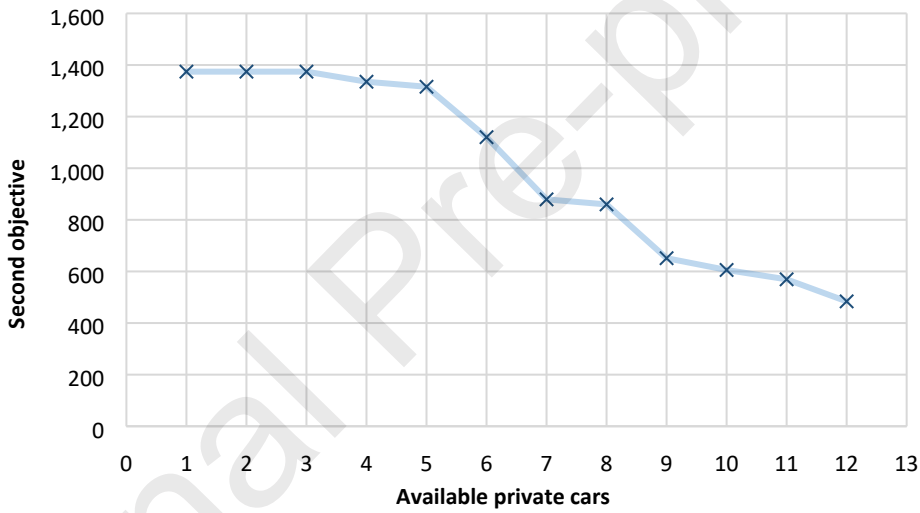
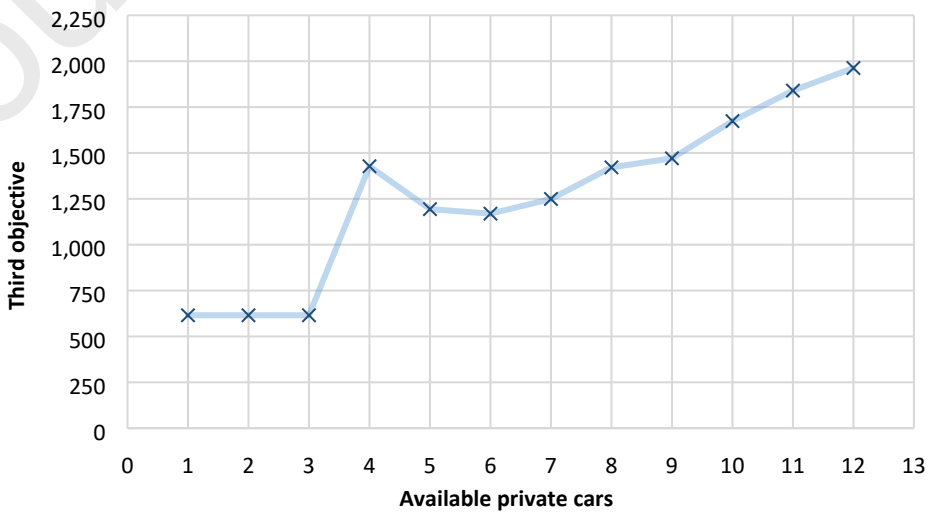


(a) Sensitivity of the first objective function



(b) Sensitivity of the second objective function



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(c) Sensitivity of the third objective function

Fig. 9. The effect of participation rate on the value of the objective functions.

In a nutshell, the numerical experiments show that the problem introduced can be a successful platform use by organizations to establish an integrated configuration of their transportation service and a carpooling program using employees' private cars. Doing so provides a convenient transportation service which motivates employees to take action in response to increasing environmental concerns by eliminating single-occupant vehicle trips for commuting.

6. Conclusions

Although many researchers have explored ride-sharing from different perspectives, there was previously no effort to study the effects of incorporating carpooling behavior into the CB service design. To do so, this study carried out integrated planning and scheduling of employees' cars and company buses, which aimed to (1) identify and cluster travel applicants who differ in terms of whether or not they chose to carpool, (2) determining the number of buses that must be rented for the company's transportation service, (3) increasing employee satisfaction, and (4) highlighting the main determinants of real practice of carpooling. A meta-heuristic algorithm based on PSACO was also adapted to efficiently solve the multi-objective optimization model. Using computational experiments, we have demonstrated what type of ride-sharing systems offer the greatest benefits. The experimental results indicate that carpooling has several prominent positive impacts on the company's total loss, employee satisfaction, and total vehicle GHG emissions. These influences on the transportation problem are directly dependent on participation in the program.

The findings of this study have to be seen in light of some limitations. For example, the implementation costs of this computer program have been ignored for the cases in which the company offers the shuttle service. In the cases where companies do not provide shuttle service and have not any commuter benefits program in place, the operational costs of developing such complex computer applications must be considered. The proposed problem provides intriguing and promising options for extending existing ride-sharing systems. Future research can pursue the following directions: (*i*) studying the potential relationship between vehicle capacity and cost allocation for each passenger, which we believe provides insight into the inherent nature of ride-sharing games, (*ii*) investigating the effects of day-to-day stochastic traffic condition data and exploring the potential benefits of expanding the problem to a robustness-oriented optimization model, and (*iii*) a passenger's potential desire to be served or not by a particular vehicle.

Credit authorship contribution statement

Mohammad Asghari: Conceptualization, Investigation, Methodology, Writing - Original Draft, Software, Validation, Visualization, Formal analysis. **Mohammad J. Mirzapour Al-e-hashem**:

Conceptualization, Methodology, Writing - Review & Editing, Formal analysis, Supervision. **Yacine Rekik**: Conceptualization, Methodology, Writing - Review & Editing, Formal analysis.

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Journal Pre-proofs

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Highlights :

- Designing of a sustainable and efficient joint carpooling and customized bus services
- Quantifying the behavior of carpooling under the customized bus alternative
- Multi objective functions involving total transportation costs; ridesharing service dissatisfaction and total carbon emissions

Journal Pre-proofs