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Minimizing CO_2 emissions in a practical daily carpooling problem

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A R T I C L E I N F O

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A B S T R A C T

Governments, as well as companies and individuals, are increasingly aware of the damages to the environment caused by human activities. In this sense, the reduction of CO_2 emissions is an important topic that is pursued through a range of practices. A relevant example is carpooling, which is defined as the act of individuals sharing a single car. In this paper we approach a practical case found in an Italian service company. Our objective is to develop an integrated web application to be used by the employees of this company to organize carpooling crews on a daily basis, so as to reach a common destination. We look for possible crews by the use of mathematical formulations and heuristic algorithms. The heuristic algorithms are then embedded into the web application to provide users with carpooling solutions. Experimental results attest for a great potential in CO_2 savings by the use of carpooling in the real-world scenario as well as in newly generated instances.

1. Introduction

The debate on the negative effects of human activities on the environment has been around for a long time, and nowadays the concern about these issues is widespread. Pollution is a plague in urban areas and a cause of illness for inhabitants. Large companies daily require that thousands of individuals travel to work, heavily increasing car use. This practice causes a wide range of problems, including high emissions of CO_2 in the atmosphere, noise pollution, and parking issues (see, e.g., Gärling and Friman [1]). Public transportation systems could mitigate the problem, but, more often than not, they are incapable of serving all the demands in a cost-effective manner, or are simply disregarded by many individuals, who prefer not to use them.

In this sense, *carpooling* can be an effective tool to help reduce traffic and pollution. Carpooling is a ridesharing practice that can be defined as the act of a group of individuals that ride a single car by splitting travel costs (see, e.g., Furuhata et al. [2]). This practice has grown more common in recent years. It is an interesting transportation habit for individuals as well as for companies, as it can reduce transportation costs and directly affect CO_2 emissions. It thus fits well with the millennium goal of the United Nations [3] that aims at ensuring environmental sustainability. Governments are also taking actions to support the carpooling practice. For instance, in Italy a law for sustainable mobility was included into the national legislation in 1998 to stimulate the use of collective transportation methods and promote the creation of innovative transport systems (see Italian Ministry of Environment [4]). Consequently, in recent years several optimization methods have been developed to provide good solutions to different carpooling practices, both focusing on the solution of real-world study cases (see, e.g., Wolfler Calvo et al. [5]) and on the development of general solution algorithms (see, e.g., Baldacci et al. [6]).

Carpooling is sometimes also denoted as *ridesharing*, although this terminology is more common in dynamic contexts (see, e.g., Agatz et al. [7,8]). Also, it should not be confused with *carsharing*, which is a kind of decentralized car rental service where travelers are allowed to pick up a car at a station, use it for the time needed, and then return it (to the same station or to a different one, according to the implemented system). Carsharing has also attracted research aimed at the minimization of CO_2 emissions. Lee et al. [9] pursued indeed this objective by determining the optimal carsharing service locations in Daejeon, a small Korean city. The reader interested in the research conducted on carsharing is referred to the recent survey by Jorge and Correia [10].

In this paper we focus our attention on carpooling and study a practical case found in a large service company, Coopservice S.coop.P.A., with headquarters in Reggio Emilia (Italy), whose aim is to encourage its employees to carpool to reduce transportation costs and CO_2 emissions. We focus on a pilot case in which all employees are headed to the same workplace but may have different daily working shifts. People with the same shift can carpool together to reach and/or return from the workplace at the same

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time. According to the classification by Wolfler Calvo et al. [5] our case is a *daily* carpooling problem, because users offer or require passages on the basis of working shifts that change day by day. Our intention is to assess, by the use of optimization algorithms and mathematical models, the amount of CO_2 emissions that can be saved in this pilot case and on newly generated instances, and then develop a web application in which employees can communicate and agree with each other on sharing rides.

The remainder of the paper is organized as follows. In Section 2 we present a brief review of the carpooling literature. In Section 3 we formally describe the problem. In Section 4 we present mathematical models and heuristic algorithms. In Section 5 we discuss the details of our study case. In Section 6 we evaluate our optimization methods by means of extensive computational results. In Section 7 a prototype of the web application is shown and then some conclusions are drawn in Section 8.

2. Brief review of carpooling literature

The practice of carpooling (also known as ridesharing) has attracted the interest of many researchers from different areas, consequently leading to a huge literature. In this section we present a brief review of some interesting results in the field. The reader interested in a deeper review is referred to the following papers: Furuhata et al. [2], who present a framework to identify key challenges in ridesharing and foster the development of effective formal ridesharing mechanisms; Chan and Shaheen [11], that focus on how the use of Internet, mobile phones, and social networking has been integrated in carpooling programs; Battarra et al. [12] and Dörner and Salazar-González [13], that survey pickup and delivery problems for freight and passenger transportation, respectively.

The carpooling literature can be roughly divided into two major approaches: a *deductive* approach and an *inductive* one. The former approach looks at carpooling through the lenses of existing literature from different research areas, and thus tries to apply existing theories (deriving from fields such as behavioral theories and applied psychology) to draw conclusions on the usage and effectiveness of possible practical carpooling systems. From this perspective, deductive studies share a somehow top-down approach. Instead, the latter approach examines existing carpooling initiatives in order to understand what correlations among variables arise in real contexts, or what individuals think that might lead them to carpool. In this sense, inductive studies start from reality and try to draw general conclusions about the carpooling phenomenon, thus sharing a bottom-up approach.

The main results on deductive and inductive approaches are surveyed in Sections 2.1 and 2.2, respectively, whereas in Section 2.3 we describe the main models and algorithms that have been developed to provide optimized solutions to carpooling problems.

2.1. The deductive approach

The deductive approach roughly follows the call of Gärling and Schuitema [14] for a behavioral framework able to help policy makers and carpooling system designers to develop effective car use reduction programs, as well as to support individuals to develop their own car use reduction goals. Gardner and Abraham [15] proposed an analysis of the literature on psychological correlates of car use with data taken from fourteen previous studies. Their research aim was to verify the impact of the *theory of planned behavior* (TPB) by Ajzen [16] on car reduction behavior. TPB is an expectancy-value theory in which the subjective perception of the probability of happening of a given behavior directly influences the process of creation of attitudes towards that behavior. Following [15], Abrahamse et al. [17] measured the impact of TPB and of the *norm-activation theory* (NAT) by Schwarz [18] on sample data from Canadian workers. While TPB looks at the mechanism through which behavioral intentions are formed, NAT is more about moral issues, i.e., about how problem awareness and perceived responsibility for consequences may modify individual attitudes towards a certain behavior. The authors highlight that individuals' attitudes and the perceived possibilities and difficulties related to reducing car use strongly influence the transportation choice.

Bamberg et al. [19] also considered TPB and NAT. They proposed and tested a conjoint self-regulation theory asserting that changes in behavior are a process of transition through successive stages. In particular, in the case of a car use reduction goal, the theory starts from the formation of the goal, then it passes through the formation of the behavioral intention to do it, and lastly it comes to choosing the alternative travel option that reduces car use. Shewmake [20] reviewed studies on the impacts of *high occupancy vehicle* lanes on carpooling, with a focus on behavioral models. Different performance measures related to welfare, congestion, and air pollution effects were surveyed, by taking into consideration papers that explicitly model carpool formation. In conclusion, behavioral theories seem to indicate that, in order to foster mixed transportation methods, both personal interest variables (e.g., the perception of alternatives), as well as personal norms should be taken into account when proposing carpooling systems.

Other important contributions derive from proposals of new models for web or app-based carpooling systems. These models try to devise carpooling systems by taking into account both contributions from the literature and from practical experiences, considering different perspectives such as social, technical, and business sustainability. Selker and Saphir [21] proposed a carpooling system that takes into account individual interests, goals, and preferences. They argued that having the same interests can reduce some negative psychological drawbacks of carpooling, as, for instance, privacy issues. They also conducted a promising pilot test within a university setting. Chen and Hsu [22] extended the model in [21], by defining other options aimed at improving the carpooling application. Ribeiro et al. [23] developed a web and app-based carpooling system, whose design benefits from an analysis of existing carpooling systems. Other web applications, more focused on optimization aspects, are discussed in Section 2.3.

2.2. The inductive approach

Governments and private organizations have created several travel plans to reduce environmental costs. This has provided researchers with the opportunity to go into the field and study existing applications. In what we call inductive studies, the authors analyzed existing carpooling initiatives and assessed whether and why individuals decided to participate.

In the United Kingdom, Cairns et al. [24] analyzed the efficacy of the travel plans of twenty employers. Their findings show that the presence of travel plans, in conjunction with parking management techniques, is capable of reducing car use. They also show that this practice can offer positive economic returns for the proposing companies because of the reduction in car parking requirements.

In Belgium, Vanoutrive et al. [25] studied commuters' choices by clustering individuals by company. This strategy is grounded on three arguments: employers can foster internal commutation patterns among employees; neighbor companies can have different accessibility options; companies are social settings where organizational culture and social norms can exert a great influence on the individual choice to commute. The authors found that carpooling initiatives could be effective only where public transportation is either weak or absent, which is consistent with previous findings by Teal [26]. They also reported that the carpooling practice had its best results in those sectors where individuals must travel to working sites that change during time, as, e.g., in the construction sector.

In Canada, Buliung et al. [27] studied *CarpoolZone*, a free-to-use online service that proposes ride matches to commuters living and/or working near each other and having similar travel times. From an analysis conducted on real data, it emerged that individuals living within 1 km of a carpool lot have greater chances of successfully creating a carpool crew. Moreover, individuals with higher auto availability feel a stronger urge to carpool, perhaps in order to share the costs associated with car travel. In a subsequent study, Buliung et al. [28] extend the analysis in [27] by using data from employers. Their study showed that the typical commuter is relatively young (less than 40) and well-paid, she/he works non-standard hours within small to medium sized companies, and she/he has access to few household vehicles. Females appeared to carpool more frequently than males. In addition, company travel plans proved to be the strongest indicator of carpool formation, especially with designated carpool parking places and emergency ride home services.

Abrahamse and Keal [29] conducted a study regarding *Let's Carpool*, a New Zealander initiative similar to CarpoolZone but aimed at increasing vehicle occupation. This service is based on a website with an online ride matching algorithm that enables users to organize carpoolings to and from work. Match search options are many and range from a certain maximum distance from home, to other criteria such as non-smoking or gender. The website shows possible matches on a map with markers indicating trip starting and arriving points and generates a list containing contact details of matches. Users are then free to contact potential matches. The study in [29] showed that the aspects of carpooling that make it preferable over public transportation are many, including money and time saving, reliability, and sociability. However, users also indicated some negative aspects of carpooling, such as lack of flexibility, absence of emergency cars, and difficult arrangement of costs.

A few studies concentrated on the assessment of individuals' opinions about carpooling. Nielsen et al. [30] analyzed, through qualitative interviews and focus groups, the perceptions of individuals from Denmark regarding carpooling. The authors highlighted that respondents never reported the environmental impact as a source of motivation towards carpooling. They also suggested that carpooling systems should be integrated with social networks, in order to build on the positive sides of carpooling that individuals perceive. A related study was held in the USA by Lee et al. [31]. Through survey data analysis the authors found out that females and younger men are more inclined towards carpooling. Moreover, commuters from urban areas to country areas are more likely to participate in carpooling. Quite surprisingly, attitudinal variables did not help in explaining the attitude towards carpooling.

2.3. Mathematical models and optimization methods

When looking for optimized carpooling solutions, the considered time frame becomes an important problem dimension. In this sense, two types of problems emerged in the related literature: the *daily carpooling problem* (DCPP), where users must agree on how to carpool on a daily basis, and the *long-term carpooling problem* (LCPP), where users form groups and organize shared rides that persist during a certain period of time.

Wolfler Calvo et al. [5] approached a real-life DCPP and developed an integrated system to organize and manage carpooling groups. Given the necessity for a fast response from the system, they opted to use a heuristic algorithm to provide optimized groups. This algorithm is the core of their optimization module and operates as a two-step procedure. In the first step a graph containing the shortest distance among each pair of users is built by using a modified version of the Dijkstra algorithm that considers traffic congestion. In the second step a problem solution is obtained by executing on the graph a greedy constructive heuristic and a refinement based on local search. Results show that instances with up to 400 employees are handled effectively. Another DCPP was solved by Baldacci et al. [6], by the use of an exact and a heuristic solution method. The exact method is a bounding based iterative procedure where at each iteration a reduced set-partitioning problem is solved, whereas the heuristic is a Lagrangian constructive procedure. Both approaches were tested on instances derived from the literature and yielded good results.

As for the LCPP, Varrentrapp et al. [32] gave a formal definition of the problem and proved its NP-completeness. Yan et al. [33] considered groups of individuals that would like to travel together rather than single individuals. They proposed a multiple commodity network flow formulation, whose objective function considers both the reduction of global costs and a fair sharing of costs among users. Furthermore, they developed a Lagrangian relaxation with subgradient optimization to provide valid lower bounds, and a Lagrangian heuristic to efficiently obtain upper bounds. The resulting solution method was tested on instances from the literature and the results indicated that it could be used to efficiently solve large size instances in a real case.

Naoum-Sawaya et al. [34] also studied a LCPP derived from a company application. In their problem a fleet of company owned vehicles must be distributed among employees. An employee that is assigned a vehicle is expected to participate in a carpool, bringing other employees to and from work. They proposed a stochastic mixed integer programming model to solve the problem while considering events in which a vehicle may be unavailable, possibly requiring rerouting. They also presented a two-step heuristic in which, at first the carpooling crews are created using the well known savings heuristic, and then the stochastic model is used to define which employees should be given the vehicles. Both approaches were tested on several instances of different sizes obtaining a good computational performance.

Instead of focusing on a particular time frame, Xia et al. [35] distinguished carpooling mainly by how users are matched into carpools and what type of information is used to achieve that. Indeed, some services consider only users requests and do not take into account spacial information to provide more suitable matchings. The authors focused on a carpooling application that makes use of both network and spacial information to match users. They proposed an integer linear programming approach, a tabu search, and a simulated annealing algorithm to solve the problem. The efficiency of their approach was evaluated under different scenarios. Another interesting study focusing on a specific scenario was performed by Bruglieri et al. [36], who designed a web application to support the use of carpooling in two universities in Milan. The core of their system is built upon a heuristic based on a guided Monte Carlo method and minimizing a multi-objective weighted function that considers distance traveled, level of service, and user preferences. Computational tests indicated that their algorithm was capable of generating good quality solutions.

3. Problem description

To formally introduce our DCPP, let us define $G = (V, A)$ as a directed graph, where $V = \{0\} \cup V'$, vertex 0 represents the workplace, vertices in V' are the employees, and $A = \{(i, j) : i \in V', j \in V, i \neq j\}$. For convenience of notation, let us partition the set of employees into two subsets, namely, those that own a car, V_c, and those that do not, V_n. Each employee $i \in V_c$ either uses her/his own

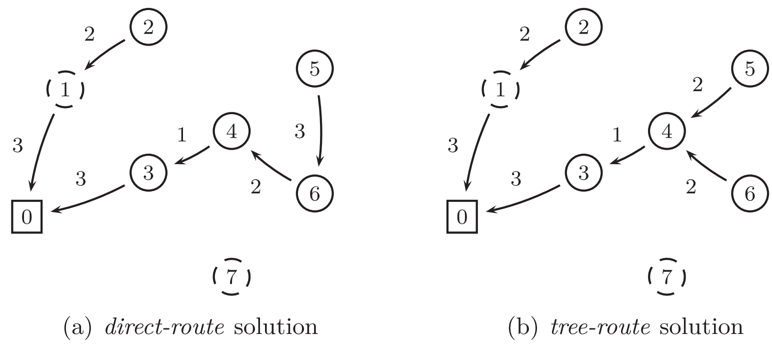


Fig. 1. Problem types $DCPP_{DR}$ (left) and $DCPP_{TR}$ (right). Vertex 0 is the workplace, vertices in solid (resp. dashed) lines are employees that own (resp. do not own) a car.

car to go directly to the workplace, possibly picking up other employees, or takes a ride from another employee owning a car. Each employee $i \in V_n$ either carpools, thus taking a ride from another employee that owns a car, or uses the public transport to reach the workplace. Vehicles have a maximum capacity of Q people. With every arc $(i, j) \in A$ is associated a non-negative cost c_{ij}, specifying the distance in km between the two vertices. In our problem we consider real distances on an urban area, so the cost matrix c is asymmetric. Let γ_c and γ_b be two coefficients estimating the amount of CO_2 emissions in kg for each km traveled by car and by public transport, respectively. Let also δ be the maximum detour, that is, the maximum allowed distance of an employee path with respect to the shortest path connecting directly the employee to the workplace. In other words, an employee i is not willing to carpool with her/his car for a path that requires more then δc_{io} km. Our DCPP is to drive all employees to the workplace by satisfying the maximum detour constraint, with the aim of minimizing the total CO_2 emission.

We consider two different problem types according to the specific solutions that we allow. In the first type, called *direct-route* DCPP ($DCPP_{DR}$), a solution is a set of routes such that each of them begins at the house of a given employee $i \in V_c$ and ends at the workplace. In this case, the first employee on the route drives her/his car and picks up the others along the route. In the second type, called *tree-route* DCPP ($DCPP_{TR}$), we allow employees to drive to intermediary points and then use a single car from there on. These intermediate points can be, in general, parking lots or employees houses. The latter type of solutions allows for some additional flexibility, but it also requires more organization and commitment among participants. This might become an inconvenience in some cases, due to waiting times and lack of parking spots at the meeting points. Note that, to limit the complexity of the $DCPP_{TR}$ problem at hand, in our tests we allowed employees to meet only at their houses, and did not include locations corresponding to parking lots. On the other hand, because of their more restrictive nature, direct-route solutions tend to result in higher costs in terms of both traveled distance and CO_2 emissions. Examples of direct-route and tree-route solutions are shown in Fig. 1(a) and (b), respectively. The workplace is vertex 0, vertices in solid and dashed lines are employees that own or do not own a car, respectively. The values on the arcs correspond to the c_{ij} distances and $Q = 4$.

The $DCPP_{TR}$ is more general than the $DCPP_{DR}$. The $DCPP_{DR}$ is already NP-hard because it contains as a special case the vehicle routing problem with unit demands (see, e.g., Baldacci et al. [6]).

4. Solution algorithms

In this section we present some solution algorithms that we implemented. We first propose a three-index integer linear programming formulation for the case of tree-route solutions. The formulation makes use of three sets of binary variables: x_{ij}^k takes value 1 if employee k travels along arc (i, j), for $(i, j) \in A$, $k \in V'$; y_{ij} takes value 1 if arc (i, j) is traveled by a vehicle, for $(i, j) \in A$; and v_i takes value 1 if employee i uses public transport instead of carpooling, for $i \in V_n$. The $DCPP_{TR}$ can be modeled as the following *tree-route formulation* (F_{TR}).

$$(F_{TR}) \qquad \min\ z_{F_{TR}} = \sum_{(i,j)\in A} \gamma_c c_{ij} y_{ij} + \sum_{i\in V_n} \gamma_b c_{i0} v_i \tag{1}$$

subject to

$$\sum_{j\in V} x_{kj}^k = 1 \qquad \forall\ k \in V_c, \tag{2}$$

$$\sum_{j\in V} x_{kj}^k = 1 - v_k \qquad \forall\ k \in V_n, \tag{3}$$

$$\sum_{i\in V'} x_{i0}^k = 1 \qquad \forall\ k \in V_c, \tag{4}$$

$$\sum_{i\in V'} x_{i0}^k = 1 - v_k \qquad \forall\ k \in V_n, \tag{5}$$

$$\sum_{i\in V'} x_{ij}^k - \sum_{i\in V} x_{ji}^k = 0 \qquad \forall\ j, k \in V', j \neq k, \tag{6}$$

$$\sum_{k\in V'} x_{ij}^k \le Q y_{ij} \qquad \forall\ (i, j) \in A, \tag{7}$$

$$\sum_{i\in V'} \sum_{j\in V} c_{ij} x_{ij}^k \le c_{k0}(1 + \delta) \qquad \forall\ k \in V', \tag{8}$$

$$\sum_{j\in V} y_{ij} = 1 \qquad \forall\ i \in V_c, \tag{9}$$

$$\sum_{j\in V} y_{ij} = 1 - v_i \qquad \forall\ i \in V_n, \tag{10}$$

$$\sum_{i\in V} y_{ij} \ge 1 - v_j \qquad \forall\ j \in V_n, \tag{11}$$

$$x_{ij}^k \in \{0, 1\} \qquad \forall\ (i, j) \in A, k \in V', \tag{12}$$

$$y_{ij} \in \{0, 1\} \qquad \forall\ (i, j) \in A, \tag{13}$$

$$v_i \in \{0, 1\} \qquad \forall\ i \in V_n. \tag{14}$$

Objective function (1) minimizes the total CO_2 emissions. Constraints (2) impose that all employees that own a car must be in a route, whereas (3) state that employees without a car might go to work by carpooling or by public transport. Constraints (4) and (5) ensure that all employees that are in a route arrive at the workplace, whereas (6) impose vehicle flow conservation. Car capacity and maximum detour cannot be exceeded, as stated by (7) and (8), respectively. Constraints (9) and (10) define that if an employee carpools, then exactly one car leaves from her/his house,

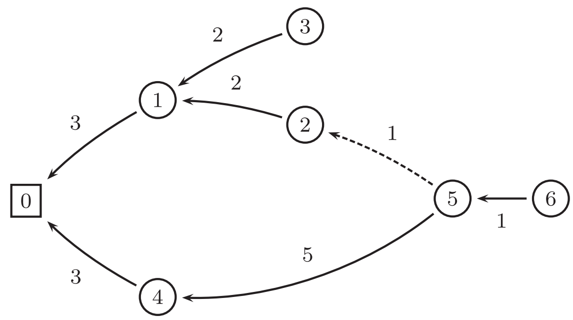


Fig. 2. Savings evaluation for algorithm H_{TR}.

and (11) specify that an employee $i \in V_n$ is either picked up by someone or does not carpool. Finally, (12), (13), and (14) define the variables' domains. Note that, if one wanted to include locations for public parking lots in the network, then formulation F_{TR} should be conveniently modified to allow more than one carpool group to use a particular parking.

Formulation F_{TR} allows tree-route solutions because the number of arcs entering a given vertex is not restricted. It can be easily adapted to the case of direct-route solutions by introducing the following set of constraints:

$$\sum_{i \in V'} y_{ij} \leq 1 \qquad \forall\ j \in V'. \tag{15}$$

Thus, the $DCPP_{DR}$ can be solved by a *direct-route formulation* (F_{DR}) defined by (1)–(15).

We notice that our formulations are indebted to the three-index model proposed by Baldacci et al. [6]. The main difference lies in the fact that the latter model takes into account the arrival time of a car at the workplace, and imposes this time to be compatible with the starting time of the working activity of each passenger in the car. Our decision problem is simpler, because the starting times of the working activities are grouped into shifts that have been predefined by the company (see Section 5 below for details). Thus, we can run our formulations for each single shift, disregarding constraints on the arrival times, as the solution will be independent from the decisions taken in the other shifts. Because of this difference our results are not directly comparable with those in [6].

Formulations F_{TR} and F_{DR} can be strengthened by fixing arcs that violate the maximum detour. Indeed, we can set $y_{ij} = 0$ for all $i, j \in V' : c_{ij} \geq c_{i0}(1 + \delta)$. These formulations are very simple and could be improved in many other ways. However, in this work we use them only with the purpose of providing an estimation of the total CO_2 emission that could result in our practical application. Our formulations could solve to proven optimality the instances of our study case in small computational times. Their execution was, however, much slower for larger-size instances and proved to be particularly sensitive with respect to some problem parameters (refer to Section 6 below). We thus focused on the development of heuristic and local search algorithms, that proved to be quick, effective, and robust, and then embedded them into our web application.

The first heuristic algorithm that we developed solves the $DCPP_{TR}$. It is based on the heuristic proposed by Esau and Williams [37] for the capacitated minimum spanning tree, and it is guided by the evaluation of savings. Consider the example depicted in Fig. 2 and, for the sake of simplicity, assume that the route capacity is 5. Let us define the *gate* $g(i)$ of a vertex i as the next vertex in the current route of i to the workplace. Then, the saving of inserting a vertex i in a different route after a vertex j is $s_{ij} = c_{i,g(i)} - c_{ij}$. For instance, in Fig. 2, $g_5 = 4$ and $s_{52} = 5 - 1 = 4$, so it might be profitable to connect 5 with 2. This choice clearly affects customer 6, whose route is changed, and customer 4, who should become a driver.

Our heuristic algorithm initially builds a solution in which every employee is directly connected to the workplace by a single arc. In this initial solution employees $i \in V_c$ use their car and employees $i \in V_n$ use public transport. Then, the following 4-step procedure is invoked:

Step 1: Find two vertices i and j belonging to different routes and yielding the feasible saving of largest positive value, if any. If no such pair is found, then go to Step 3;
Step 2: Remove arc $(i, g(i))$ from the solution, add arc (i, j), set the new gate of i as $g(i) = j$, and then return to Step 1;
Step 3: Remove from the solution the arc $(i, g(i))$ of any $i \in V_n$ that is assigned to the beginning of a route (as she/he cannot be a driver), and reroute i directly to the workplace by public transport. Repeat until all routes begin with a vertex $i \in V_c$;
Step 4: Evaluate the resulting CO_2 emissions.

The solution obtained by our constructive heuristic is then passed to two local search algorithms. The first algorithm is based on a standard *swap* operator that attempts interchanging all possible pairs of vertices, both belonging to the same route or to two different routes. Each interchange is evaluated with respect to feasibility and the one yielding the largest cost reduction, if any, is selected. The second algorithm also works using a best improvement policy, and is based on a standard *move* operator that attempts to move each vertex to any other position in any route. The two local searches are invoked one after the other, until none of them provides an improvement. The heuristic procedure composed by first invoking the constructive algorithm and then the two local search algorithms is denoted as H_{TR} in the following.

The second heuristic procedure that we implemented, called H_{DR} in the following, solves the $DCPP_{DR}$ instead. It is based on simple adaptations of H_{TR} that verify that each step of the constructive heuristics and of the two local search algorithms maintains direct routes.

5. Case study

Coopservice S.coop.P.A. provides services on several sectors, including facility management, security, waste disposal, and third-party logistics. It has a total workforce of about 11,000 people and operates all over the Italian territory. The company provided us with a pilot case containing data for 135 employees working at the hospital Santa Maria Nuova, located in Reggio Emilia (Italy), close to the company headquarters. Most employees perform sanitation services at the hospital and have working shifts that change day-by-day.

The data include detailed information on the shifts for a period ranging from February to December 2012. A first analysis that we performed to understand the distribution of the shifts along the week is shown in Fig. 3. The figure shows the number of employees working per week day. This number is usually around 80 during working days, decreasing to about 70 during Saturdays, and to 40 on Sundays. A direct consequence of the small number of employees working on Sundays is that there are considerably less carpooling options on these days. Therefore, we removed data regarding Sunday shifts from our study, ending up with a set of 276 days. The few evident fluctuations in Fig. 3 represent holidays with a small number of employees at work. These situations are predictable and do not have a significant impact on the overall performance of the carpooling application.

Table 1 provides further insight into the study case by dividing the employees in those driving their own car and those taking

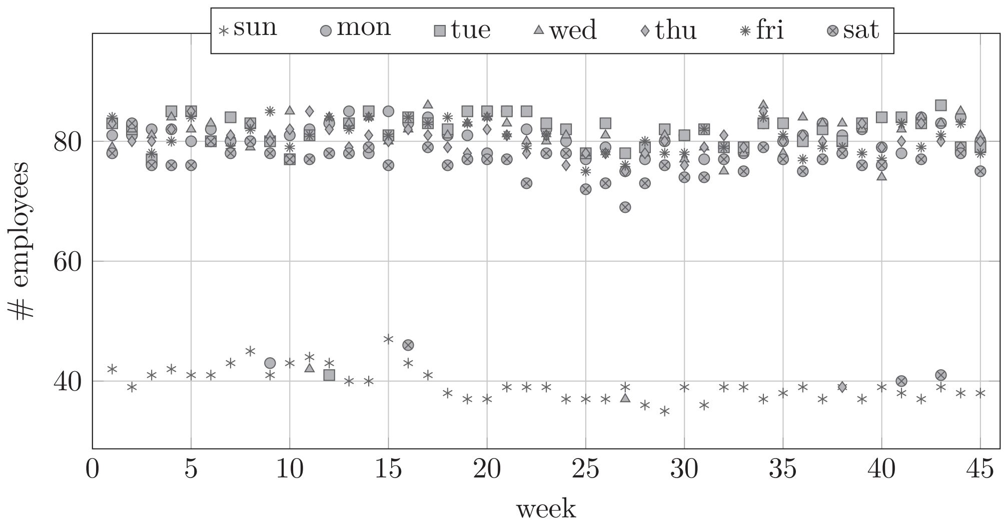


Fig. 3. Distribution of employees per weekday.

Table 1
Average number of employees per transportation method.

Transportation	Weekday					
	Mon	Tue	Wed	Thu	Fri	Sat
Car	33.57	33.43	32.89	33.52	33.72	30.58
Public	46.77	46.74	45.76	45.87	46.72	43.67
All	80.34	80.17	78.65	79.39	80.43	74.24

Table 2
Average number of employees per shift.

Shift type	Weekday					
	Mon	Tue	Wed	Thu	Fri	Sat
Outbound	6.19	6.80	6.33	6.80	6.48	4.87
Return	10.30	9.33	10.11	10.15	9.61	9.96
Both	14.11	14.00	14.22	14.87	13.96	13.18

public transport. By looking at the numbers, we can notice there is large space in the cars to accommodate the people that are now using the public transport.

An important factor, that might heavily affect the probability of success of a carpooling application in this context, is the number of different shift typologies. The higher is the number of different shifts, the fewer are the possible matching options for carpooling. Indeed, in our study case only employees that start and/or finish working at the same hour on that day are allowed to carpool together. We found a total of 171 different shift typologies during the period considered on the study. However, some of them are much more common than others. For instance, the shifts 6:00–12:30 and 14:00–20:30 are the most frequent, with frequency rates of 27% and 22%, respectively. Furthermore, the 11 most common shifts account for more than 80% of all entries. Table 2 shows the average number of employees per shift considering shifts that share the same starting time (outbound), the same ending time (return), and the number of shifts sharing both the starting and ending time (both). The results indicate that possible carpooling groups sharing only one leg of the trip are probably denser and may yield higher savings. Altogether, these findings seem to suggest that deploying a carpooling application in this scenario could lead to interesting reductions in traveled distance and CO_2 emissions.

To evaluate the distances between each pair of vertices, we developed an application that takes as input a digital map of the region and a list of the geographic coordinates of employee houses and workplace, and produces as output a matrix containing the value of the shortest paths between each pair of points. The application first reads the map and represents it as a directed graph. Then it takes the list of coordinates for which the distance matrix should be evaluated.

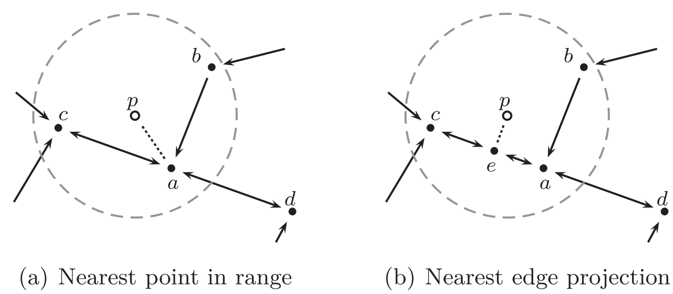


Fig. 4. Details of the map-matching procedure.

A *map-matching* procedure is necessary to properly insert the set of coordinates into the graph. Map-matching is the problem of inserting recorded geographic coordinates of the real world in a map, typically making use of a Geographic Information System (see, e.g., Quddus et al. [38]). The problem is particularly challenging when the coordinates originate from a path, that should thus be allocated to existing roads. In our case, the problem simply requires to match the static coordinates of the employees' houses and of the workplace into the graph that we use to represent the road network. To this aim we implemented a simple two-step procedure that works as follows. Suppose a given point p must be located in the map. At first, we search for all vertices in a given distance range from p and select the *nearest vertex* as the best candidate for the matching. An example is depicted in Fig. 4(a), where the nearest vertex is a. In case no vertex is found, we expand the diameter of the range and repeat the process until a match is found. Secondly, we project p into all edges in a given range, and determine the *nearest projection*. In the example shown in Fig. 4(b) the nearest projection is e, over the arc (a, c). The option giving the minimum distance is then chosen. If this results in the nearest vertex, then we simple match p into this vertex. If instead it results in the nearest projection, then we divide the selected arc into two arcs, create a new vertex corresponding to the projection, and then map p into the new vertex.

Table 3
Average results for the 2-way scenario on Set 1 instances (CO_2 in kg).

Weekday	No CP	F_{TR}			H_{TR}			F_{DR}			H_{DR}		
	CO_2	CO_2	Red(%)	sec	CO_2	Red(%)	sec	CO_2	Red(%)	sec	CO_2	Red(%)	sec
Mon (47)	99.4	78.1	21.3	0.5	79.1	20.4	0.0	78.9	20.5	0.5	79.9	19.5	0.0
Tue (46)	97.3	75.8	22.0	0.5	76.9	20.9	0.0	76.7	21.0	0.5	77.7	20.1	0.0
Wed (46)	98.1	75.9	22.9	0.6	76.9	21.9	0.0	76.8	22.0	0.7	77.8	21.0	0.0
Thu (46)	99.7	77.9	21.8	0.4	78.9	20.8	0.0	78.8	20.9	0.5	79.8	19.9	0.0
Fri (46)	100.9	78.4	22.2	0.5	79.5	21.1	0.0	79.4	21.2	0.5	80.5	20.1	0.0
Sat (45)	94.6	69.7	26.3	0.6	70.5	25.5	0.0	70.4	25.5	0.6	71.7	24.2	0.0
avg	98.4	76.0	22.7	0.5	77.0	21.7	0.0	76.9	21.8	0.5	77.9	20.8	0.0

Table 4
Average results for the 1-way scenario on Set 1 instances (CO_2 in kg).

Weekday	No CP	F_{TR}			H_{TR}			F_{DR}			H_{DR}		
	CO_2	CO_2	Red(%)	sec	CO_2	Red(%)	sec	CO_2	Red(%)	sec	CO_2	Red(%)	sec
Mon (47)	99.4	72.1	27.3	2.2	73.4	26.1	0.0	72.9	26.5	2.4	74.4	25.0	0.0
Tue (46)	97.3	70.0	27.9	2.5	71.3	26.5	0.0	70.9	27.0	2.9	72.3	25.4	0.0
Wed (46)	98.1	70.4	28.4	2.7	71.8	27.0	0.0	71.2	27.6	2.8	72.8	26.0	0.0
Thu (46)	99.7	72.0	27.6	2.7	73.4	26.3	0.0	72.9	26.7	3.0	74.3	25.3	0.0
Fri (46)	100.9	72.4	28.1	2.6	73.8	26.8	0.0	73.4	27.2	2.7	75.0	25.6	0.0
Sat (45)	94.6	66.2	29.9	1.9	67.4	28.7	0.0	67.0	29.0	1.8	68.8	27.1	0.0
Avg	98.4	70.6	28.2	2.4	71.9	26.9	0.0	71.4	27.3	2.6	73.0	25.7	0.0

6. Computational evaluation

In this section we present a computational evaluation of the mathematical formulations and heuristic algorithms that we developed. The coefficients for relating CO_2 emissions to the traveled distances have been set to $\gamma_c = 0.17$ kg/km and $\gamma_b = 0.07$ kg/km, following LCA-lab [39]. Unless stated otherwise, the maximum detour from the direct path to the workplace has been set to δ=17%, in accordance with Rietveld et al. [40]. The digital map of the region was taken from the free OpenStreetMap database (http://www.openstreetmap.org/). Some manual adjustments were needed in order to complete the information given by the database (concerning roundabouts, rural areas, etc.). All algorithms were implemented in C++ and the computational experiments were performed on a PC with Intel Core i7-3770 3.40 GHz and 8 Gb of RAM. The integer linear programs were solved with IBM Cplex 12.6.1, using the default options. We evaluate our algorithms on two sets of instances: Set 1 (whose results are discussed in Section 6.1) corresponds to all shift groups in the 276 days of our study case, whereas Set 2 (discussed in Section 6.2) contains 80 more challenging instances obtained by merging together customers from instances in Set 1.

Clearly, an employee has to perform two trips every day, one to go to the workplace and another one to return. This allows for some flexibility on how to select which employees can carpool together. Basically, we decided to perform our evaluation on two different scenarios. In the first scenario, called *two-way grouping* (2-way), we attempt to group employees that have the exact same shift, i.e., the same start times for both outbound and return trips. Our algorithms are then invoked to determine the CO_2 emissions for the outbound trip. The emissions for the return trip are evaluated by reverting the (asymmetric) cost matrix by setting $c_{ij} = c_{ji}$ for all $(i, j) \in A$, and then executing again our algorithms. The daily emissions are evaluated by summing the two solution values. In the second scenario, called *one-way grouping* (1-way), we propose a different solution for each of the two trips, attempting to group employees that have the same start time in the outbound trip independently from the return trip, or vice versa. In this case carpooling solutions are computed for both trips, once again taking into account the asymmetric matrix but in this case also considering possible different groups.

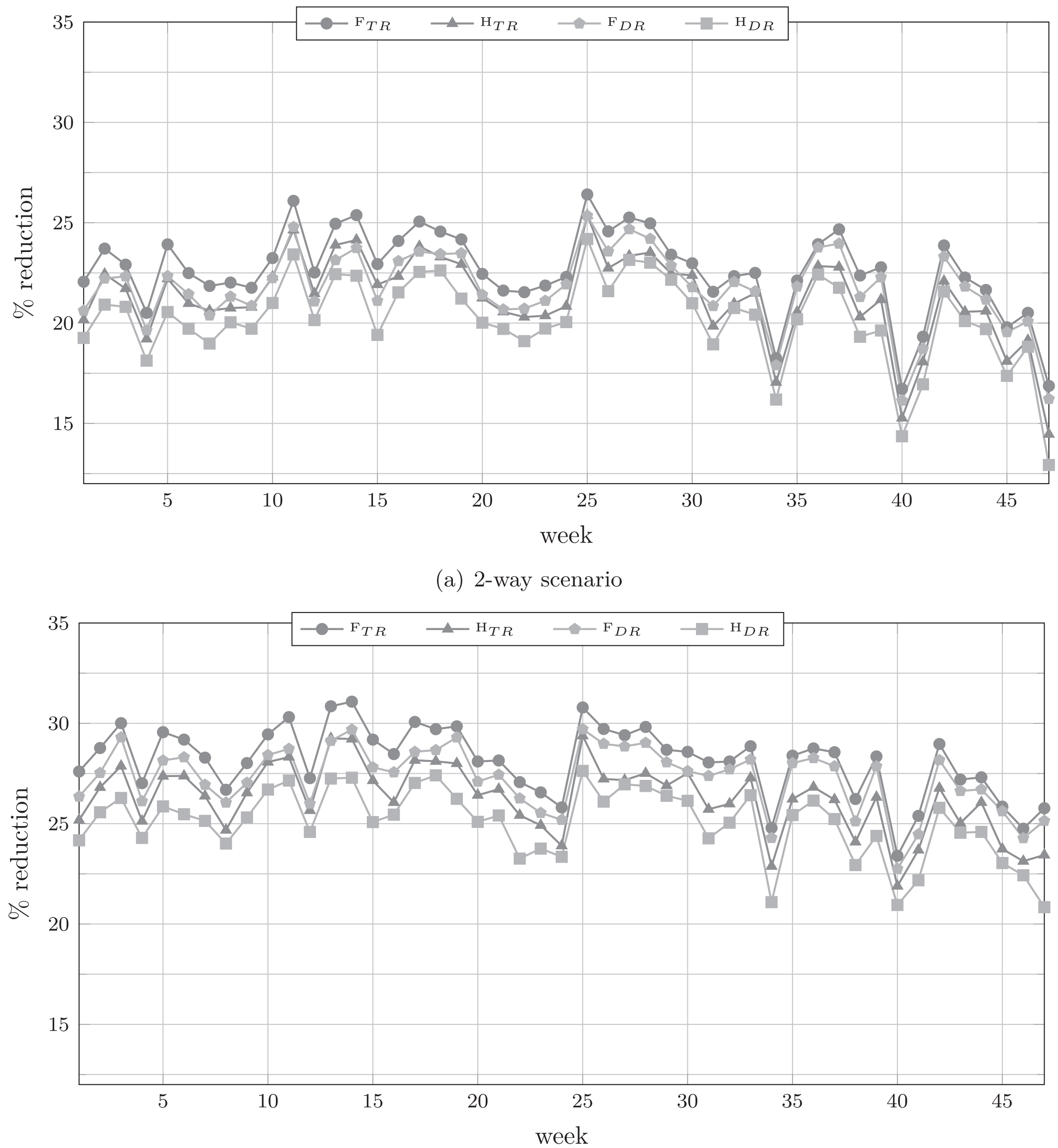
6.1. Results for the study case

In Table 3 we present average results per weekday for the 2-way scenario on the instances in Set 1. The first column gives the weekday and in parenthesis the number of days for the particular weekday. In column ‘no CP’ we provide the average daily emissions for the *non-carpooling* case (average values are evaluated with respect to all days in the row). This corresponds to the solution in which every employee $i \in V_c$ takes her/his car to go directly to the workplace and every employee $i \in V_n$ uses public transport. This provides an *upper bound* on the optimal solution value. For each of our four approaches we then show the average CO_2 emissions in kg, the percentage reductions with respect to the no CP case, and the elapsed computational time in seconds.

The exact approaches manage to reduce on average the emissions by around 22%, which is a great improvement and shows the potential benefits of carpooling. Also the heuristic algorithm H_{TR} significantly reduces CO_2 emissions, showing a surprisingly great potential for the practical application and yielding high quality solutions that are very close to the optimal ones. The same holds for H_{DR}, that provides reductions that are on average just 1% far from the optimal ones. We also notice that the behavior of the constructive heuristics is quite good even if the local search is not used: the average reduction would decrease from 21.7% to 21.4% for H_{TR} and from 20.8% to 20.3% for H_{DR}.

Similarly, Table 4 shows average results for the 1-way scenario. The gain within this type of scenario is even greater, and formulation F_{TR} manages to reach an average reduction of about 28%. The larger reductions obtained with respect to the 2-way scenario are due to the fact that, for the 1-way, the sizes of the groups of employees that can carpool together are larger. The larger group sizes are also the cause of the slightly longer computing times required by the formulations, which however remain very low. Also in this case the performance of the heuristic algorithms is satisfactory, as they provide in very quick times solutions that are very close to the optimal ones.

In Fig. 5 we depict once again the average percentage reductions in CO_2 emissions with respect to the no CP case, but in this case we highlight the evolution for the 45 weeks of the considered time interval. The number of the week is reported on the x-axis, and the average percentage reduction obtained in the week by a



(b) 1-way scenario

Fig. 5. Average % reductions per week over the non-carpooling case on Set 1.

given optimization technique on the *y*-axis. Results by all the developed techniques are presented, by considering the 2-way scenario in Fig. 5(a) and the 1-way scenario in Fig. 5(b).

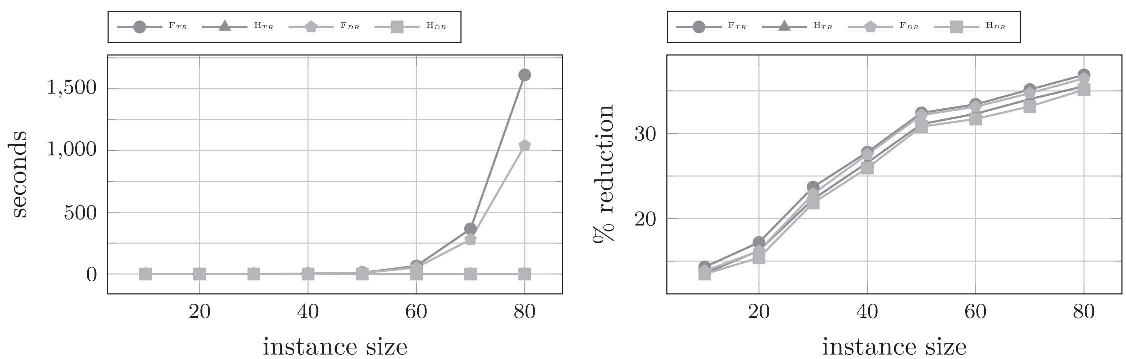
By looking at the figure, it is evident that the solutions provided by the heuristics and by the formulations are very close. The highest possible reductions are obtained for the 1-way case, for which the two formulations yielding tree-route and direct-route solutions show quite similar results. The potential savings found by F_{TR} ranges between 5.7 and 38.8 CO_2 kg per week, which corresponds to reductions from 14.5% to 41.6%. Also the results by the heuristics are very good and quite close to those of the two formulations. Overall our techniques allow to obtain reductions that are usually between 10.8% and 41.6% of the emissions of the non-carpooling case. Comprehensibly, the 2-way case shows lower reductions, but also in this case the performance of F_{TR}, F_{DR}, H_{TR}, and H_{DR} are very close to one another, usually ranging between 8.1% and 40.8%. By evaluating the total emissions in the whole period of 276 days, we found out that the total difference between the non-carpooling case (worst scenario) and the solution by F_{TR} under the 1-way case (best scenario) amounts to approximately 7.7 tons of CO_2.

6.2. Results on randomly created instances

As it will be described in the next section, the optimization algorithms that we developed must be invoked a large number of times within our web application. They must indeed suggest carpool solutions for any possible starting and ending time of a shift, considering the next seven days. Thus, they must be both quick and robust. Both the heuristic and the mathematical formulations quickly obtained good results for the instance in Set 1, which are however of quite limited size. In this section we discuss their behavior on larger-size instances that could better reflect other real-world cases. We build our second set of instances by randomly selecting *n* customers among those available in the instances of Set

Table 5
Average results for Set 2 instances (CO_2 in kg).

n	No CP	F_{TR}			H_{TR}			F_{DR}			H_{DR}		
	CO_2	CO_2	Red(%)	sec	CO_2	Red(%)	sec	CO_2	Red(%)	sec	CO_2	Red(%)	sec
10 (10)	12.1	10.4	14.3	0.0	10.4	13.6	0.0	10.4	13.8	0.0	10.4	13.5	0.0
20 (10)	27.0	22.2	17.2	0.1	22.5	16.2	0.0	22.5	16.2	0.1	22.7	15.4	0.0
30 (10)	42.6	32.3	23.7	0.6	32.9	22.3	0.0	32.6	22.9	0.7	33.1	21.8	0.0
40 (10)	59.2	42.7	27.8	2.5	43.4	26.6	0.0	42.8	27.5	2.4	43.7	25.9	0.0
50 (10)	71.2	48.0	32.4	11.2	48.9	31.1	0.0	48.2	32.2	8.3	49.1	30.8	0.0
60 (10)	80.6	53.6	33.4	60.7	54.5	32.3	0.1	53.8	33.1	55.0	55.0	31.7	0.0
70 (10)	91.7	59.4	35.2	343.2	60.5	34.0	0.1	59.8	34.7	253.2	61.2	33.2	0.1
80 (10)	101.4	64.0	36.9	1586.8	65.4	35.6	0.1	64.4	36.5	1291.2	65.8	35.1	0.1
Avg	60.7	41.6	27.6	250.7	42.3	26.5	0.0	41.8	27.1	201.4	42.6	25.9	0.0



(a) Average CPU time in seconds (b) Average reductions over the no CP case

Fig. 6. Average results per instance size for the instances of Set 2.

1 and supposing them to work on the same shift. We attempted 8 values of n $(10, 20, \ldots, 80)$ and created 10 random instances for each value, thus producing 80 instances in total. As all employees share the same shift, there is no difference between 2-way and 1-way scenarios. The results that we obtained are given in Table 5.

The mathematical formulations solve very quickly the small instances to proven optimality, but they require much larger times when n increases. In particular, for n=80 both F_{TR} and F_{DR} required more than 1000 s for a couple of instances. The heuristic algorithms are always very quick and provide solutions that are on average just 1% away from the optimal ones. In this case the local search algorithms are a bit more effective than for the Set 1 instances: if removed, the average reduction would decrease from 26.5% to 25.2% for from H_{TR} and from 25.9% to 25.0% for H_{DR}.

The computational behavior of our algorithms is also depicted in Fig. 6. The left part shows the evolution of the average CPU time. The right part shows that the solution quality is very similar for the four algorithms, and that the opportunity for CO_2 reduction gets larger when n increases.

We also evaluated the sensitivity of our algorithms with respect to some problem parameters. We first varied the maximum detour, originally set to δ=17%, by considering also 34% and 51%. We gave a time limit of 600 s (300 for the outbound trip and 300 for the return trip) to our formulations. We found that the heuristics remained very quick and efficient. On the other side, the formulations required larger times when δ increases. For F_{TR}, the number of instances unsolved to proven optimality both in the outbound and in the return trips showed a sharp increase, being 10 for δ=17%, 27 for δ=34%, and 32 for δ=51%. Similarly, for F_{DR}, this value was 9 for δ=17%, 24 for δ=34%, and 32 for δ=51%.

The formulations were also sensitive to the number of employees owning a car. For example, considering again a time limit of 600 s, keeping δ=17%, and supposing that all employees owned a car, we experienced an increase in the number of solutions unsolved to proven optimality in both trips from 10 to 23 for F_{TR}, and from 9 to 18 for F_{DR}. Also in this case the heuristics showed instead a robust behavior in terms of CPU effort and solution quality.

7. Web application

A working prototype of a web application has been deployed at the company for testing. The application is divided into two main modules, the *optimization core* and the *visual core*, that communicate with each other by means of a MySQL database to store and retrieve data processed during operations.

Fig. 7 depicts the basic structure of the application. The optimization core contains two subroutines and, similar to what is done in Wolfler Calvo et al. [5], it runs on a daily basis to provide carpooling solutions for every shift starting and ending times of the following seven days. The *MapAnalyzer* is first run to analyze information regarding the employees of the company and update the file containing the shortest paths, if needed, by accessing the OpenStreetMap database (saved in ShapeFile format). Then, the routine *GenSolutions* reads information regarding the employees and their shortest paths, invokes one of our heuristic algorithms, and stores the solutions in the database using a GeoJSON format. The prototype is equipped with both heuristic algorithms that we developed (so it can solve both $DCPP_{DR}$ and $DCPP_{TR}$) and uses H_{TR} as default. The server side part (the *back-end* in Fig. 7) of this module was built using Java EE technology interacting with a MySQL database, while the client side part (the *front-end* in Fig. 7) was implemented using HTML, JavaServer Pages, and JavaServer Faces.

The application is available only to those employees of Coopservice S.coop.P.A. who decided to participate in the carpooling process. Every time a user accesses the application via the web, the visual core reads from the database the suggestions proposed by the optimization core and shows the appropriate ones to the user. The user can then communicate via email with other participants,

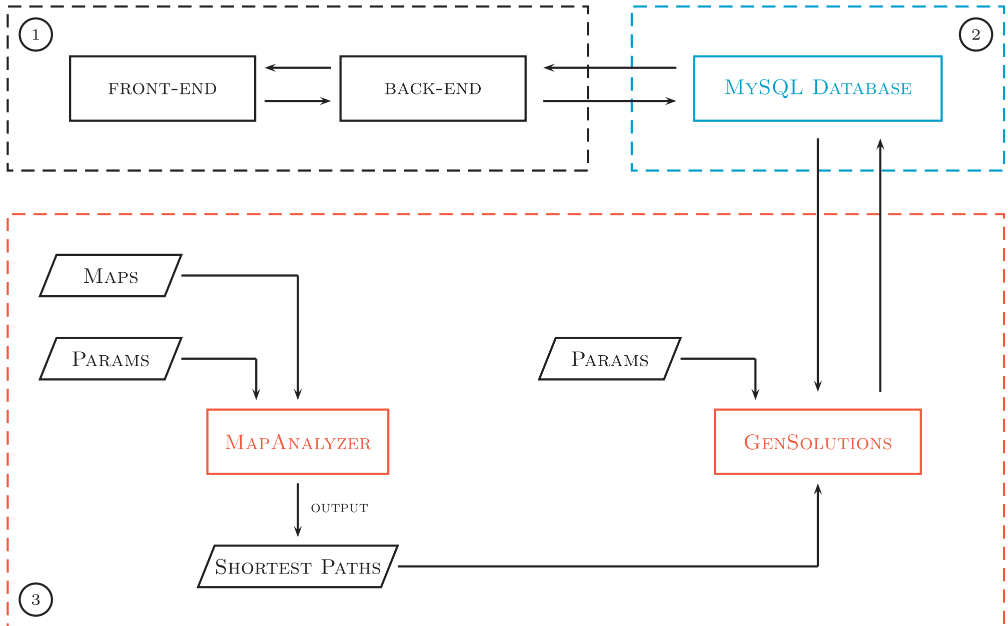


Fig. 7. System architecture and communication between modules (1- visual core; 2- database; 3- optimization core).

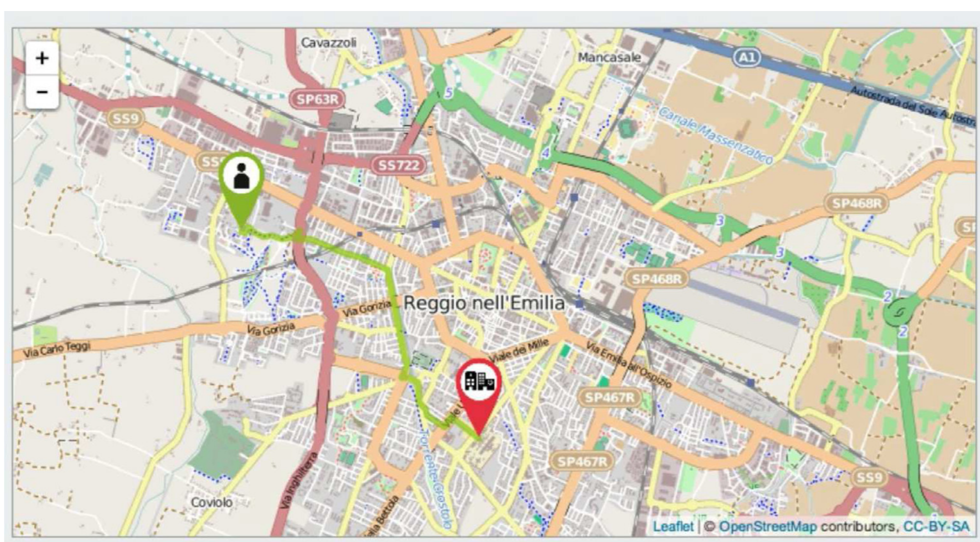


Fig. 8. Web application prototype: view of the direct route to the workplace.

choosing them among the suggested carpools or by simply looking at the closest ones. Fig. 8 shows a simple screen shot of the application, where a user sees on the map her/his location, the workplace, and the shortest path to get there. Notice that the system does not force any carpool and users are able to refuse to accept a ride request. Moreover, it does not suggest a way for sharing costs, as this aspect is left to common agreements among participants.

8. Conclusions

In this paper we approached a practical daily carpooling problem with the aim of reducing CO_2 emissions. We presented a brief survey of the related literature, and then we solved a real-world case study by means of two mathematical formulations and two heuristic algorithms. Moreover, we developed a prototype of a web application. In this application users are provided with the suggested carpools obtained by the use of the heuristics, and can easily communicate with each other to organize carpools according to their wishes. The computational experiments that we performed indicate a great potential for CO_2 reductions. More specifically, under the 2-way grouping strategy (where employees use the same carpool both on the way to work and on the return way) the potential reduction is about 22%, while for the 1-way grouping strategy (where employees can use different carpools for the two trips) this number increases to about 28%. The results also indicate that the company can directly affect the efficiency of the carpooling practice by optimizing employees' shifts in order to create denser groups, which is an interesting direction for future research. Another interesting direction consists in finding appropriate strategies for sharing costs among users.

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