

Time-dependent sustainable vehicle routing problem in city logistics

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Abstract: In this paper the time-dependent sustainable vehicle routing problem (VRP) is introduced as one of the few studied areas of VRPs. Different challenges in city logistics including traffic congestion, path flexibility, and heterogeneous vehicles are also considered. The purpose of the problem is to design the service routes and determining optimal departure time from depot in such a way that the amount of fuel consumed is minimized, and the workload of different drivers is balanced for more job satisfaction. Fuel consumption is a function of travelled distance, speed, load, and vehicle characteristics. The problem is formulated as a bi-objective mixed-integer linear programming (MILP) model and solved by an augmented ϵ -constraint method. To solve large-sized instances, two meta-heuristic algorithms based on genetic and fireworks algorithms are developed. To increase the efficiency of these algorithms, a clustering-based heuristic method is proposed to generate good initial solutions. Numerical tests represent a better performance of the fireworks algorithm. Results show that striking workload balance among drivers has negligible effects on the increment of fuel consumption. Also, optimization of departure time and stopping at the depot during rush hours has a considerable impact on the total fuel consumed.

KEYWORDS: Time-dependent vehicle routing problem, Sustainable supply chain management, City logistics, Equity, Meta-heuristics.

1. Introduction

Recent economic and technological advancements have led to increased attention to sustainable development concepts, focusing on environmental and social issues. This includes planning considering environmental factors such as reducing pollution and natural resource consumption, as well as social factors such as job creation, labor laws, and customer satisfaction, in addition to economic factors [1]. From the operational point of view, the integration of environmental and social aspects along with economic aspects in the decision making process of organizations is known as Triple-Bottom-Line (TBL) Dimensions of Organizational Sustainability [2]. The classical view of supply chain management primarily focuses on economic goals and financial performance, while the "sustainable supply chain management" concept aims to integrate environmental and social aspects alongside economic aspects [3].

One of the most important decisions in many supply chains is transportation planning and vehicles routing. On the one hand, the transportation costs in supply chain networks is a major part of the system costs, and on the other hand, such activities cause some negative environmental and social effects such as air pollution. Green logistics is a rather new concept in supply chain management in which distribution management is performed with the aim of minimizing environmental and economic costs [4]. In the vehicle routing problem (VRP) literature, this issue is known as green vehicle routing problem (GVRP) that has been introduced since 2007 [5]. For instance, Kara et al.[6] proposed a type of GVRP called

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“energy minimizing VRP” in which the amount of fuel consumption is assumed as a function of the distance traveled and the vehicle weight. However, one of the most popular studies in this field which has been widely developed later entitled “pollution routing problem (PRP)” was carried out by Bektas and Laporte [7]. The PRP aims to design service routes and determine the vehicle speed in each route considering both economic (i.e., fuel cost, drivers’ wages, and etc.) and environmental objectives (i.e., pollution rate). Kramer et al. [8] proposed a hybrid method to solve PRP in which, an integer programming formulation is combined with a local search method. In another study, Kramer et al. [9] investigated a case of this problem in which, optimized speed of vehicles is determined according to the customers’ time window. They also considered the departure time from the depot as a decision variable. Furthermore, Rauniyar et al. [10] recently proposed a development of Genetic Algorithm (GA) in order to solve PRP in a multi-objective framework in which total fuel consumption and total traveled distance are both minimized.

The fuel consumption rate and pollutant gas emissions in PRP are influenced by factors such as vehicle load and speed, traveled distance, and vehicle specifications [11]. Vehicle speed is directly affected by traffic congestion especially in city logistics. According to the researches, in addition to the costs incurred for delays due to the traffic congestion, it could even increase emissions by up to 300% [12]. In classic VRP, vehicle speed is assumed fixed and the travel time between two points is proportional to the length of that route, but in city logistics with considering route traffic, the travel time depends on further factor such as traffic condition at departure time. Peak rush hour is one of the most important factors affecting urban traffic. These rush hour times have a regular and predictable pattern. Considering the traffic conditions of different hours in vehicle routing and scheduling and also stopping at depot during heavy congestion hours could be an opportunity to increase the efficiency of the transportation system and reduction of air pollution as well. Furthermore, previous studies demonstrate that ignoring time-dependent travel times will result in poor evaluation of trips durations with a significant error compared to actual duration [12]. Franceschetti et al. [13] proposed time-dependent pollution-routing problem (TDPRP) with the aim of minimizing fuel costs and drivers wages considering traffic congestion. Their algorithm determines the optimal route, speed, and departure time for each vehicle. One of their main ideas is to stop vehicles at the depot as well as customer nodes (after service) to avoid traffic during rush hours. Later in another study, they likewise proposed a metaheuristic algorithm to solve TDPRP [14].

In the classic VRP, there is only one path between the two points but in city logistics there are usually several routes between two points one of which is preferred depending on traffic conditions and times of day. Moreover, nowadays using satellite navigation services such as Google map have become globally more and more popular in city logistics. So taking into account the information of proposed routes via these services in VRP can lead the model output to be more accurate and feasible. For instance, Figure 1 depicts the different routes suggested by Google map between points A and B in Tehran metropolis at different times of a day. As shown in Figure 1, the suggested routes and travel time are different at different times of the day. Also as can be seen in Figure 2, the average travel time between peak and off-peak hours is significantly different. In addition, this traffic condition usually has a regular and predictable pattern for various daytimes [15]. Thanks to the day by day growth of information technology (IT), such information is easily accessible by services (e.g., Google Maps API (application programming interface)) and can be considered as VRP parameters.

[please insert Figure 1 about here]

[please insert Figure 2 about here]

The number of studies concerning the path flexibility in TDVRP is very few. Setak et al.[16] investigated the TDVRP problem with alternative routes and homogenous vehicles. They used the Tabu Search heuristic method to solve the problem. However, in their study, the environmental aspects have not been taken into account. As one of the first studies in the context of PRP, Ehmke et al. [17] Investigated a TDVRP to minimize CO₂ emissions and transportation costs, in which transportation costs depends on the route's length and vehicle load .Qian et al. [18] studied TDVRP with time window in which the optimal speed and routes are determined while minimizing pollution. Recently Huang et al. [15] performed TDVRP to minimize fuel costs considering multiple paths between two customer nodes in the road network. Path selection was one of the main decisions in their study and the speed in each time period of a day was assumed equal to the traffic speed. However, their method is inefficient in solving large scale instances. Androutopoulos et al. [19] examined TDVRP as a bi-objective problem to minimize total travel time and fuel consumption in which routing and path selection were performed simultaneously. Their study was recently developed into a multi-trips VRP by Raeesi et al. [20]. In which, total travel time, total fuel consumed, and vehicle hiring cost were minimized as three various objective functions.

In most studies on TDVRP, by dividing the day into several time intervals, the vehicle speed is assumed as a step function of time of the day and based on that the travel time is calculated using a piecewise linear function. This method is based on the idea proposed by Ichoua et al.[21] in 2003. This method, despite its widespread use, has some disadvantages. Firstly, due to the different traffic conditions, it is not possible to assume the same travel speed in various regions at a specific time. Secondly, in city logistics, there are usually several streets, highways, and the like, between two points. while considering the information of whole these streets in TDVRP will greatly complicate the problem. In addition, such information is not readily available. Also, from mathematical viewpoint, using such a method to model congestion becomes far more complicated by increasing the number of intervals during the day.

For considering path flexibility, in some researches path finding is performed simultaneously with routing ([20],[15]). Since distribution systems may encounter new customers daily, consideration of their location and traffic information in those regions is a very time consuming and even impossible task. However, thanks to services such as Google maps API (application programming interface), for any two specific points, suggested routs between them and also length and travel time of each rout could be readily obtained at various hours of the day. Hence, in the present paper, the modeling of this problem is conducted based on the availability of such information.

In addition to the pollution, another aspect of environmental concerns is the optimal utilization of resources. This has led to a focus on reverse flows throughout the supply chain and planning for collecting returned products. In this regard, many manufacturing companies have turned to integrated planning for direct and reverse flows in order to increase system efficiency and use the maximum chain capacity, especially in the transportation sector. fresh grocery supply chain (distribution of fresh products and returning the outdated products for use in other industries) is a good example of such networks. From the routing problem viewpoint, integration of flows leads to cost saving. For instance, integration of distribution and collection will result in utilization of the maximum capacity of the vehicles throughout their journey. This goal can be achieved by implementing models such as vehicle routing problem with simultaneously pickup and delivery (VRPSPD), where the customer demand is delivered and the returned goods are picked up at the same time. From PRP perspective, simultaneous pickup and delivery is of great importance because one of the factors affecting the fuel consumption rate is the vehicle load. There are few studies in this field available in the literature. For example, Majidi et al. [22] proposed an adaptive

large neighborhood search heuristic to solve this problem. In another study, Bravo et al.[23] proposed a metaheuristic to solve the multi-objective form of this problem in which the total number of served customers, total travel time, and total emitted greenhouse gases were considered as various objectives. Likewise, Paul et al. [24] examined this problem in a bi-objective framework to minimize travel time and total fuel consumption as well. Despite the above-mentioned investigations, no article has studied this problem considering traffic congestion [25]. However, it is important that the routing is accomplished in a way that the vehicles travel both shorter distances and times with the maximum payload. This topic is comprehensively studied in the current article.

Heterogeneous vehicles in the transportation fleet is another challenge in city logistics. Different types of vehicles have different capacities and specifications with various fuel consumption and emission rates. Koc et al. [26] proposed a development of the PRP with heterogeneous vehicles showing that using heterogeneous vehicles without determining the optimal speed is more effective than using homogeneous vehicles with determining the optimal speed in reduction of the total costs. In another study, Cheng et al. [27] developed the PRP by considering inventory costs, environmental factors, and heterogeneous vehicles to minimize total inventory and routing costs.

Since heterogeneous vehicles have different capacities, this obviously affects the drivers' workload. Equity as one of the most important social aspects of the routing problems deals with balancing the workload of vehicle drivers (In terms of traveled distance, travel time, and etc.) which is related to the issue of fair payments and driver satisfaction. On the one hand, balancing the workload between different drivers leads to more satisfaction and increment of the quality of customer service as well. On the other hand, it prevents unnecessary overtime of some vehicles and as a consequence extra routing costs. Matl et al. [28] study reveals that when VRP is solved only with economic objective, the workload difference between different vehicles is significant, so that the longest tour on average is about twice the shortest tour. This problem is known as "vehicle routing problem with route balancing" in the literature [29]. Usually in such problems workload is balanced between different vehicles through minimizing the longest journey and or minimization of the difference between the longest and the shortest trip. It is worth mentioning that solving the routing problem solely through consideration of workload balance objective can also result in an enhancement of the total traveled distance. Therefore, many studies examine this problem in the form of a bi-objective problem in which on the one hand the total costs are minimized and on the other hand the workload is balanced. In this regard, Halvorsen et al. [30] have studied the differences between varied workload balance criteria in bi-objective VRP and their effect on pareto-optimal solutions. In the context of GVRP, there is a rather few studies in the literature that address the workload balancing [31]. Fredy et al. [32] recently provided a multi-objective model in which total costs, total emissions as well as the difference between the longest and the shortest tour are minimized. However, with regard to a study by Dundar et al.[1], the social dimension is the least studied sub-dimension of sustainability in VRP area. One of the most important factors affecting drivers' working time is traffic congestion, while, there is a lack of studies on the workload balancing in the time-dependent VRP.

To conclude, the contributions of this study are as follows: (1) introducing the time-dependent sustainable routing problem in which various economic, environmental and social aspects of vehicle routing problem in addition to different challenges in city logistics are considered. (2) Investigating the effect of vehicle load on fuel consumption in the time-dependent VRP with simultaneously pickup and delivery in which the vehicle load maybe increased by returned products during the journey. It is important that the routing is accomplished in a way that the vehicles travel shorter time with the maximum payload.

- (3) analyzing the impacts of various vehicles workload balancing (in terms of travel time) on fuel consumption in a time-dependent routing problem with heterogeneous vehicles with different capacities.
(4) developing two meta-heuristic algorithms to solve large instances.

2. Problem definition and mathematical modeling

This section introduces the time-dependent sustainable routing problem with simultaneously pickup and delivery. The logistics network studied here is a network with direct and reverse flows with a central depot and $|C|$ customers in which each customer has a specific demand and returned products. The planning horizon is a day, and each vehicle starts its journey from the depot and returns to the depot after serving a subset of customers. After each vehicle reaches a customer, its demand is delivered and the returned goods are picked up at the same time. There are $|H|$ different types of vehicles and a total of $|K|$ vehicles in the heterogeneous fleet. Shortage is not allowed and the vehicle's capacity constraint along the tour must be satisfied. Each customer has a service time and post-service waiting is not allowed at the customer nodes.

As a challenge in city logistics, there are multiple paths between any two points which are preferred at different times of a day and depending on traffic conditions at departure time. For this purpose, according to the traffic congestion at different times of the day, a workday could be divided into different time intervals so that in each interval the traffic congestion is relatively stable and different from other intervals. For instance, a day is divided into three time intervals including morning congestion which is followed by period of free flow in the middle hours of the day and then afternoon rush hours. In general, a day could be divided into N time intervals, in each of which the best path between two points as well as the travel time in that path are the pre-defined parameters of the problem. In the following, traffic congestion modeling is explained in more detail. Stopping at the depot during peak hours and optimizing departure time from the depot is one of the operational approaches of this study to avoid congestion during rush hours.

From the social responsibility viewpoints and in order to obtain drivers satisfaction, balancing the workload of different vehicles during the day is considered as one of the objectives of the current problem. However, solving the routing problem solely through consideration of workload balancing objective can increase the total fuel consumption. Therefore, this problem is addressed as a bi-objective problem, aiming to minimize total fuel consumption while maintaining a balanced workload between different vehicles. Before development of a MILP formulation, we need to define a mathematical function to estimate the fuel consumption as a function of traveled distance, vehicle speed, vehicle load, and etc.

2.1 Fuel Consumption calculation

One of the most comprehensive mathematical models to estimate the fuel consumption in the transportation fleet is proposed by Barth et al. ([33],[34]) in which, the total amount of fuel consumed F^m (liters) by a vehicle type m ($m \in H$) for traversing distance d (meters) in t (seconds) with weight M^m (kg) is estimated as follows:

$$F^m = \lambda \left(k^m N^m V^m t + M^m \gamma^m \alpha d + \beta^m \gamma^m \frac{d^3}{t^2} \right) \quad (1)$$

where $\lambda = \varepsilon / (\kappa\psi)$, $\alpha = \tau + g\sin\theta + gC_r\cos\theta$, $\gamma^m = 1 / (1000n_f^m\eta)$, $\beta^m = 0.5C_d^m\rho A^m$

In Equation (1), M^m represents the total vehicle weight, which is the sum of curb weight and payload. Based on study by Cheng et al. [27], other parameters' definition and typical values are given in Tables 1 and 2. Parameters that are independent of vehicle type (vehicle common parameters) are presented in Table 1. Also for vehicle specific parameters, vehicles are grouped into three categories according to their weight and capacity and parameter' values for each of them are presented in Table 2.

Figure 3(a) shows variations of fuel consumption versus different speed for various vehicle types in which vehicles load is assumed to be 75% of their maximum payloads. It is found that for each vehicle type the fuel consumption has its minimum amount at a speed of 30-40 km/h, and fuel consumption rate is greatly different for various vehicle types at a specific speed. Also in Figure 3(b) the vehicles speed is 35 km/h and the effect of the vehicle load on fuel consumption is depicted. As can be seen, fuel consumption rate can rise up to 60% depending on the vehicle weight for different vehicle types. Therefore, it makes sense to consider the influence of vehicle speed and characteristics in VRP, especially in city logistics where the traffic congestion has a direct impact on vehicle speed, and also in VRPSPD in which vehicle load does not necessarily decrease during the tour and customer visit sequence must be planned in such a way that vehicle travels short distances at its maximum payload which has a great impact on fuel consumption reduction.

[please insert Figure 3 about here]

[please insert Table 1 about here]

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2.2 An integer linear programming formulation

In this section we formulate our problem as a bi-objective MILP model.

Sets:

- $C = \{0, 1, 2, \dots, |C|\}$ Set of all nodes (depot and customers) $i, j \in C$
- $C_0 = C \setminus \{0\}$ Set of customers
- $K = \{1, 2, 3, \dots, |K|\}$ Set of vehicles $k \in K$
- $H = \{1, 2, 3, \dots, |H|\}$ Set of vehicles type $m \in H$
- $N = \{1, 2, 3, \dots, |N|\}$ Set of time intervals during the day $n \in N$

Parameters:

- c'_{ijn} Travel distance from node i to node j , if vehicle leaves node i within time interval n
- t'_{ijn} Travel time from node i to node j , if vehicle leaves node i within time interval n
- q_k Capacity of vehicle k
- d_j Delivery demand of customer j
- p_j Quantity of returned product of customer j
- r' Duration of workday

- a'_{km} Binary parameter that is 1 if vehicle k is type m
 s_i Service time at customer i
 M Large positive constant

Decision variables:

- x_{ijk} Binary variable that is 1 if vehicle k travels from node i to node j
 x'_{ijkn} Binary variable that is 1 if vehicle k leaves node i to node j within time interval n
 t_k Total travel time of vehicle k
 l_{ki} Load of vehicle k after leaving node i
 l'_{kijn} Load of vehicle k after leaving node i to node j within time interval n
 u_{ik} Sub tour elimination variable
 a_{ki} Amount of products delivered to customer i by vehicle k
 b_{ki} Amount of products picked up from customer i by vehicle k
 w_{ki} Departure time of vehicle k from node i

$$\text{Min } Z_1 = \sum_{i \in C} \sum_{j \in C} \sum_{k \in K} \sum_{n \in N} \sum_{m \in H} a'_{km} \lambda \left[x'_{ijkn} k_m N_m V_m t'_{ijn} + (x'_{ijkn} W_m + l'_{kijn}) \gamma_m \alpha c'_{ijn} + x'_{ijkn} \beta_m \gamma_m \frac{(c'_{ijn})^3}{(t'_{ijn})^2} \right] \quad (2)$$

$$\text{Min } Z_2 = \text{Max } \{t_k\} \quad (3)$$

s.t.

$$\sum_{i \in C} \sum_{i \neq j} x_{ijk} \leq 1 \quad \forall j \in C_0 \quad (4)$$

$$\sum_{i \in C} x_{ijk} = \sum_{i \in C} x_{jik} \quad \forall j \in C_0, k \in K \quad (5)$$

$$\sum_{j \in C_0} x_{0jk} = \sum_{j \in C_0} x_{j0k} \quad \forall k \in K \quad (6)$$

$$\sum_{j \in C_0} x_{0jk} \leq 1 \quad \forall k \in K \quad (7)$$

$$\sum_{i \in C_0} \sum_{j \in C_0, i \neq j} x_{ijk} \leq M \times \sum_{j \in C_0} x_{0jk} \quad \forall k \in K \quad (8)$$

$$u_{ik} - u_{jk} + (|C|)x_{ijk} \leq |C| - 1 \quad \forall i, j \in C_0 (i \neq j), k \in K \quad (9)$$

$$x_{ijk} = \sum_{n \in N} x'_{ijkn} \quad \forall i, j \in C (i \neq j), k \in K \quad (10)$$

$$l_{k0} = \sum_{j \in C_0} a_{kj} \quad \forall k \in K \quad (11)$$

$$l_{ki} \geq l_{kj} - a_{ki} + b_{ki} - M(1 - x_{jik}) \quad \forall i \in C_0, j \in C (i \neq j), k \in K \quad (12)$$

$$l'_{kijn} \leq q_k (x'_{ijkn}) \quad \forall i, j \in C (i \neq j), k \in K, n \in N \quad (13)$$

$$l_{ki} = \sum_{j \in C (j \neq i)} \sum_{n \in N} l'_{kijn} \quad \forall i \in C, k \in K \quad (14)$$

$$a_{kj} + b_{kj} \leq M \times \sum_{i \in C, i \neq j} x_{ijk} \quad \forall j \in C_0, k \in K \quad (15)$$

$$\sum_{k \in K} a_{kj} = d_j \quad \forall j \in C_0 \quad (16)$$

$$\sum_{k \in K} b_{kj} = p_j \quad \forall j \in C_0 \quad (17)$$

$$t_k = \sum_{i \in C_0} \sum_{j \in C (j \neq i)} \sum_{n \in N} x'_{ijkn} (s_i + t'_{ijn}) + \sum_{j \in C_0} \sum_{n \in N} x'_{0,jkn} (t'_{0,jn}) \quad \forall k \in K \quad (18)$$

$$t_k + w_{k0} \leq r' \quad \forall k \in K \quad (19)$$

$$w_{kj} \geq w_{ki} + x'_{ijkn} (t'_{ijn} + s_j) - M (1 - x'_{ijkn}) \quad \forall i \in C, j \in C_0 (i \neq j), k \in K, n \in N \quad (20)$$

$$w_{kj} \leq w_{ki} + x'_{ijkn} (t'_{ijn} + s_j) + M (1 - x'_{ijkn}) \quad \forall i \in C, j \in C_0 (i \neq j), k \in K, n \in N \quad (21)$$

$$x_{ijk}, x'_{ijkn} \in \{0, 1\} \quad (22)$$

$$t_k, l_{ki}, l'_{kijn}, u_{ik}, a_{ki}, b_{ki}, w_{ki} \geq 0 \quad (23)$$

$$1 \leq u_{ik} \leq |C| \quad \forall i \in C_0, k \in K \quad (24)$$

In the proposed mathematical model, the first objective function is equal to the total fuel consumed by all vehicles during their tours which is function of distance traveled, speed (travel time), load of vehicles and their physical characteristics. Second objective function tries to balance workload of different vehicles as much as possible by minimizing the duration of the longest tour. Constraints (4) - (10) are routing constraints according to the VRP assumptions. constraint (9) is the sub-tour elimination constraint. Calculating the vehicle load after leaving each node and checking the capacity of the vehicle is done using constraint (11) - (14). Constraints (15) and (17) are constraints on customer requirements (pickup/delivery demand) satisfaction constraints. Total travel time of each vehicle is calculated by expression (18) and restricted by constraint (19). Constraints (20) and (21) are used to express the temporal relationship between arrival time, service time and departure time of each vehicle at each customer. Finally, constraints (22) - (24) are variable specification constraints.

To linearize the second objective function, $Min Z_2$ must replace Expression (3). Also the following constraint should be added to constraints (4) - (24):

$$Z_2 \geq t_k \quad \forall k \in K \quad (25)$$

Traffic congestion modeling

In addition to the above equations, one of the most important parts of the MILP model is how to create a relationship between variables w_{ki} and x'_{ijkn} , so that $\sum_{j \in C (j \neq i)} x'_{ijkn}$ is equal to 1 if departure time of vehicle k at node i is in the time interval n . For this purpose, as we said earlier, a day can be divided into

N time intervals as $\{TI_0, TI_1, TI_2, \dots, TI_N\}$ in which TI_{n-1} and TI_n are lower and upper bounds of time interval n ($n \in N$). Also $TI_0 = 0$ and $TI_N = r'$ (duration of the workday). In each time interval, the best path between two points as well as the travel time in that path are the problem inputs (c'_{ijn}, t'_{ijn}) . The relation between w_{ki} and x'_{ijkn} is as follows:

$$\left\{ \begin{array}{l} \sum_{j \in C(j \neq i)} x'_{ijk1} = 1 \quad TI_0 \leq w_{ki} < TI_1 \\ \sum_{j \in C(j \neq i)} x'_{ijk2} = 1 \quad TI_1 \leq w_{ki} < TI_2 \\ \dots \end{array} \right. \quad \forall i \in C. k \in K \quad (26)$$

To linearization of above equation, we must define a new continuous decision variable λ'_{kin} ($0 \leq \lambda'_{kin} \leq 1$) and three new constraints as follows:

$$w_{ki} \geq \lambda'_{kin} TI_{n-1} + (1 - \lambda'_{kin})(TI_n - \varepsilon) - M \left(1 - \sum_{j \in C(i \neq j)} x'_{ijkn} \right) \quad \forall i \in C. k \in K. n \in N \quad (27)$$

$$w_{ki} \leq \lambda'_{kin} TI_{n-1} + (1 - \lambda'_{kin})(TI_n - \varepsilon) + M \left(1 - \sum_{j \in C(i \neq j)} x'_{ijkn} \right) \quad \forall i \in C. k \in K. n \in N \quad (28)$$

$$\lambda'_{kin} \leq \sum_{j \in C(i \neq j)} x'_{ijkn} \quad \forall i \in C. k \in K. n \in N \quad (29)$$

According to above constraints, if vehicle k leaves node i within time interval n , λ'_{kin} can be greater than 0 and variable w_{ki} becomes a convex combination of lower bound and upper bound of time interval n . also depending on the selected time interval in which vehicle k departs node i to go to node j , travel time (t'_{ijn}) and travel distance (c'_{ijn}) from node i to node j is taken into account in the model as pre-defined parameters.

3. Solution approach

In this section, augmented ε -constraint method (AUGMECON) is used as an exact solution algorithm to solve the bi-objective MILP model. Also, two multi-objective meta-heuristic algorithms based on genetic and fireworks algorithms are developed to solve large-scale instances. in order to increase the efficiency of the two meta-heuristic algorithms a local search method has been used in each iteration. Also to increase the problem solving speed in meta-heuristics, a clustering algorithm is developed to create a good and feasible initial solution. Duo to the conflict of two objectives, the goal of solution methods is to achieve a set of non-dominated (pareto front, efficient) solutions. In a bi-objective minimization problem with objective functions OF_1 and OF_2 , a feasible solution i is an efficient solution if there is no feasible solution j such as $OF_1(j) \leq OF_1(i)$ and $OF_2(j) \leq OF_2(i)$ (with at least one strict inequality). if we

replace \leq with $<$ we obtain weakly efficient solutions[35]. In multi objective problems we usually don't look for weakly efficient solutions because they may be dominated by efficient solutions.

3.1 Augmented ε -constraint method

The ε -constraint method is one of the most well-known exact methods for solving multi-objective models that has been widely used in the literature [36]. In this method, by optimizing one of the objective functions using the another objective function as constraints, the multi-objective model becomes an equivalent single-objective model. The formulation of the ε -constraint method in our two-objective model is as follows:

$$\begin{aligned}
 & \text{Min } OF_1 \\
 & \text{Subject to:} \\
 & \quad OF_2 \leq \varepsilon_2 \\
 & \quad \text{Constraints (4)-(29)}
 \end{aligned} \tag{30}$$

By changing ε_2 and solving the single-objective model, set of non-dominated solutions (pareto set) is obtained. The range of ε_2 can be determined according to the best and worst possible values of the second objective function which are calculated using lexicographic optimization method. In this method, the best value of second objective function (OF_2^{min}) is equal to the optimal value of OF_2 in the single-objective model with second objective function. The worst value of second objective function (OF_2^{max}) is the optimal solution of the single-objective model with second objective function under constraint $OF_1 = OF_1^{min}$. In the same way, the best and worst values of the first objective function can be obtained, and through this, the beginning and end points of pareto front are determined. Then the different values of ε_2 are determined by dividing $[OF_2^{min} \text{ } OF_2^{max}]$ into q equal parts as follows. The larger value of q , the more points on the pareto front.

$$\varepsilon_2^l = OF_2^{max} - \frac{(OF_2^{max} - OF_2^{min})}{q} \times l \quad l = 0, 1, \dots, q \tag{31}$$

Despite the many advantages of the ε -constraint method, this method does not guarantee the achievement of efficient solutions (guarantees the achievement of weakly efficient solutions). To address this weakness, Mavrotas [35] proposed AUGMECON method. Formulation of this method for our bi-objective model is as follows in which δ is a small number (0.000001-0.0001).

$$\begin{aligned}
 & \text{Min } OF_1 - \delta \times s_2 \\
 & \text{Subject to:} \\
 & \quad OF_2 + s_2 = \varepsilon_2 \\
 & \quad (s_2 > 0) \\
 & \quad \text{Constraints (4)-(29)}
 \end{aligned} \tag{32}$$

This method ensures that if alternative optima arise in the single-objective model (Expression 32) then a solution is selected that results in the best value of the second objective function.

3.2 Non-dominated Sorting Genetic Algorithm-II (NSGA-II)

The NSGA_II is a population-based meta-heuristic algorithm, which is a development of the classic GA for solving multi-objective problems [37] widely used to solve the VRP in many previous studies [38]. Steps of this algorithm is presented in Figure 4.

[please insert Figure 4 about here]

3.2.1 Solution representation

The efficiency of a meta-heuristic algorithm is significantly affected by its solution representation, which should be simple and not occupy a large amount of computer memory. As shown in Figure 5, each chromosome comprised of two parts. The first part consists of N_v genes and the second part consists of N_c+N_v-1 genes in which N_v is the number of vehicles and N_c is the number of customers. Gene values in the first part represent time between start of workday and departure time of each vehicle at depot (in seconds). In second part, gene values represent customers. The 0 value signifies the end of one vehicle's tour and the beginning of the next vehicle's tour. Figure 5 shows 2 chromosomes in an instance with 3 vehicles and 10 customers. In Figure 5(a) vehicle 1 leaves the depot 3652 seconds right after the start of workday to serve customers 1,5,10, respectively. After reaching each customer, its demand is delivered and returned products are picked up simultaneously, and then it returns to the depot with the returned products. In Figure 5(a), vehicle 2 serves customers 2,3,4 and customers 6,9,8,7 are assigned to vehicle 3. In the second part of chromosome in Figure 5(b), two 0 values next to each other indicate that vehicle 2 is idle in this solution.

[please insert Figure 5 about here]

3.2.2 Crossover and mutation operators

In each iteration and according to P_c and P_m a number of chromosomes is selected (parents) and new chromosomes (offspring) are generated using crossover and mutation operators.

Crossover operator:

The crossover operators used in this paper generate two new offspring by combining two selected parents. In this research, an arithmetical crossover operator is used to combine the first part of parents and *order crossover* and *position-based crossover* are used to combine second parts (one of these two operator is chosen at random). To generate the first part of the offspring, the convex combination of the first part of parent 1 and the first part of parent 2 is used, in which multipliers are generated randomly. Steps of the *order crossover* operator are described in Figure 6. Steps of the *position-based operator* are quite similar to the *order crossover*, except that in the first step a set of positions are randomly selected instead of a substring. Figure 7 shows an example of crossover operators in which red genes in offspring are taken from parent 1 and green genes are taken from parent 2.

[please insert Figure 6 about here]

Mutation operator:

Mutation operators are used to exploitation of solution space in GA. After selecting a chromosome to apply the mutation operator, the *uniform* mutation is used in the first part of the chromosome and for the second part, one of the *scramble*, *inversion*, or *displacement* operators is used randomly. In the *uniform* mutation, R_m percent of the genes in the first part of the parent are randomly selected and each of them is

replaced by a random value in the feasible range of departure time. *Scramble* mutation selects a set of positions at random and then swaps the values on these positions (Figure 8(a)). In *inversion* mutation two positions within the parent are randomly selected and then the substring between them is inverted (Figure 8(b)). *Displacement* mutation selects a substring randomly and inserts it in a random position (Figure 8(c)).

[please insert Figure 7 about here]

[please insert Figure 8 about here]

3.2.3 Chromosomes evaluation and penalty function

In each chromosome, according to the customers assigned to each vehicle, the vehicle payload during the tour can be calculated. Also, the distance traveled and the total travel time for each vehicle are determined according to its departure time at the depot. Afterward, total amount of fuel consumed (OF_1) and the duration of the longest tour (OF_2) can be determined. Now we want to handle infeasible chromosomes which can be occurred in two cases. The first case is when the load of a vehicle exceeds its capacity along the tour and the second case is when a vehicle returns to the depot after finishing the workday. One of the common approaches to handling infeasible chromosomes is to use penalty functions. In this case, the objective function value of infeasible chromosomes, depending on the amount of violation of the constraints, is penalized, and their chances of presence in the next generation are reduced.

Accordingly, the objective function values of feasible chromosomes are equal to OF_1 and OF_2 . However, in cases of exceeding the capacity and travel time constraints, penalized objective functions are calculated by equations (33) and (34), respectively, where P_1 and P_2 are penalty coefficients, K' is the set of vehicles whose capacity has been violated, and K'' is the set of vehicles that have violated the travel limit constraint.

$$POF_1 = P_1 \times \left(\sum_{k \in K'} \frac{\text{maximum payload of vehicle } k}{\text{capacity of vehicle } k} \right) \times OF_1 \quad (33)$$

$$POF_2 = P_2 \times \left(\sum_{k \in K''} \frac{\text{total travel time of vehicle } k}{\text{duration of workday}} \right) \times OF_2 \quad (34)$$

3.2.4 Next generation selection

The selection process of NSGA-II is showed in Figure 9 in which *PopSize* of all parents and offspring are selected as the population of the next generation. This process includes two steps. Non-dominated sorting and crowding distance sorting. In non-dominated sorting process, each chromosome is assigned a rank after evaluation all chromosomes. Firstly, non-dominated chromosomes are selected and assigned the rank 1 which are the chromosomes of the first front (f_1). Then they are temporary removed and non-dominated chromosomes are selected from remaining and are assigned the rank 2 (f_2). The above process is repeated until all chromosomes are assigned a rank. Also to estimate the density of solutions surrounding each chromosome, the *crowding distance* index is calculated for all chromosomes of each front. The crowding distance of i -th chromosome (CD_i) in its front is calculated using equation (35) in which x_{i-1} , x_i and x_{i+1} are three consecutive chromosomes in a particular front, $f_1(x_i)$ and $f_2(x_i)$ are the

value of the two objective functions at chromosome i . also (f_1^{max}, f_2^{min}) and (f_1^{min}, f_2^{max}) are the value of both objective functions at boundary points. High CD for a chromosome indicate the low density of solutions surrounding it and to keep diversity of next population, chromosomes with a higher CD have a higher priority for being selected.

$$CD_i = \frac{f_1(x_{i+1}) - f_1(x_{i-1})}{f_1^{max} - f_1^{min}} + \frac{f_2(x_{i+1}) - f_2(x_{i-1})}{f_2^{max} - f_2^{min}} \quad (35)$$

Finally, for the next generation, we select the solution with the lower rank between two points. Also if two chromosomes belong to the same front then we select the solution with larger CD .

[please insert Figure 9 about here]

3.2.5 Local search method

At the end of each iteration and after selecting the next generation, to exploit the solution space, a local search method is used to improve the chromosomes of the first front (f_1). This method in the neighborhood of a solution looks for a better solution, as shown in Figure 10.

[please insert Figure 10 about here]

3.3 Multi objective fireworks algorithm

Fireworks algorithm (FA) is a relatively new swarm intelligence metaheuristic algorithm with a more rapid convergence speed and global solution accuracy compared to typical particle swarm optimization (PSO) algorithm [39]. This algorithm has been recently used in many studies in engineering field ([40],[41],[42],[43]). However, most researchers have used FA to deal with single-objective or continuous optimization problems [44]. So it is meaningful to explore the utility of FA to solve our discrete bi-objective problem.

In this algorithm, searching the solution space is equivalent to the explosion process of fireworks in which shower of sparks fills the space around a central point (firework) and each spark can be viewed as a neighbor solution around a particular solution. The radius of explosion and the number of generated sparks are two main FA parameters which are related to the value of objective function. A firework (solution) with high quality value of objective function denotes that it is located in a promising area. Hence to exploit this area, FA generates large population of sparks with small explosion radius. In contrast, to explore the solution space, the algorithm generates small population of sparks with a large explosion radius for low quality fireworks. In this study, we propose a multi objective version of FA shown in Figure 11. Note that the solution representation in this algorithm is similar to the NSGA-II.

[please insert Figure 11 about here]

Explosion process and sparks generation:

According to the rank of each solution (firework), the explosion radius and the number of sparks are determined, and then the neighborhood solutions (sparks) around each firework are generated. For

firework i , explosion radius (A_i) is calculated by Equation (36) in which r_i is the rank of firework i after the non-dominated sorting process and eps is a small number [40].

$$A_i = \max \left\{ \frac{r_i - \min \{r_i\}}{\max \{r_i\} - \min \{r_i\} + eps}, a_f \right\} \quad (36)$$

Also the number of sparks around the firework i (S_i) is calculated by Equation (37) as follows:

$$S_i = \text{round} \left(\frac{\max \{r_i\} - r_i}{\max \{r_i\} - \min \{r_i\} + eps} \times (b_f \times \text{PopSize} - a_f \times \text{PopSize}) + a_f \times \text{PopSize} \right) \quad (37)$$

According to equations (36), (37), we can generate more sparks with a small explosion radius for better fireworks (solutions with lower rank).

To generate each spark, the first part of the firework i is changed using a uniform mutation operator in which $R_m = A_i$. Also, according to the rank of firework i (r_i), one of the three operators of expression (38) is used to change the second part of firework i . This process is repeated until all S_i sparks are generated.

$$\text{if} \begin{cases} r_i < \frac{\max \{r_i\}}{3} + 1 \rightarrow \text{Use the scramble mutation operator } (R_m = A_i) \\ \frac{\max \{r_i\}}{3} + 1 \leq r_i < \frac{2 \times \max \{r_i\}}{3} + 1 \rightarrow \text{Use the inversion mutation operator} \\ \frac{2 \times \max \{r_i\}}{3} + 1 \leq r_i \rightarrow \text{Use the displacement mutation operator} \end{cases} \quad (38)$$

As can be seen, for better fireworks (firework with lower r_i), an operator is used that makes fewer changes to them.

3.4 A clustering algorithm to generate initial solution

The main challenge of metaheuristic algorithms, particularly in large instances, is finding an initial feasible solution. In this section we propose a hierarchical clustering algorithm (Figure 12) that efficiently generates initial feasible solutions for metaheuristic algorithms. In this algorithm to ensure that the travel time constraint is not exceeded, the departure time of all vehicles at the depot is considered a uniform random number in time interval 1.

[please insert Figure 12 about here]

4. Computational results and sensitivity analysis

In this section, the proposed solution algorithms are evaluated by designing and solving instances with different sizes. Also, as this problem is bi-objective, multiple suitable criteria are introduced to assess

algorithms' performance. In addition, by performing sensitivity analysis, some managerial insights are derived.

4.1 Instance design

To generate numerical instances, the workday is assumed 7:00-17:00, which includes three time intervals according to the traffic situation; morning congestion [7:00-9:00] which is followed by period of free flow in the middle hours of the day [9:00 -15:00] and then afternoon rush hours [15:00-17:00]. If a vehicle leaves the origin i to the destination j in the time interval 2, the distance between i and j (c'_{ij2}) is assumed equal to Euclidian distance between the two points (in meter) in which the coordinates of each node is a uniform random number on (0,20000). Also the coordinates of depot are assumed (10000,10000). The travel time from node i to node j in the time interval 2 (t'_{ij2}) is calculated according to c'_{ij2} and traffic speed. According to the study by Huang et al.[15], and also the information obtained for the travel time using Google Map, the average traffic speed in the time interval 2 is assumed to be 35 km/h. Additionally, travel time during rush hours (time intervals 1 and 3) is randomly assumed 40-70% longer than travel time in time interval 2. Due to the different paths between two nodes i and j , various paths in different intervals can be used. Therefore, it is assumed that the length of the path which is used in intervals 1 and 3 can be up to 5% less or more than $c'_{ij2} \cdot d_j$ and p_j are uniform random numbers on (300,400) and there are two types of light and medium vehicles in the fleet. Other data used in the fuel consumption function are based on the study by Cheng et al. [27]. Finally, a label is defined for each numerical instance. For example, label "2-3-10" denotes 2 light vehicles, 3 medium vehicles and 10 customers.

4.2 Evaluation of the solution methods

4.2.1 Performance metrics

In this section, five performance metrics are introduced to evaluate efficiency of our solution methods ([45],[40]). In the following metrics, n is the number of non-dominated solutions on the pareto front, (f_1^{best}, f_2^{best}) is the ideal point (the best values obtained for each of the objective functions in all algorithms), $f_{i,total}^{max}$ and $f_{i,total}^{min}$ are the maximum and minimum values obtained for the objective function i in all algorithms. f_1^i and f_2^i are also the value of each objective functions at solution i .

The mean ideal distance (MID) metric as the average distance between non-dominated solutions of the algorithm and the ideal point, is calculated by Equation (39).

$$MID = \frac{\sum_{i=1}^n \sqrt{\left(\frac{f_1^i - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}} \right)^2 + \left(\frac{f_2^i - f_2^{best}}{f_{2,total}^{max} - f_{2,total}^{min}} \right)^2}}{n} \quad (39)$$

To calculate quality metric (QM) as another index, first all the non-dominated solutions obtained from different algorithms are placed in a set, and after sorting them using the non-dominated sorting method, a pareto front is obtained. The share of each algorithm in the pareto front is equal to the corresponding QM index of that algorithm. A number of pareto solutions (NPS) is the next metric which

is equal to the number of final non-dominated solutions obtained by the algorithm. Uniformly distribution of non-dominated solutions on pareto front is measured using the spacing metric (SM) which can be calculated by Equation (40).

$$SM = \sqrt{\frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n-1}} . \text{ where } d_i = \min_{j(i \neq j)} \left\{ \left| \frac{f_1^i - f_1^j}{f_{1,total}^{max} - f_{1,total}^{min}} \right| + \left| \frac{f_2^i - f_2^j}{f_{2,total}^{max} - f_{2,total}^{min}} \right| \right\} \quad (40)$$

The diversification metric (DM) is the other metric which shows the diversity of non-dominated solutions on the pareto front and is calculated by Equation (41).

$$DM = \sqrt{\left(\frac{\max(f_1^i) - \min(f_1^i)}{f_{1,total}^{max} - f_{1,total}^{min}} \right)^2 + \left(\frac{\max(f_2^i) - \min(f_2^i)}{f_{2,total}^{max} - f_{2,total}^{min}} \right)^2} \quad (41)$$

Better algorithms have smaller values of SM and MID, and also the larger values of QM, NPS and DM for an algorithm indicate the higher quality of the solutions obtained by the algorithm.

4.2.2 Tuning metaheuristics' parameters using Taguchi method

Metaheuristics parameters significantly impact final solutions quality. Hence, they should be tuned before solving main numerical instances. For this reason, Taguchi method is used as one of the common methods [46]. The initial step in this method is identifying the parameters of each algorithm and the levels they can have. As represented in Table 3, there are five parameters in each algorithm, each of which has three levels. Appropriate levels of each parameter are determined through conducting preliminary experiments and reviewing similar papers [40].

Further, the performance of each algorithm on different combinations of parameters values are tested. According to the Taguchi method, an orthogonal array L_{27} is used. This means that an instance is solved by each of the metaheuristics for 27 different combinations of parameters values. The numerical instance used in this section, is a medium-sized instance (4-2-50) and solution results for different combinations are presented in Table 1 in Supplementary data. After each execution and calculating the performance metrics, we normalize each of them using Equation (42).

$$x_{normalized} = \frac{|x - x_{worst}|}{x_{max} - x_{min}} \quad (42)$$

Where x is the original value, x_{worst} is the worst value, x_{max} is the largest value and x_{min} is the lowest value of the metric. This technique gets all scaled metrics in the range (0, 1), also after this transformation, the larger values of each metric indicate higher quality solutions. After normalization, the weighted mean of the normalized metrics is calculated and used as the response (R) in the Taguchi method. Duo to the greater importance of MID and QM, these two metrics are allocated weight of 2 and the other metrics are allocated weight of 1 (See Table 2 in Supplementary data). This process is repeated two times for each algorithm (the number of replications is 2). After calculating response variables for each combination, the signal-to-noise ratio (S/N) is obtained by Equation (43).

$$S / N = -10 \text{Log} \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{R_i^2} \right) \quad (43)$$

Where R_i is the response in Taguchi method, and n is the number of replications. The aim of Taguchi method is to find maximum “mean of S/N ratio” and “mean of response variables” (mean of means). Final results are shown in Figure 13 (See Table 3 in Supplementary data for more details). As can be seen in Figure 13 (a), best levels for NSGA-II parameters are $A3, B3, C3, D2, E3$. Also according to Figure 13 (b), best levels for parameters of MOFW are $A3, B2, C2, D2, E3$. Note that all plots in Figure 13 are obtained by Minitab 19.

[please insert Table 3 about here]
[please insert Figure 13 about here]

4.2.3 A comparison analysis

Eight numerical instances are designed in various sizes and then solved using the three proposed algorithm. The AUGMECON method is coded in GAMS software and the small-sized numerical instances are exactly solved employing CPLEX solver. To solve large-sized instances, two proposed metaheuristic algorithms are coded in MATLAB R2018b. All algorithms are executed on a PC with Intel core i7 CPU (1.73 GHz) and 8 GB of RAM. Due to the different structure of the two proposed metaheuristics, the CPU time is considered as the termination criterion instead of the maximum iteration. We compute the average of performance metrics for instances 1-4 based on 15 replications, also these metrics are computed for instances 5-8 based on 10 replications (see Tables 4,5). Because this problem is classified under NP-hard problems, exact solutions is only achieved for the first four small-sized instances. These four instances are also solved using metaheuristics. Comparing the performance metrics of metaheuristics with AUGMECON method, it is concluded that the two proposed metaheuristics have a high ability to achieve a good pareto-front in a reasonable time. However, the metrics in other instances (especially QM) indicate that the performance of proposed MOFA is better than NSGA-II.

[please insert Table 4 about here]
[please insert Table 5 about here]

4.3 Pareto-front analysis

To evaluate the effect of workload balancing on fuel consumption, the pareto-front is analyzed in eight designed instances and the results are presented in Tables 6-8. The values of the objective functions 1 and 2 are shown in columns OF_1 and OF_2 , respectively. AVG and STD columns denote mean and standard deviation of the total travel time of the vehicles. The column UV shows the total number of vehicles used at the specific solution. The results presented in table 6 and 7 imply that balancing workload among drivers has negligible effect on increasing fuel consumption. As can be seen, STD can be significantly reduced by a negligible increase in fuel consumption (approximately 1.5%).

Modeling and solving the problem as a single objective model with the aim of balancing the workload will result in a significant decrease in the duration of the longest tour and STD , but a remarkable increase in fuel consumption (see Table 8). Therefore, the single-objective model fails to provide acceptable solutions from an economic and environmental point of view. While, modeling the problem as a multi-objective model and tradeoff between different objectives, the workload is well balanced and simultaneously economic and environmental goals can be achieved.

[please insert Table 6 about here]

[please insert Table 7 about here]
[please insert Table 8 about here]

4.4 Impact of departure time optimization on fuel consumption

One of the approaches of this study in dealing with traffic congestion is stopping at the depot during peak hours and optimizing the departure time. The impact of this policy on the total fuel consumed is analyzed in this section. For this purpose, each of the instances designed in the previous section is solved as a single-objective problem (with the first objective function) in two modes with two different settings; one with departure time optimization and the other without optimizing the departure time ($w_{k0}=0$). As can be seen in Table 9, optimizing the departure time has a considerable effect on the total fuel consumed.

[please insert Table 9 about here]

5. Conclusions and future researches

In this paper, the time-dependent sustainable routing problem in city logistics is introduced, in which different economic, environmental, and social factors are considered. There are different challenges in city logistics, i.e., traffic congestion, path flexibility, and heterogeneous fleets affecting total travel time and fuel consumption. So this study focuses on drivers' job satisfaction by balancing the workload (in terms of worktime) as a social objective and minimizing total fuel consumed as an environmental objective.

Two different bi-objective meta-heuristic algorithms are developed based on genetic and fireworks algorithms to solve large-sized instances. For efficiency enhancement of these algorithms, a local search method is utilized and a clustering based heuristic method is proposed to generate good initial solutions. Solving various instances shows that the fireworks algorithm has a better performance. Additionally, the results of solving numerical instances can be analyzed from a managerial point of view as follows:

- Generally, different aspects of sustainability are in conflict with each other. The concern about the increase in operational costs is one of the main reasons why managers of logistics systems ignore environmental and social issues. But the results of this article show that balancing workload has negligible effects on increment of fuel consumption.
- In dealing with traffic congestion, stopping at the depot during peak hours and optimizing the departure time can be significantly effective in reduction of fuel consumption.
- Numerical experiments represent that solving this problem as a single-objective model with the aim of balancing the workload fails to provide acceptable solutions from an economic and environmental viewpoint. While, modeling the problem as a multi-objective model and tradeoff between different objectives, the workload is well balanced and simultaneously economic and environmental goals can be achieved.
- In city logistics to simplify transportation planning, managers often overlook traffic congestion information and path flexibility. However, this disregard makes the results impossible to implement in practice due to the significant difference between assumptions and reality.

Future researches based on the present study could be performed in various areas as follows:

- Development of a hybrid solution approach to combine metaheuristics and exact algorithms with the aim of achieving optimal solutions in a shorter time or obtaining better heuristic solutions can be proposed as a future research topic.
- The transportation fleet in city logistics usually consists of small and medium-sized vehicles, which makes the vehicles return to the depot several times a day for reloading. Developing the current problem into a multi-trip VRP and analyzing its effect on workload balance can be examined as another future research topic.
- Some economic factors such as drivers' wages as well as vehicles hiring costs as a new objective function and tradeoff among various economic, environmental and social objective functions can be further investigated.
- Effective utilization of Google maps API to access historical traffic data and real-time traffic info and time specific optimal route especially in areas that have accurate real time data can be recommended for future studies.

The supplementary data is available at:

<file:///C:/Users/SHAMILA/Downloads/Supplementary%20data.pdf>

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Figure captions:

Figure 1. Two popular proposed paths by Google Map, from Azadi Square to Vanak Square in Tehran, Iran

Figure 2. Average travel time pattern of the path with a length of 12.4 km in Figure 1

Figure 3. Fuel consumption of each type of vehicles under different speeds and loads

Figure 4. Pseudo-code of the NSGA-II

Figure 5. Solution representation

Figure 6. Procedure of order crossover

Figure 7. Order crossover (a) and position-based crossover (b)

Figure 8. Scramble (a), inversion (b) and displacement (c) mutation operators

Figure 9. Next generation selection

Figure 10. Procedure of local search method

Figure 11. Pseudo-code of the Multi Objective Fireworks Algorithm (MOFA)

Figure 12. Procedure of proposed clustering algorithm

Figure 13. Mean of S/N ratios plot and Mean of Means plot for each level of factors in NSGA-II (a) and MOFW (b)

Table captions:

Table 1. Definition of vehicle common parameters

Table 2. Definition of vehicle specific parameters

Table 3. Parameter setting of proposed metaheuristics algorithms

Table 4. Results of *QM*, *NPS* and *DM* metrics for 8 test instance

Table 5. Results of *SM* and *MID* metrics for 8 test instance

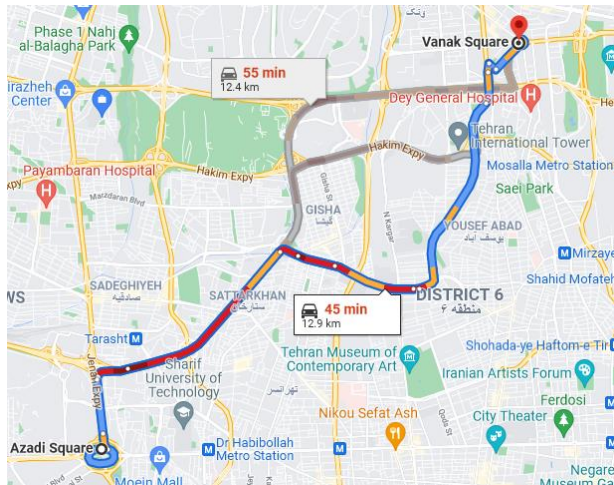
Table 6. Optimal solution of single-objective problem with the first objective function

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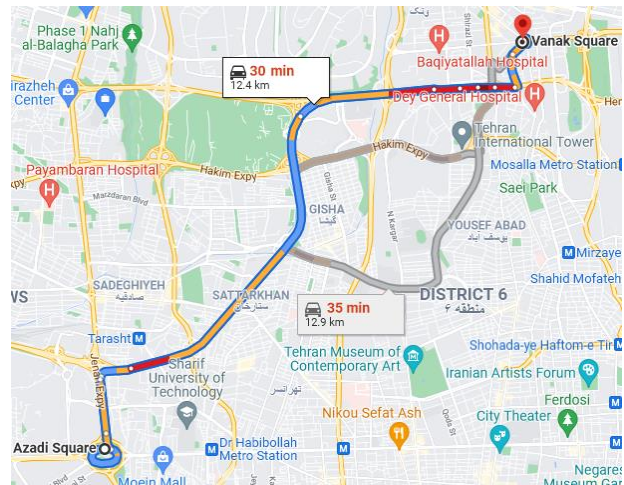
Table 8. Optimal solution of single-objective problem with the second objective function

Table 9. Total fuel consumed under different settings

Figures:



(a) morning rush hours



(b) hours with medium congestions

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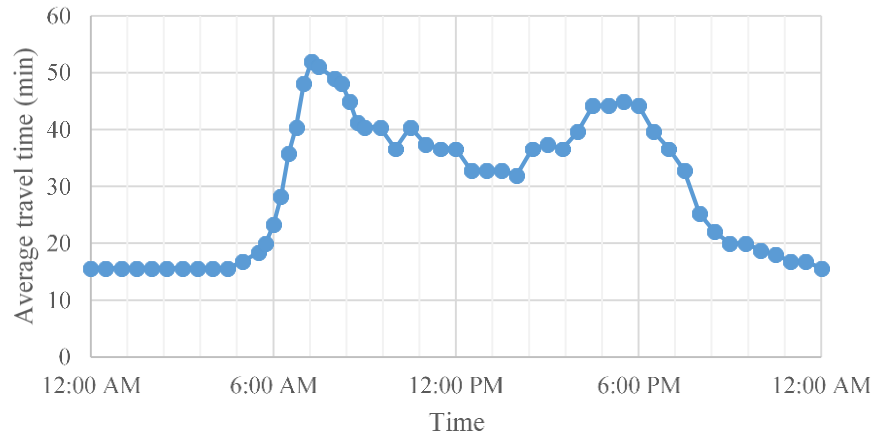


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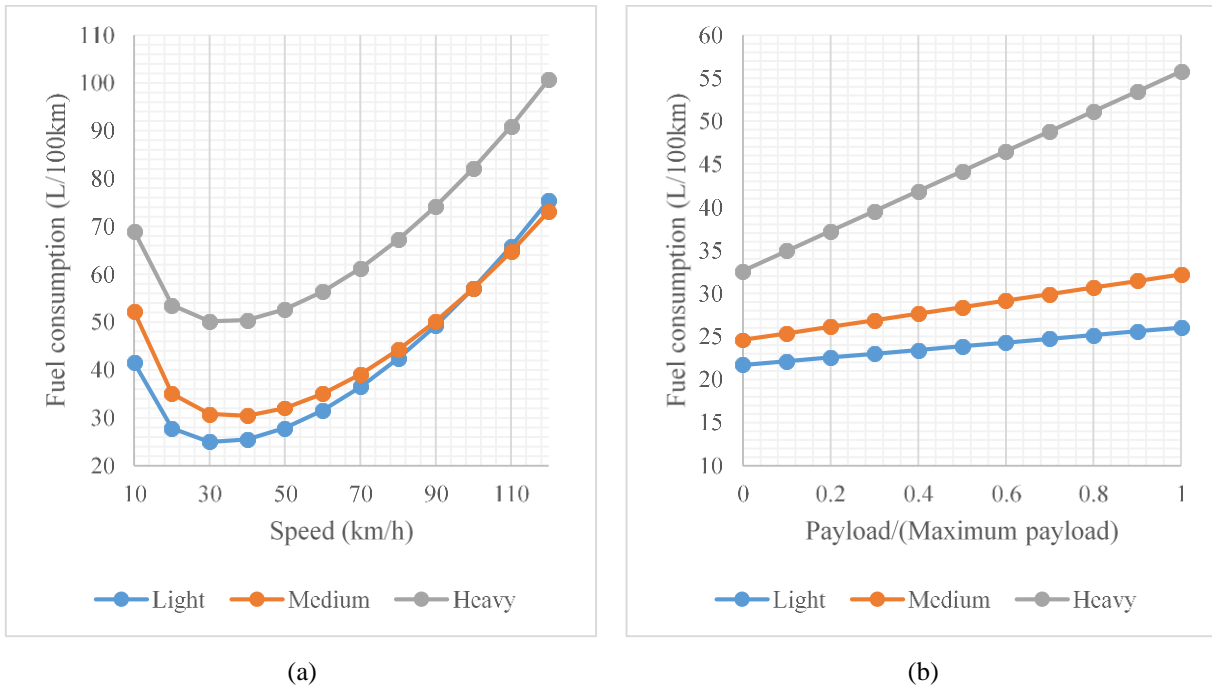


Figure 3. Fuel consumption of each type of vehicles under different speeds and loads

Begin

- Set NSGA-II parameters: maximum number of iterations(I_{max}), population size($PopSize$), probability of mutation(P_m), probability of crossover(P_c), mutation rate(R_m), number of solutions in the neighborhood(N_{is})
- Generate initial population

Repeat

- Select $P_c\%$ of population and generate offspring using crossover procedure
- Select $P_m\%$ of population and generate offspring using mutation procedure
- Evaluate all chromosomes and penalize infeasible solutions by adding a penalty term to their objective functions
- Select next generation considering crowding distance and non-dominated sorting procedure
- Implement the local search method to improve quality of next generation members

Until the termination criterion (I_{max}) is met

End

Figure 4. Pseudo-code of the NSGA-II

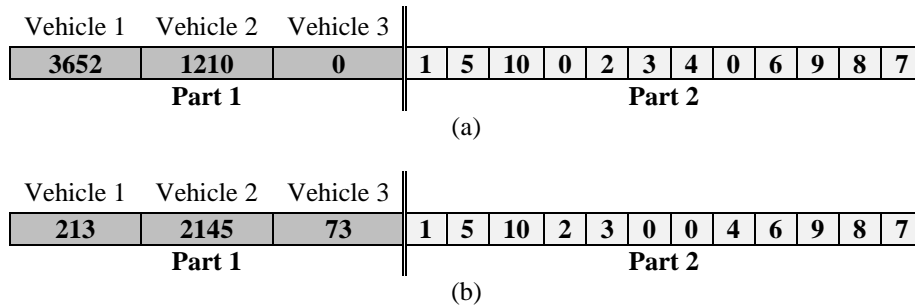


Figure 5. Solution representation

Step1: select a substring from the second part of parent 1 at random

Step2: copy the selected substring in step 1 and all zeros in second part of parent 1 into the corresponding positions of the child

Step3: place other costumers into the unfixed position of the child from left to right according to the order of their sequence in parent 2

Figure 6. Procedure of order crossover

Parent 1	1213	50	150	1	5	10	0	2	3	4	0	6	9	8	7
child	547	1121	200	1	5	10	0	2	3	7	0	6	8	9	4
Parent 2	456	1200	260	10	2	0	1	5	3	7	6	0	8	9	4

(a)

Parent 1	1213	50	150	1	5	10	0	2	3	4	0	6	9	8	7
child	673	972	253	10	5	1	0	2	3	7	0	6	9	8	4
Parent 2	456	1200	260	10	2	0	1	5	3	7	6	0	8	9	4

(b)

Figure 7. Order crossover (a) and position-based crossover (b)

Parent	4591	123	1232	1	5	10	0	2	3	4	0	6	9	8	7
Child 1(a)	4591	123	1232	1	5	3	0	2	4	9	0	6	10	8	7
Child 2(b)	4591	123	1232	1	3	2	0	10	5	4	0	6	9	8	7
Child 3(c)	4591	123	1232	1	5	10	0	2	6	9	8	3	4	0	7

Figure 8. Scramble (a), inversion (b) and displacement (c) mutation operators

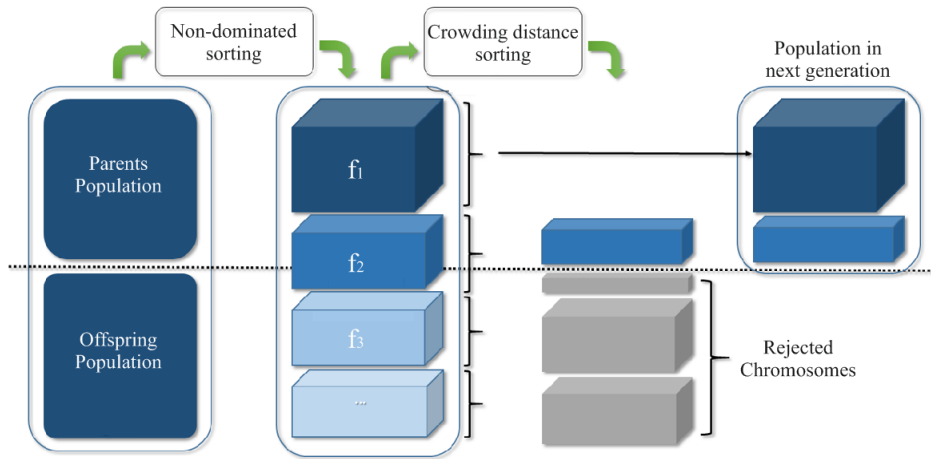


Figure 9. Next generation selection

```

Begin
For all chromosomes of the first front do
   $i=0$ 
  While ( $i \leq N_{ls}$ ) do
    In the first part of the chromosome pick up  $R_m\%$  of genes at random and increase or decrease its value by  $R_m\%$ .
    In the second part of the chromosome select two genes at random and swap their values.
    If primary chromosome is dominated by new chromosome, then
      Replace primary chromosome with improved chromosome
    Break
  End
   $i=i+1$ 
End
End
End

```

Figure 10. Procedure of local search method

```

Begin
- Set MOFA parameters: maximum number of iterations( $I_{max}$ ), population size( $PopSize$ ), control parameters used to determine explosion radius and the number of sparks( $af, bf$ ) in which ( $af < bf < 1$ ), mutation rate( $R_m$ ), number of solutions in the neighborhood( $N_k$ )
- Generate initial population of fireworks
  Repeat
    - Evaluate the population and sort them using non-dominated sorting method
      For each firework in the population do:
        Determine the number of sparks
        Determine the explosion radius
        Generate the sparks
      End
    - Evaluate all fireworks and new generated sparks
    - Select next generation considering crowding distance and non-dominated sorting procedure
    - Implement the local search method to improve quality of next generation members
  Until the termination criterion ( $I_{max}$ ) is met
End

```

Figure 11. Pseudo-code of the Multi Objective Fireworks Algorithm (MOFA)

```

Begin
Enter the problem parameters
  Repeat
    -  $AC = \{\}$  Set of costumers who are assigned to vehicles
    -  $RC = \{\text{all costumers}\}$  Set of costumers who are not assigned to vehicles
    For each vehicle ( $k=1:|K|$ ) do:
      - If the vehicle  $k$  is empty, select a customer at random from the  $RC$  and assign it to the vehicle, else calculate the distance between each member of  $RC$  and the last customer on the tour of the vehicle  $k$ . Add the nearest customer to the end of the tour.
      - If a feasible tour is generated for the vehicle  $k$ , update  $AC$  and  $RC$  else don't update them and  $k=k+1$ 
      - If the generated tour is infeasible and  $k=|K|$ , assign all remaining customers in  $RC$  to vehicle  $k$  and break
    End
  Until an feasible solution is generated
End

```

Figure 12. Procedure of proposed clustering algorithm

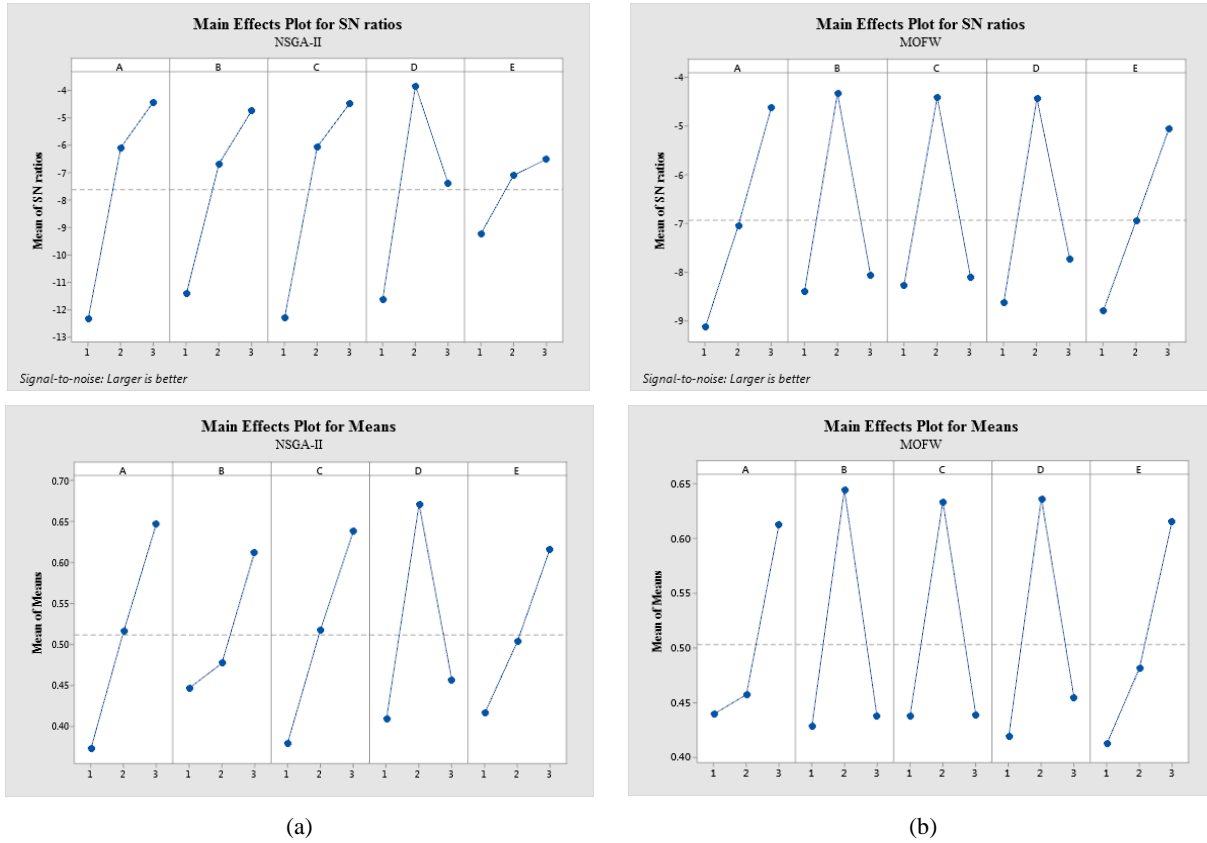


Figure 13. Mean of S/N ratios plot and Mean of Means plot for each level of factors in NSGA-II (a) and MOFW (b)

Tables:

Table 1. Definition of vehicle common parameters

Notation	Description	Typical values
ε	Fuel-to-air mass ratio	1
g	Gravitational constant (m/s ²)	9.81
ρ	Air density (kg/m ³)	1.2041
C_r	Coefficient of rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/s to L/s)	737
θ	Road angle	0
τ	Acceleration (m/s ²)	0

Source: Cheng et al. [27]

Table 2. Definition of vehicle specific parameters

Notation	Description	Vehicle type
----------	-------------	--------------

		Light	Medium	Heavy
w^m	Curb weight (kg)	4672	6328	13,154
Q^m	Maximum payload (kg)	2585	5080	17,236
k^m	Engine friction factor (kJ/rev/L)	0.25	0.20	0.15
N^m	Engine speed (rev/s)	39	33	30.2
V^m	Engine displacement (L)	2.77	5.00	6.66
C_d^m	Coefficient of aerodynamics drag	0.6	0.6	0.7
A^m	Frontal surface area (m ²)	9.0	9.0	9.8
n_{tf}^m	Vehicle drive train efficiency	0.40	0.45	0.50

Source: Cheng et al. [27]

Table 3. Parameter setting of proposed metaheuristics algorithms

Levels	NSGA-II															MOFA																
	PopSize(A)					P _c (B)			P _m (C)			R _m (D)			N _{is} (E)			PopSize(A)			Af(B)			Bf(C)			R _m (D)			N _{is} (E)		
	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	D3	E1	E2	E3	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	D3	E1	E2	E3		
50	70	100	0.5	0.6	0.7	0.2	0.3	0.4	0.1	0.2	0.3	10	15	20	50	70	100	0.05	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	10	15	20			
Best	✓			✓			✓			✓			✓			✓			✓			✓			✓							

Table 4. Results of *QM*, *NPS* and *DM* metrics for 8 test instance

#	Instances	CPU Time (sec)		NSGA-II			MOFA			AUGMECON		
		Meta	AUGMECON	<i>QM</i>	<i>NPS</i>	<i>DM</i>	<i>QM</i>	<i>NPS</i>	<i>DM</i>	<i>QM</i>	<i>NPS</i>	<i>DM</i>
1	1-1-8	300	556	1	3	1.42	1	3	1.42	0.5	2	1.42
2	2-1-15	400	1824	1	6	1.41	1	6	1.41	0.75	3	1.41
3	2-1-20	500	4625	0.45	4	1.391	1	7	1.41	0.6	3	1.41
4	3-1-25	700	12721	1	7	1.41	0.73	4	1.39	0.66	2	1.41
5	2-2-35	1000		0.55	3	1.84	0.85	6	1.46			
6	4-2-50	2000		0.68	5	1.29	0.93	7	1.414			
7	5-3-70	4000		0.33	3	0.8	0.86	10	1.41			Out of memory
8	7-4-100	7200		0.5	3	0.913	1	6	1.43			

Table 5. Results of *SM* and *MID* metrics for 8 test instance

#	Instances	CPU Time (sec)		NSGA-II		MOFA		AUGMECON	
		Meta	AUGMECON	<i>SM</i>	<i>MID</i>	<i>SM</i>	<i>MID</i>	<i>SM</i>	<i>MID</i>

1	1-1-8	300	556	1.14	1.0056	1.14	1.0056	1.14	1.0084
2	2-1-15	400	1824	0.145	0.787	0.315	0.871	0.258	0.875
3	2-1-20	500	4625	0.859	0.919	0.29	0.984	0.22	0.975
4	3-1-25	700	12721	0.097	0.908	0.826	0.895	0.12	1
5	2-2-35	1000		0.59	0.93	0.46	1.49		
6	4-2-50	2000		0.309	0.87	0.2931	1.08		
7	5-3-70	4000		0.267	0.73	0.074	0.88		Out of memory
8	7-4-100	7200		0.103	0.589	0.151	0.534		

Table 6. Optimal solution of single-objective problem with the first objective function

#	OF_1	$OF_2(sec)$	AVG	STD	UV
1	18.6	6433	5939	698	2
2	21.52	7237	5837	2265	3
3	22.99	8075	6898	1686	3
4	26.7	7059	6338	701	4
5	33.92	10787	8277	1733	4
6	48.36	11392	7936	2261	6
7	65.5	12072	8537	2099	8
8	88.125	13653	8872	2727	11

Table 7. Pareto-front analysis with about 1 to 3 % increase in fuel consumption compared to optimal solution

#	OF_1		$OF_2(sec)$		AVG		STD		UV
	Value	GAP(%)	Value	GAP(%)	Value	GAP(%)	Value	GAP(%)	
1	18.81	1.1	6332	-1	5971	0.5	435	-37	2
2	21.99	2.1	7051	-2.5	5910	1.2	1596	-29	3
3	23.42	1.9	7900	-2.1	7028	1.8	1102	-34	3
4	27.2	1.8	6739	-4.5	6505	2.6	456	-35	4
5	34.3	1.2	10112	-6	8312	0.4	1539	-11	4
6	49.42	2.1	10862	-4.6	8083	1.8	1554	-31	8
7	66.4	1.3	11816	-2.1	8624	1	2008	-4.3	8
8	89.6	1.6	12125	-11.1	8998	1.4	2579	-5.4	11

Table 8. Optimal solution of single-objective problem with the second objective function

#	OF_1		$OF_2(sec)$		AVG		STD		UV
	Value	GAP(%)	Value	GAP(%)	Value	GAP(%)	Value	GAP(%)	

1	19.27	3.6	6284	-2.3	6059	2	319	-54	2
2	23.57	9.5	6297	-12.9	6097	4.4	189	-91	3
3	24.6	7	7395	-8.4	7136	3.4	224	-86	3
4	28.74	7.6	6711	-4.9	6543	3.2	169	-75	4
5	35.6	4	9648	-10	8743	5	922	-46	4
6	50.54	4.5	10055	-11	8416	6	1242	-45	6
7	78.2	19	11131	-7	9460	10	1741	-17	8
8	104.73	18	11974	-12	9060	2	2370	-13	11

Table 9. Total fuel consumed under different settings

	Instance number							
	1	2	3	4	5	6	7	8
With departure time optimization	18.6	21.52	22.99	26.7	33.92	48.36	65.5	88.12
Without departure time optimization	19.91	22.56	23.97	27.35	34.62	50.75	67.8	89.98
Saving (%)	6.5	4.6	4.1	2.4	2	4.7	3.4	2.1

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