Article

**A Novel Travel Time Estimation Model for Modeling Green Time-Dependent Vehicle Routing Problem in Food Supply Chain**

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**Abstract.** In a green time-dependent vehicle routing optimisation problem, if the travel time is not well estimated, the values of the objective function (emissions) for different solutions will be obtained with less accuracy, which leads to wrong decision-making. The purpose of this paper is to propose an accurate travel-time estimation model. The model was developed by considering different multiple traffic modes through a continuous approach. Moreover, in this model, it was assumed that the route between two nodes was a combination of different segments (i.e. expressway, boulevard, main street, auxiliary street, alley, etc.), and speed level varied along the route and depended on the segments of the route. Congestion is a key factor affecting the delivery time of food to customers. To assess the reliability of the model, data from the delivery and sales network of the oldest and biggest beverage manufacturer in Iran was used. A new congestion pattern was identified based on the analysis of 272 routes and several rules were described that proved the above assumption about congestion. The travel-time estimated for 30 random vehicles with random departure times were compared with data from Google Maps through statistical analyses.

**Keywords:** Vehicle Routing Problem, Intermediate node, Green transportation, Multiple traffic modes, Food Supply Chain

1. Introduction

The vehicle routing problem (VRP) is one of the key issues in logistics as many companies face this problem during the delivery of their products. The problem was proposed by Dantzig and Ramser in 1959 for the first time [1] and since then, it has been widely studied. The wide variation in human and goods transportation systems has led to the development of different varieties of VRP which, despite their similarities, vary evidently in their limitations and decision-making variables and parameters. VRP has been proposed in the literature in two ways (i) the classic models that are concerned with economic aspects (such as considering the operation total time or the traversed distance as an objective function) and (ii) the green models in which the researchers pay attention to the environmental parameters. In green models, objective functions are formulated to minimize emissions, which have been proposed since 2006. Different parameters impact the vehicles’ emissions, including (1) speed, (2) payload, (3) congestion, (4) fleet, and (5) road gradient [2, 3]. Congestion is a crucial parameter in modelling green transportation. It causes delay, which in turn means higher costs for delivery companies and service providers (i.e., the food industry). Delays in the delivery of food in this industry not only lead to more emissions from food trucks but also results in delivery delays, spoilage, and food waste.

Congestion is, by nature, a complicated and stochastic phenomenon, and its modelling requires statistical analysis of vehicles’ congestion and speed on different routes. Congestion affects vehicle speed on different routes. To model congestion, the Green Time-dependent Vehicle Routing Problem (GTDVRP) has emerged in the literature. In this problem, the speed of the vehicle depends on time (traffic periods) and the travel time of the vehicle depends on speed and its departure time from the origin node, see Figure 1. Furthermore, the estimation method of travel time is crucial and has two main aspects. First, the approach to modelling congestion has been categorised into 4 groups in literature [4], namely (i) Simple, (ii) Discrete, (iii) Continuous and (iv) Stochastic. The simple models consider a simple linear relation among variables and as expected, have not attracted significant researchers’ attention (e.g. [5]). In the discrete approach, the time horizon is divided into small segments. Travel time for each edge (distance between two consecutive nodes) is supposed to be a step function of departure time from the origin node. This approach has been utilised in the literature [6-8]. However, the most important weakness of this approach was that it does not consider the FIFO condition. In a real-world scenario, travel time constantly changes over time. In the continuous approach, unlike the discrete one, the travel time function is continuous, and speed over time is a discrete function. The most well-known model of this condition is from [4], which has been used in several studies [9-15]. In the stochastic approach, attempts are made to explain the stochastic nature of travel time using Markov chain theory or stochastic variables [16-19]. The continuous approach has been used more than other approaches in the literature. Nevertheless, the main shortcoming is that route segmentation is not considered. In fact, in this approach, the average speed is given by the rule of thumb while considering route segmentation; rather to be measured for all routes in different periods. The route between two nodes (i.e., warehouse and customers) is composed of different sections. These sections include highways, boulevards, main streets, bystreets, and alleys in urban zones. Each section has a different speed level and traffic lights (if any) may force the driver to stop before entering the next section. Therefore, in this paper, the authors define an intermediate node with transition time for the first time. This transition time must be considered to estimate travel time more accurately.

Figliozzi [20], and Maden et al. [5], assumed that the traffic density was higher at the beginning of the day and afternoon; however, it was lower during the day for all routes. Liu et al [11] assumed that 8:00 to 9:00 and 18:00 to 19:00 were set as the traffic congestion periods, and the rest of the time was set as the normal driving periods. Androutsopoulos and Zografos [21] used the same assumption with different periods (i.e. 0-20 min, 20-30 min, and 30-50 min). In other words, 4 traffic periods have been considered in which the second and third periods were rush hours while in the ﬁrst and last periods, trafﬁc density was considered lower [22, 23]. Nonetheless, in [13] the first and third periods had high congestion while the other periods had lower congestion. However, Raeesi and Zografos [24] assumed that the 2nd and 4th traffic periods had congestion, whereas the two rest periods were non-congested. Franceschetti et al. [25] and Jabali et al. [26] considered three-time regions: 1) congestion region, 2) transient region (combination of congestion region and free-flow region), and 3) free-ﬂow region for all routes. In this regard, Lu, Chen, Hao, & He [27] developed this model considering 5-time regions with two transition times. The authors [28-30] deﬁned arcs as either congested or non-congested. Tikani and Setak [15] defined three traffic zones, namely: light, medium and heavy. None of the above research considered actual behaviour scenarios. Routes, especially those located in the city centre, may have congestion during the day (morning to afternoon) while routes away from the city centre are less congested. Therefore, it should not be assumed that a route in a specific period has congestion. Moreover, all routes in specific periods have the same congestion pattern. Congestion not only depends on the time but also the route, see Section 4.3. Therefore, in this paper, the authors assumed that a segment of the route may have simultaneously different congestion modes (i.e., low, medium, and high) and free-flow modes in a period. It is worth mentioning that GIS-based software like Google Maps proved this assumption. Moreover, each segment of the route has a speed profile that averages speed in each period and is calculated by the percentage of the route that has multiple congestion modes and free-flow modes. The proposed model can be used by organisations that seek to solve their transportation planning problem in the form of vehicle routing by taking into account environmental issues and timely delivery of goods (especially food), as this model increases accuracy.

This paper first introduces the continuous approach in which Ichoua et al.'s model is reviewed. Next, the proposed model is introduced in Section 3. The fourth section is devoted to presenting the application and validation of the proposed model through a case study in which new congestion patterns based on Google maps data are considered. Finally, the discussion and conclusion are presented.

2. Literature Review

As previously discussed, Ichoua et al. [4] categorised travel-time estimation models into four groups, namely simple, discrete, continuous, and stochastic. The simple approach represents a simple linear relation among variables while in the discrete approach, the travel-time step function has been considered. This approach suffers the basic shortcoming of not complying with FIFO features. To solve this problem, Ichoua et al. [4] and Fleischmann et al.[31] proposed the continuous travel-time function and travel-speed piecewise function (Figure 1) with different computational algorithms for estimating travel time. The first algorithm (Ichoua et al. [4]) presented was employed more by the scholars compared to the second (Fleischmann et al.[31]) in the literature (e.g. [32]). With a different method, Horn [33] considered acceleration/deceleration (A/D) rate in his model. He proposed a model with linear piecewise travel speed and quadratic piecewise travel time. His work was developed in further research by [34-36]. These models required archived point-based historical speed data for their implementation. Estimation of travel time without having instantaneous speed data of the vehicle was not possible. None of the mentioned models considered a real case scenario. They considered macroscopic data (i.e., every 15 min) instead of the instantaneous speed of the vehicle, which leads to a decrease in the accuracy of travel time estimation. Therefore, data gathering is the main challenge of implementing these models in the real world while Google Maps data about congestion is easily available for all routes and times that can be used for estimation of travel time. Furthermore, the congestion pattern was assumed to be similar for all routes in these models.

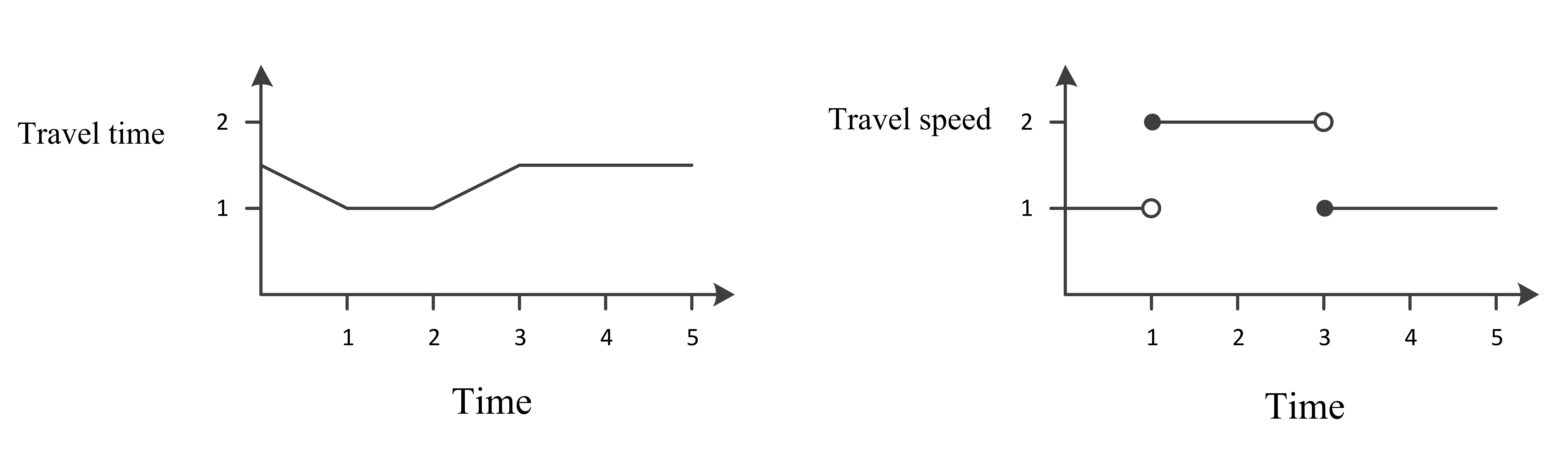
Table 1 illustrates related works since 2010 in which the continuous approach has been used more than other approaches. The authors considered different assumptions for the congestion period. As mentioned previously, it should not be assumed that a route only in a specific period has congestion. Congestion has stochastic nature, and it can happen at any time of the day and also depends on the route. Thus, those models which considered congestion to be random are closer to a real scenario. The algorithms proposed in some studies have been tested based on real data. There are 6-speed profiles in the literature including increasing, decreasing, V shape, shape, random, and constant [9]. Previous studies have included one or more speed profiles for all routes while, due to the dependence of congestion on the route, the algorithm proposed in this paper supports all speed profiles. None of the previous studies have considered an intermediate node, multiple traffic modes, and route dependency. Therefore, it can be concluded that previous studies lack an effective representation of a real situation.

**Table 1.** An overview of related works since 2010

| References | Approach | Congestion Period | | | | | Case Study | Speed profile | | | | | | Intermediate Node | Multiple Traffic Modes | Route Dependency |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| JM | M&A | M | JA | S | I | D | V |  | R | C |
| [5] | Stochastic |  |  |  |  |  | \* |  |  |  |  |  |  |  |  |  |
| [37] | continuous |  | \* |  |  |  |  |  |  | \* |  | \* |  |  |  |  |
| [38] | continuous |  | \* |  |  |  |  |  |  |  |  | \* | \* |  |  |  |
| [20] | continuous |  | \* |  |  |  | \* |  |  |  |  | \* | \* |  |  |  |
| [8] | Discrete | \* |  |  |  |  | \* |  |  |  |  |  |  |  |  |  |
| [26] | continuous |  |  | \* | \* |  |  |  | \* | \* |  |  |  |  |  |  |
| [39] | continuous |  | \* |  |  |  |  |  |  |  |  | \* | \* |  |  |  |
| [25] | continuous | \* |  |  |  |  |  | \* |  |  |  |  |  |  |  |  |
| [40] | continuous |  |  |  |  | \* |  |  |  |  |  | \* |  |  |  |  |
| [16] | Stochastic |  |  |  |  | \* | \* |  |  |  |  |  |  |  |  |  |
| [29] | continuous |  |  |  |  | \* | \* |  |  |  |  | \* | \* |  |  |  |
| [41] | continuous |  | \* |  |  |  |  |  |  |  | \* | \* |  |  |  |  |
| [42] | continuous |  |  | \* |  |  |  |  |  | \* |  |  |  |  |  |  |
| [17] | Stochastic |  |  |  |  | \* | \* |  |  |  |  |  |  |  |  |  |
| [22] | continuous |  |  | \* |  |  |  |  |  | \* |  |  | \* |  |  |  |
| [6] | Stochastic |  |  |  |  | \* | \* |  |  |  |  |  |  |  |  |  |
| [23] | continuous |  |  | \* |  |  | \* |  |  | \* |  |  | \* |  |  |  |
| [43] | continuous |  |  | \* |  |  | \* |  |  | \* |  |  |  |  |  |  |
| [10] | continuous |  | \* |  |  |  |  |  |  |  | \* |  |  |  |  |  |
| [13] | continuous |  | \* |  |  | \* |  |  |  |  | \* | \* | \* |  |  |  |
| [11] | continuous |  | \* |  |  |  |  |  |  |  |  | \* |  |  |  |  |
| [27] | continuous |  | \* |  |  |  |  |  |  |  | \* |  |  |  |  |  |
| [44] | continuous |  |  | \* |  |  | \* |  |  | \* |  |  |  |  |  |  |
| [45] | continuous |  |  |  |  | \* |  |  |  |  |  | \* |  |  |  |  |
| **This paper** | continuous |  |  |  |  | \* | \* | \* | \* | \* | \* | \* | \* | \* | \* | \* |

JM, just morning; M&A, morning and afternoon; M, midday; JA, just afternoon; S, stochastic; I, increasing; D; decreasing; V, V shape; , shape; R, random; C, constant

Since Ichoua et al.’s algorithm has been used more than other methods in previous research, it is described in this section. In this method, as in the discrete approach, a day is divided into several short time intervals at which the mean speed is different. The main strength of this model is that in the movement from the origin node to the destination since the route can fall in different time intervals, the speed is not constant, which should be taken into consideration in travel-time estimation.



**Figure 1**. Continuous travel time function

To calculate travel time, the authors supposed that the vehicle leaves node *i* at and the edge (*i,* *j*) belongs to class c (). It is supposed that is the distance between nodes *i* and j and is the travel speed depending on class *c* and time interval . Besides, *t and* indicate the present time and the arrival time, respectively. Therefore, travel time is calculated as follows.

|  |  |
| --- | --- |
| (1) |  |

This algorithm meets FIFO features and is closer to reality. Moreover, stopping at nodes is not necessary (unlike the discrete approach).

3. Methodology

In this section, to describe the proposed algorithm, some notations are introduced in Table 2. Then, the intermediate node, calculation of mean speed, and proposed algorithm are described in Sections 3.1, 3.2, and 3.3, respectively.

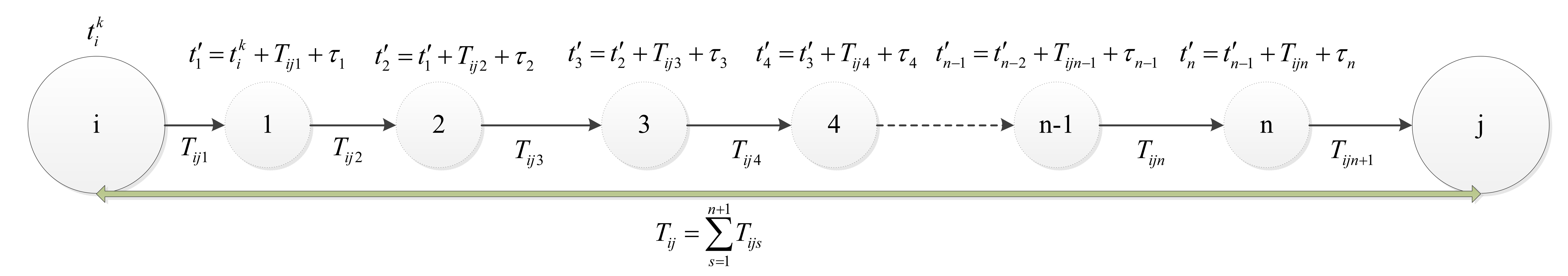
**Table 2.** Definitions of indexes

| **Notation** | **Definition** |
| --- | --- |
| *N* | Nodes related to warehouse and customers (a warehouse is indicated by *o*) |
| *i, j* | Nodes |
| *f* | Four traffic modes include 1) Free-flow mode (green colour), 2) low congestion (orange colour 3) medium congestion (red colour), and 4) high congestion (crimson colour) based on Google Maps. |
| *s* | Route segment |
| *t* | Traffic period. Here each day is divided into different time intervals. Each time interval represents one traffic period. For example, 3th time interval is the third traffic period. |
|  | The departure time of vehicle *k* from *i*th node |
|  | Speed (km/h) at segment *s* of the route from node *i* to *j* in traffic mode *f* |
|  | The average speed at segment *s* of the route from node *i* to *j* in traffic mode *f* |
|  | Travel-time of segment *s* of the route from node *i* to *j* |
| *S* | The set of all urban roads (alley, auxiliary street, main street, boulevard, expressway) |
|  | Distance of segment *s* of the route from node *i* to *j* (meter) |
|  | Transition time from segment *s* to *s*+1 on the route from node *i* to *j* (equal to intermediate nodes on the route from node *i* to *j*) (seconds) |
|  | Number of traffic periods |
|  | Bottom of the range in traffic period *t* (the range for this period is equal to ) |
|  | Percentage of the traversed distance in segment *s* of the route from node *i* to *j* in traffic mode *f* and traffic period *t* |

The review of the literature and the reviewed models indicate that speed is a crucial factor in environmental pollution. The basic issue (often ignored during modelling) is that speed is a function of the route, varying in different routes. The speed of a vehicle on an expressway is higher than that on main or auxiliary streets or is higher on the intercity roads than in urban areas. In a transportation problem, the traversed distance between two nodes can be a combination of different segments. Any change of the road type (from one segment to another) requires an intermediate node. In this situation, the route nature changes since in this node, the change occurs in terms of the vehicle speed, for instance, when a vehicle veers from an auxiliary street into the main one, which is wider and more crowded. This typically happens at intersections and assuming a traffic light, the time to cross the intermediate node should be considered. Here, the average stoppage time at a red light can be considered as the time needed to go through the intermediate node. Therefore, is considered in the modelling. On some occasions, road type change happens due to a junction or roundabout (without traffic light). In case of congestion, the vehicle stops and starts again (repetitiously), which is like moving through congested traffic modes, and the time is calculated by dividing the distance by the speed. Thus, can be considered zero.

|  |  |
| --- | --- |
|  | (2) |

The time passing through the intermediate node is considered as the previous cases, i.e., with or without traffic light stoppages. A conceptual model of the intermediate nodes in a green transportation model is presented in Figure 2.



**Figure 2.** The conceptual framework of intermediate nodes (small circles are intermediate nodes)

In this framework, the route between the main nodes of *i* and *j* involves *n* intermediate nodes, which means the route comprises *n*+ 1 segments. Each segment, with a potentially different speed, should be taken into consideration in determining the travel time between the two main nodes. Any segment of the route would have a different average speed in traffic periods because of a different combination of the four traffic modes, which plays a crucial role in estimating the travel time. Below, the calculation process is explained. If a vehicle traverses segment *s* of the route from *i* to *j* in the traffic period *t*, travel time will be equal to . Since travel time in a route varies depending on congestion intensity, it is crucial to determine what percentage of the route is traversed according to the intensity of congestion. Therefore, travel time is presented and simplified in four parts as follows.

|  |  |
| --- | --- |
| (3) |  |
| (4) |  |
| (5) |  |

Since the speed is measured by meters per second (m/s), the obtained value should be divided by 3.6 (speed conversion unit from kilometers per hour (km/h) to meters per second (m/s). The formula to convert from km/h to m/s is m/s = km/h ÷ 3.6). Therefore,

|  |  |
| --- | --- |
| (6) |  |

By calculating for all sections of the routes through Eq (6), the travel time for these sections can be measured. Speed varies in different time intervals, which makes it possible to calculate travel time if the departure time from the source node is given. A vehicle may arrive at the destination within the same time interval (or traffic period) as a departure time interval. Otherwise, the vehicle traverses different segments of the route within different time intervals at different average speeds. In this case, the travel-time function will be a step function (Figure 1). In Figure 1, it is evident that speed is a discrete, step function while the travel-time function is continuous and piecewise. It is a complex function that requires information from the time interval in which the departure time from the origin node has occurred as well as the percentage of the route that was traversed within the time interval. However, to achieve this goal, an algorithm applicable to the MATLAB program can be used. It is supposed that the vehicle *k* leaves node *i* in traffic period *t* (). The logic of the algorithm is presented in Pseudocode 1. It is a new algorithm in which the concept of intermediate node is considered. To incorporate this concept, the travel-time calculation should be conducted based on different segments of the route *s* from the origin *i* to the destination *j*. In line with this goal, this algorithm is a cyclical algorithm by measuring the travel time for different segments until they arrive at the destination node. In each repetition, the value is calculated and saved, and the travel time from *i* to *j* is equal to the sum of these saved values for different segments of the route.

The logic of the algorithm is that if the start and end time of the trip (), which is calculated by equation (5), occurs at one traffic period, travel time is equal to the end time minus the start time. Otherwise, it must be determined that the end time of the trip occurs at which traffic period. A loop (while-end) has been employed to calculate the end time of the trip in each segment of the route between two nodes. Then, the travel time is equal to the end time minus the start time.

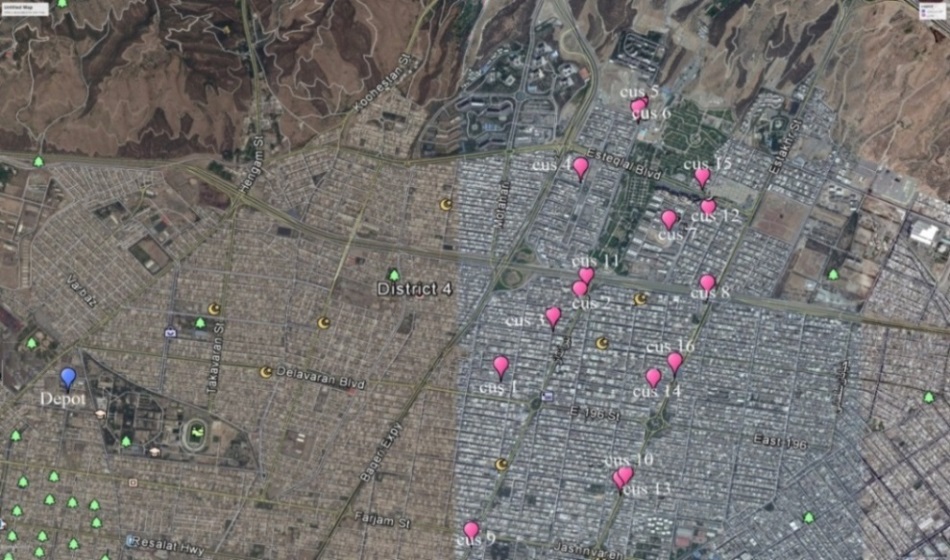
**Algorithm 1.** Pseudo code of calculating travel time between two consecutive nodes (*i,j*)

|  |
| --- |
| Input: *i,j*, *t*, , *s*,,,, ; Output: ,  1: **set** ,  2: **for**  to  3: **set**  4: **find** *t*  in which departure time of the vehicle () has occurred ()  5: **if** ()**then**  6: **set**  7: **set**  8: **set**  9: **if** () **then**  10: **set**  11: **else**  12: **while** () **do**  13: **set**  14: **set**  15: **set**  16: **set**  17: **end while**  18: **set**  19: **end if**  20: **else**  21: **set**  22: **set**  23: **set**  24: **set**  25: **if** () **then**  26: **set**  27: **else**  28: **while** () **do**  29: **set**  30: **set**  31: **set**  32: **set**  33: **end while**  34: **set**  35: **end if**  36: **end if**  37: **save**  38: **set**  39: **end for**  40: **set** |

The output of the above algorithm is , which determines the time spent by a vehicle to move from the origin (*i*) to the destination (*j*) due to the departure time of the origin (*i*). This value plays an essential role in solving Time Dependence Vehicle Routing Problem (TDVRP) in which obtaining the objective function requires calculating the travel time between consequence nodes in a solution. A solution is generally composed of a depot, customer nodes, and vehicles.

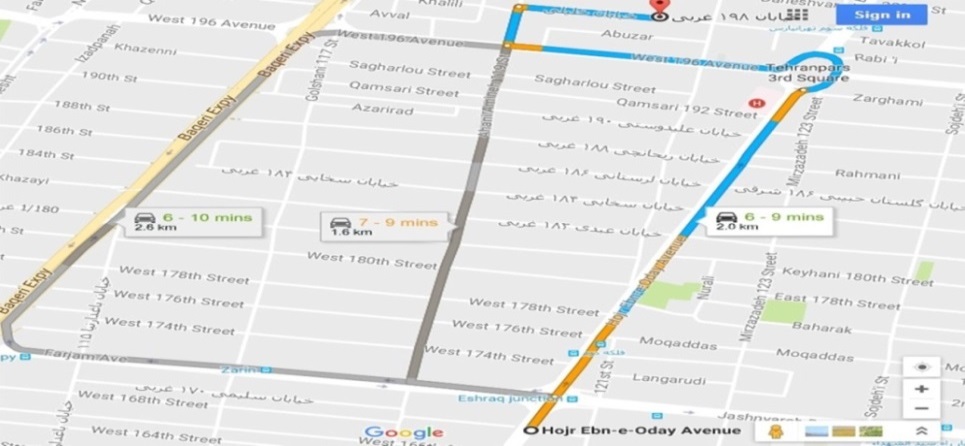
4. Case Study and Results

The authors have considered a large, popular beverage company in Iran with its unique production and delivery facilities that were established in 1955 as a case study. Before the victory of the Islamic Revolution, this company marketed its products under the license of foreign companies, whereas after the revolution it participated in the market with a different brand. This industry group has significantly expanded its activities in recent years. At first, they started operations with only one production line, while currently, 13 companies in different cities in Iran and several foreign companies in other countries produce different products under its license. Since the most modern extract production unit in the Middle East belongs to this industry group, it has produced beverages with various flavours and tastes. It holds a region-based caterpillar retail sales policy, dividing each geographical location (e.g., Tehran) into different sales regions with their respective vehicles and marketing and sales agents. As the case study, the Tehranpars region was selected and received data from 1045 assigned vehicles in a working day.



**Figure 3.** Warehouse and customer positions

In the above figure, the locations of the warehouse and customers are marked in blue and pink respectively. The sales strategy is pre-visit, and the order differs daily. On the specified day, 16 customers were served by a delivery vehicle. The statistical population (number of routes) is 272 (). Google Maps is capable of routing between two or more specified points. Figure 4 presents the output of Google Maps for routes from customer 9 to customer 1. It offers two routes (i) Hojr Ebn-e Oday Avenue-West 196 Avenue, and (ii) Farjam Avenue-Baqeri Expressway as the alternative. Moreover, the route is typically marked in blue; however, it may alter in different segments based on congestion intensity over different hours of a day and days of a year. There are four traffic modes in this software marked in green (free flow), orange (low congestion), red (medium congestion), and crimson (high congestion). A single route includes all four modes. Because in a time interval of an hour each minute can vary in terms of congestion, a pessimistic view is adopted in estimating congestion intensity. Twenty-minute cuts (the program’s default) were considered for traffic periods (as a case in point, 7:00, 7:20, and 7:40 for the first traffic period) and the worst was chosen as representative of that period. These traffic data included the working hours of the delivery trucks from 7:00 to 15:00 (the company’s delivery hours).



**Figure 4.** Google Maps’ routing from customer 9 to customer 1

Google Maps data were used to estimate the speed in different routes within the Tehran Pars sales region. For different road types, two points were specified, and their distance was divided by the travel time estimated by Google Maps to calculate the speed. Moreover, location reports sent by the vehicle ZAMZAM00273 on a predefined day, which also included speed information, were also utilised to improve speed estimation. Table 3 presents the average speed of the vehicle on different urban road types and congestion modes.

**Table 3.** Speed estimates for the inner-city roads

| **No.** | **Road type (S)** | **Average speed (km/h) in congestion modes** | | | |
| --- | --- | --- | --- | --- | --- |
|  |  | **congestion** |  |
| **Green (free-flow)** | **Orange (low)** | **Red (medium)** | **Crimson (high)** |
| 1 | Expressway | 50-60 | 20 | 10 | 5 |
| 2 | Boulevard | 40-50 | 20 | 10 | 5 |
| 3 | Main Street | 30-40 | 20 | 10 | 5 |
| 4 | Auxiliary Street | 20-30 | 20 | 10 | 5 |
| 5 | Alley | 15 | …… | …… | …… |

Accordingly, 272 routes were identified and analysed. Therefore, a new congestion pattern was identified. This pattern had several rules as follows.

* **Congestion highly depends on the road type**. The congestion pattern was not similar in different road types. For instance, Figure 5 reveals that the congestion pattern of the route between customer 6 and the depot varied from one section (Esteghlal Boulevard) to another section (Hengam Avenue). On Esteghlal Boulevard, the free-flow traffic mode had the largest share in all periods; however, this amount fluctuated between 70 and 92%. High congestion in both sections was not anticipated during the given traffic period wherein the Hengam Avenue section, free-flow traffic mode had the largest share until 9:00 and then low congestion replaces it until the end of the traffic period (i.e., 15:00).

|  |  |
| --- | --- |
|  |  |

**Figure 5.** Traffic modes of the different sections of the route between customer 6 and depot

* **Congestion patterns in the same road types were different.** As an illustration, on Zeinodin Expressway, the pattern was uniform and only a free-flow traffic mode existed during the given traffic period. Nevertheless, both free-flow mode and low congestion existed on Baqeri Expressway.

|  |  |
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|  |  |

**Figure 6.** Traffic modes of the expressway sections of the route between customer 14 and depot

* **Congestion highly depended on the time.** Each section of the route in different traffic modes illustrated different behaviour during the whole period as follows.
* Uniform behaviour (i.e., free-flow traffic mode on Zeinodin Expressway)
* Sinusoidal behaviour (i.e., free-flow traffic mode on Baqeri Expressway)
* Cosine behaviour (i.e., low congestion on Baqeri Expressway)
* Ascending behaviour (i.e., low congestion on Hengam Avenue)
* Descending behaviour (i.e., free-flow traffic mode on Hengam Avenue)
* Oscillating behaviour (i.e., free-flow traffic mode and low congestion on Esteghlal Boulevard)

Based on the above rules, each section of the route had a different speed profile. Assuming that the average speed of Expressway, Boulevard, Main Street, and Auxiliary Street were equal to 55, 45, 35, and 25 (km/h), respectively. The speed profiles of Zeinodin and Baqeri Expressway of the route between customer 14 and depot were as in Figure 7. As mentioned earlier, there were 6-speed profiles in the literature including increasing, decreasing, V shape, shape, random and constant. The speed profile of Baqeri Expressway was constant while for Zeinodin Expressway was random.

|  |  |
| --- | --- |
|  |  |

**Figure 7**. speed profiles of Zeinodin and Baqeri Expressway of the route between customer 14 and depot

The output of the proposed model was compared with Google Maps’ estimation model and two models presented in [23] and [22]. The last two models were selected because their studies were conducted in Iran and the speed profile proposed in them was based on the traffic pattern of this country. Both were designed regardless of intermediate nodes, multiple traffic modes, and dependence of speed profile on a route. Moreover, the above assumptions were not considered for calculating travel time. For validation, 272 routes were analysed and their parameters for this model were computed. In this section, to check the efficiency of the proposed model, a random sample of 30 routes (out of the 272) was presented. The departure time for each of the routes was randomly chosen using MATLAB (version 2012). Table 4 denotes the travel times based on the proposed algorithm logic in equation (7). Google Maps’ estimations, which are based on the date and departure time for each route, were also included.

**Table 4.** Travel-time estimation for 30 random samples

| **No** | **Route** | **Departure time** | | **Proposed model estimation (min)** | Without intermediate node, multiple traffic modes, and route dependency | | **Google estimation (min)** |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Hour** | **Minute** |
| **Alinaghian & Naderipour [23]** | **Naderipour & Alinaghian [22]** |
| 1 | 1-2 | 7 | 33 | 3.4706 | 1.95 | 1.733333 | 4 |
| 2 | 0-2 | 13 | 6 | 10.1396 | 7.2 | 4.430769 | 10 |
| 3 | 5-1 | 13 | 47 | 5.2694 | 4.95 | 3.046154 | 5 |
| 4 | 1-12 | 13 | 51 | 9.1104 | 8.4 | 5.169231 | 9 |
| 5 | 9-2 | 11 | 44 | 6.4734 | 2.4 | 2.181818 | 7 |
| 6 | 3-4 | 7 | 43 | 8.1017 | 7.05 | 6.266667 | 7 |
| 7 | 3-15 | 9 | 5 | 7.8736 | 6 | 5.454545 | 8 |
| 8 | 7-4 | 11 | 6 | 3.1863 | 1.92 | 1.745455 | 4 |
| 9 | 4-9 | 14 | 10 | 10.1989 | 7.05 | 4.338462 | 10 |
| 10 | 10-5 | 14 | 14 | 13.3933 | 10.35 | 6.369231 | 13 |
| 11 | 9-6 | 13 | 6 | 11.211 | 8.85 | 5.446154 | 11 |
| 12 | 6-11 | 13 | 47 | 8.1976 | 4.95 | 3.046154 | 7 |
| 13 | 8-7 | 7 | 57 | 8.0336 | 7.8 | 6.933333 | 7 |
| 14 | 11-7 | 13 | 6 | 6.277 | 6.6 | 4.061538 | 6 |
| 15 | 12-8 | 13 | 47 | 2.8682 | 1.8 | 1.107692 | 4 |
| 16 | 15-8 | 13 | 51 | 3.7801 | 2.55 | 1.569231 | 4 |
| 17 | 12-9 | 11 | 44 | 10.0803 | 4.2 | 3.818182 | 12 |
| 18 | 11-10 | 7 | 43 | 5.1244 | 3.3 | 2.933333 | 6 |
| 19 | 16-10 | 9 | 5 | 1.454 | 1.08 | 0.981818 | 2 |
| 20 | 14-11 | 11 | 6 | 2.9711 | 1.56 | 1.418182 | 3 |
| 21 | 16-11 | 14 | 10 | 2.7063 | 1.8 | 1.107692 | 3 |
| 22 | 11-16 | 14 | 14 | 3.1024 | 1.95 | 1.2 | 5 |
| 23 | 13-12 | 8 | 10 | 11.2049 | 9.9 | 8.8 | 12 |
| 24 | 16-12 | 14 | 16 | 9.8184 | 8.7 | 5.353846 | 10 |
| 25 | 14-13 | 14 | 10 | 3.2247 | 2.1 | 1.292308 | 5 |
| 26 | 13-14 | 10 | 38 | 2.6125 | 1.14 | 1.036364 | 3 |
| 27 | 13-16 | 13 | 0 | 2.2063 | 1.2 | 0.738462 | 3 |
| 28 | 15-14 | 8 | 3 | 4.4721 | 3.15 | 2.8 | 6 |
| 29 | 16-14 | 10 | 9 | 0.5761 | 0.264 | 0.24 | 1 |
| 30 | 16-15 | 13 | 52 | 9.7121 | 8.55 | 5.261538 | 8 |

As a result, the findings of the proposed model were not significantly different from those of Google Maps. Therefore, the authors formulated three hypotheses in which the results of the proposed model, Alinaghian & Naderipour’s model and Naderipour & Alinaghian’s model, were compared with those of Google Maps based on the dependent-samples T-test. A dependent-sample T-test was run (p<0.05) using SPSS (version 21) to test these hypotheses (Table 5-7). Based on the results, due to the significance value (two-tailed) being larger than 0.05 for the first hypothesis, the null hypothesis was not rejected. Meaning that there was no significant difference between the estimation of the proposed model and those of Google Maps. Therefore, the proposed model was valid. On the contrary, the p-value for the second and third hypotheses were less than 0.05. Hence, the two model estimations were less than Google maps results. Therefore, the null hypothesis was rejected. As a result, these models were examined less accurately.

**Table 5.** Paired Samples Test between proposed model and Google map

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Paired Differences** | | | | | **T** | **df** | **Sig. (2-tailed)** |
| **Mean** | **Std. Deviation** | **Std. Error Mean** | **95% Confidence Interval of the Difference** | |
| **Lower** | **Upper** |
| Pair 1 | google - Proposed | .271657 | .889936 | .162479 | -.060651 | .603964 | 1.672 | 29 | .105 |

**Table 6.** Paired Samples Test between Alinaghian & Naderipour’s model and Google map

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Paired Differences** | | | | | **T** | **df** | **Sig. (2-tailed)** |
| **Mean** | **Std. Deviation** | **Std. Error Mean** | **95% Confidence Interval of the Difference** | |
| **Lower** | **Upper** |
| Pair 1 | google - Alinaghian | 1.876200 | 1.668691 | .304660 | 1.253100 | 2.499300 | 6.158 | 29 | .000 |

**Table 7.** Paired Samples Test between Naderipour & Alinaghian’s model and Google map

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Paired Differences** | | | | | **t** | **df** | **Sig. (2-tailed)** |
| **Mean** | **Std. Deviation** | **Std. Error Mean** | **95% Confidence Interval of the Difference** | |
| **Lower** | **Upper** |
| Pair 1 | google - Naderipour | 3.170617 | 1.853967 | .338486 | 2.478334 | 3.862900 | 9.367 | 29 | .000 |

5. Discussion

Travel-time estimation is a crucial issue in the time-dependent vehicle routing problem. In a green time-dependent vehicle routing optimisation problem, if the travel time is not well estimated, the optimal solution is not obtainable. On the other hand, the values of the objective function (emissions) for different solutions resulted in less accuracy, which leads to incorrect decision-making. Therefore, the obtained solution is not capable of minimising the amount of pollution. In this study, attempts were made to develop a model to estimate travel time more accurately. The analysis of Google maps data in this paper (Section 4.3) represents a new congestion pattern that has not been addressed in previous research. In this pattern, congestion not only depends on the time but also the route. Therefore, this paper added route dependency as a new concept to the literature. Furthermore, these data denoted that the route between two nodes may have different multiple traffic modes which should be considered in modeling and have been neglected so far. Due to the dependence of speed on the type of route and the need for route segmentation in real-world modeling, the concept of intermediate node is introduced in this paper for the first time.

The proposed model assumes that a route has different sections, and each section has four traffic modes. Therefore, considering the intermediate node in modeling is inevitable, which divides a route into different segments. Accordingly, a computational algorithm was developed with different traffic modes (free-flow, low congestion, medium congestion, and high congestion) which were validated against Google Maps. In this context, there was no significant difference between the outputs of this model and those of Google Maps. On the other hand, two other algorithms Alinaghian & Naderipour [23], and Naderipour & Alinaghian [22] were compared with the above methods in which intermediate node, multiple traffic modes, and route dependency were not considered. The results showed that these two algorithms cannot estimate travel time like Google Maps and their results are significantly different from Google Maps. Therefore, given that Google Maps’ travel-time estimation model is known as a reference model and is based on reality, the accuracy of the proposed model in this paper is higher than the previously proposed models.

6. Conclusions

In this paper, the authors proposed a new model for estimating travel time in which intermediate node, route dependency, and multiple traffic modes have been considered. We acknowledge that the closer the estimated travel time is to reality, the better the results and decision-making process. We compared the results of this model with those of Google maps and two previous models to investigate the effect of the above assumptions on the quality of estimates by statistical analysis. The results showed that using the above assumptions in modeling leads to an increase in the quality of estimations. The main advantage of the proposed model compared to other models is the better representation of reality. However, data collection is difficult to implement this model. However, if an API service in which parameters of the proposed model were determined by online navigational and GPS platforms and applications (e.g., Google Maps, Waze) could be employed, the problems of data gathering and validation would be reduced significantly. Recently national navigation and GPS in Iran have been developed called the “Iranian Neshan application - Persian map and router”. This application could also provide all the required information to estimate the parameters of the proposed model. Companies that distribute goods among retailers can use the above algorithm to model and solve the time-dependent vehicle routing problem to schedule the delivery of goods to retailers by their vehicles. Furthermore, through the installation of GPS systems on vehicles and the use of navigation systems, companies can check the driver's performance with the planned route each day that is obtained from solving the above problem and employ it as an indicator for evaluating the performance of drivers. Companies should implement their developed model based on the above-proposed algorithm for each day. This is because the congestion pattern that may be different. Meanwhile, daily customer demand changes and the set of customers to be served on one day may be different from other days.

The most important limitation of the above algorithm is in data collection. In this method, time intervals of one hour are assumed to require less data collection. Considering the average speed for a part of the route in different traffic periods and the instantaneous change of the speed level from one interval to another interval are other modelling limitations that exist in other methods as well. The collected data is limited to inner-city routes only while intercity routes and the combination of intercity and routes between two nodes can also be considered in solving the model. For future research, developing a new green time-dependent vehicle routing problem with intermediate nodes and multiple traffic modes are applicable. It is also suggested to compare the results of the proposed algorithm with other possible models [34-36] with the same case study. Ichoua et al [4] developed their model in both static and dynamic modes. The model proposed in this paper is developed based on static mode. As opposed to the static problem, in dynamic mode, the number of service requests is not known completely ahead of time; nonetheless, are rather dynamically revealed as time goes by. Therefore, the authors suggest designing a dynamic version of the proposed model in further investigations by considering intermediate nodes, multiple traffic modes, and route dependency. Intercity routes (i.e., based on the type of route including freeway, highway, etc.) with different speed levels and travel times were considered in the proposed model. Moreover, the proposed model in this article was tested in a case study of a company in the emerging economy of Iran. Although the model has the potential to be universal, larger-scale studies should be carried out and the application of this model to non-city-specific nodes should be explored in the future by other scholars.

References

1. Canhong Lin, K. L. C.; G.T.S. Ho, S. H. C.; Lam, H. Y., Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Systems with Applications* **2014,** 41, 1118-1138.
2. Demir, E. Models and Algorithms for the Pollution-Routing Problem and Its Variations. PhD thesis, UNIVERSITY of SOUTHAMPTON, SOUTHAMPTON, 2012.
3. Demir, E.; Bektaş, T.; Laporte, G., A review of recent research on green road freight transportation. *European Journal of Operational Research* **2014,** 237, (3), 775-793.
4. Ichoua, S.; Gendreau, M.; Potvin, J.-Y., Vehicle dispatching with time-dependent travel times. *European Journal of Operational Research* **2003**, (144), 379–396.
5. Maden, W.; Eglese, R. W.; Black, D., Vehicle routing and scheduling with time-varying data: A case study. *Journal of the Operational Research Society* **2010,** 61, (3), 515-522.
6. El-Berishy, N. M.; Scholz-Reiter, B., Development and implementation of a green logistics-oriented framework for batch process industries: two case studies. *Logist. Res* **2016,** 9, 1-10.
7. Goodchild, A. *Cost, emissions, and customer service trade-off analysis in pickup and delivery systems*; University of Washington: Washington, 2011.
8. Pitera, K.; Sandoval, F.; Goodchild, A., Evaluation of Emmissions Reduction in Urban Pickup Systems. *Transportation Research Record: Journal of the Transportation Research Board* **2011,** 2224, 8-16.
9. Alizadeh-Foroutan, R.; Rezaeian, J.; Mahdavi, I., Green vehicle routing and scheduling problem with heterogeneous fl eet including reverse logistics in the form of collecting returned goods. *Applied Soft Computing* **2020,** 94.
10. Heni, H.; Coelho, L. C.; Renaud, J., Determining time-dependent minimum cost paths under several objectives. *Computers and Operations Research* **2019,** 105, 102-117.
11. Liu, C.; Kou, G.; Zhou, X.; Peng, Y.; Sheng, H.; Alsaadi, F. E., Time-dependent vehicle routing problem with time windows of city logistics with a congestion avoidance approach. *Knowledge-Based Systems* **2020,** 188.
12. Pan, B.; Zhang, Z.; Lim, A., Multi-Trip Time-Dependent Vehicle Routing Problem with Time Windows. *European Journal of Operational Research* **2020**.
13. Rincon-Garcia, N.; Waterson, B.; Cherrett, T. J.; Salazar-Arrieta, F., A metaheuristic for the time-dependent vehicle routing problem considering driving hours regulations – An application in city logistics. *Transportation Research Part A* **2020,** 137, 429-446.
14. Sun, P.; Veelenturf, L. P.; Dabia, S.; Woensel, T. V., The Time-Dependent Capacitated Proﬁtable Tour Problem with Time Windows and Precedence Constraints. *European Journal of Operational Research* **2018,** 264, (3), 1058-1073.
15. Tikani, H.; Setak, M., Effi cient solution algorithms for a time-critical reliable transportation problem in multigraph networks with FIFO property. *Applied Soft Computing* **2019,** 74, 504-528.
16. Chen, P. W.; Nie, Y. M., Stochastic optimal path problem with relays. *Transportation Research Part C* **2015,** 59, 48-65.
17. Li, Q.; Nie, Y. M.; Vallamsundar, S.; Lin, J.; Homem-de-Mello, T., Finding Efficient and Environmentally Friendly Paths for Risk-Averse Freight Carriers. *Netw Spat Econ* **2016,** 16, 255- 275.
18. Nasri, M. I.; Bekta¸s, T.; Laporte, G., Route and Speed Optimization for Autonomous Trucks. *Computers and Operations Research* **2018,** 100, 89-101.
19. Tajik, N.; Tavakkoli-Moghaddam, R.; Vahdani, B.; Mousavi, S. M., A robust optimization approach for pollution routing problem with pickup and delivery under uncertainty. *Journal of Manufacturing Systems* **2014,** 33, (2), 277-286.
20. Figliozzi, M., The impacts of congestion on time-deﬁnitive urban freight distribution networks CO2 emission levels: Results from a case study in Portland, Oregon. *Transportation Research Part C: Emerging Technologies* **2011,** 19, 766-778.
21. Androutsopoulos, K. N.; Zografos, K. G., An integrated modelling approach for the bicriterion vehicle routing and scheduling problem with environmental considerations. . *Transportation Research Part C* **2017,** 82, 180–209.
22. Naderipour, M.; Alinaghian, M., Measurement, evaluation and minimization of CO 2 , NO x , and CO emissions in the open time dependent vehicle routing problem. *Measurement* **2016,** 90, 443-452.
23. Alinaghian, M.; Naderipour, M., A novel comprehensive macroscopic model for time-dependent vehicle routing problem with multi-alternative graph to reduce fuel consumption: A case study. *Computers & Industrial Engineering* **2016,** 99, 210-222.
24. Raeesi, R.; Zografos, K. G., he multi-objective Steiner pollution-routing problem on congested urban road networks. *Transportation Research Part B* **2019,** 22, 457–485.
25. Franceschetti, A.; Honhon, D.; Woensel, T. V.; Bektas, T.; Laporte, G., The time-dependent pollution routing problem. *Transportation Research Part B: Methodological* **2013,** 56, 265-293.
26. Jabali, O.; Woensel, T. V.; Kok, A. d., Analysis of travel times and CO2 emissions in time-dependent vehicle routing. *Production and Operations Management* **2012,** 21, (6), 1060-1074.
27. Lu, J.; Chen, Y.; Hao, J.-K.; He, R., The Time-Dependent Electric Vehicle Routing Problem: Model and Solution. *Expert Systems with Applications* **2020,** 161.
28. Çimen, M.; Soysal, M., Time-dependent green vehicle routing problem with stochastic vehicle speeds: An approximate dynamic programming algorithm. *Transportation Research Part D* **2017,** 54, 82-98.
29. Soysal, M.; Bloemhof-Ruwaard, J. M.; Bektaş, T., The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations. *Int. J. Production Economics* **2015,** 164, 366-378.
30. Soysal, M.; imen, M. C., A Simulation Based Restricted Dynamic Programming Approach for the Green Time Dependent Vehicle Routing Problem. *Computers and Operations Research* **2017,** 88, 297-305.
31. Fleischmann, B.; Gietz, M.; Gnutzmann, S., Time-Varying Travel Times in Vehicle Routing. *Transportation Science* **2004,** 38, (2), 160-173.
32. Mancini, S., A combined multistart random constructive heuristic and set partitioning based formulation for the vehicle routing problem with time dependent travel times. *Computers and Operations Research* **2017,** 88, 290-296.
33. Horn, M. E. T., Effcient Modeling of Travel in Networks with Time-Varying Link Speeds. *NETWORKS* **2000,** 36, (2), 80-90.
34. Androutsopoulos, K. N.; Zografos, K. G., A bi-objective time-dependent vehicle routing and scheduling problem for hazardous materials distribution. *EURO J Transp Logist* **2012,** 1, 157-183.
35. Androutsopoulos, K. N.; Zografos, K. G., An integrated modelling approach for the bicriterion vehicle routing and scheduling problem with environmental considerations. *Transportation Research Part C* **2017,** 82, 180–209.
36. Raeesi, R.; Zografos, K. G., The multi-objective Steiner pollution-routing problem on congested urban road networks. *Transportation Research Part B* **2019,** 22, 457–485.
37. Kuo, Y., Using simulated annealing to minimize fuel consumption for the time-dependent vehicle routing problem. *Computers & Industrial Engineering* **2010,** 59, (1), 157-165.
38. Figliozzi, M., Vehicle routing problem for emissions minimization. *Transportation Research Record: Journal of the Transportation Research Board* **2010,** 2197, (1), 1-7.
39. Saberi, M.; Verbas, I. O., Continuous approximation model for the vehicle routing problem for emissions minimization at the strategic level. *Journal of Transportation Engineering* **2012,** 138, (11), 1368-1376.
40. Xiao, Y.; Konak, A., A simulating annealing algorithm to solve the green vehicle routing & scheduling problem with hierarchical objectives and weighted tardiness. *Applied Soft Computing* **2015,** 34, 372-388.
41. Zhang, J.; Zhao, Y.; Xue, W.; Li, J., Vehicle routing problem with fuel consumption and carbon emission. *Int. J. Production Economics* **2015,** 170, 234-242.
42. Xiao, Y.; Konak, A., The heterogeneous green vehicle routing and scheduling problem with time-varying trafﬁc congestion. *Transportation Research Part E* **2016,** 88, 146-166.
43. Huang, Y.; Zhao, L.; Woensel, T. V.; Gross, J.-P., Time-dependent vehicle routing problem with path ﬂexibility. *Transportation Research Part B* **2017,** 95, 169-195.
44. Saint-Guillain, M.; Paquay, C.; Limbourg, S., Time-Dependent Stochastic Vehicle Routing Problem with Random Requests: Application to online police patrol management in Brussels. *European Journal of Operational Research* **2020,** 292, (3), 869-885.
45. Fan, H.; Zhang, Y.; Tian, P.; Lv, Y.; Fan, H., Time-dependent multi-depot green vehicle routing problem with time windows considering temporal-spatial distance. *Computers and Operations Research* **2021,** 129, 105211.