Heterogeneous Green Vehicle Routing Problem with Hierarchical Objectives: Case Study

Hagar H. Amer, Hala A. Farouk, Khaled S. El-Kilany
Department of Industrial and Management Engineering
College of Engineering and Technology
Arab Academy for Science, Technology, and Maritime Transport
Abo-Kir Campus, P.O. Box 1029, Alexandria, Egypt
hagar.amer@hotmail.com, mail@halafarouk.info, kkilany@aast.edu

Abstract
Green Vehicle Routing Problem (GVRP) addresses the primary sources of carbon emissions, which is distribution. This paper aims to fulfill the demand for a set of customers using a fleet of vehicles originating from a single depot with the primary objective of minimizing carbon dioxide equivalent emissions. This work defines a mixed-integer linear programming model that considers heterogeneous vehicles, customer time window constraints, service time at each customer, and vehicle capacity constraints in GVRP. The model is studied on a real-life case study using three objectives functions; the classical vehicle routing problem objective of minimizing the total travel distance, minimizing the deviation of a fleet of vehicles' traveling speed from the optimum traveling speed, and directly minimizing the total amount of emissions produced. This work also studies the effect of varying vehicle velocity and distance on the amount of emissions produced. The computational results show that up to 9% and 21% reduction in emissions and fuel consumption can be achieved compared to distance-oriented solutions and velocity oriented solutions, respectively.

Keywords
Green Vehicle Routing Problem, Emissions, Green Logistics, Heterogeneous Fleet, Time Windows

1. Introduction
Green Logistics has lately received a great deal of attention from governments and business organizations all over the globe (Lin *et al.*, 2014). This scope of attention is a part of almost every modern supply chain network, where transportation and logistics operations within a city, region, or even among nations have caused severe global climate changes (Demir, Bektaş and Laporte, 2014). The Keeling Curve in (*The Keeling Curve*, 2019) shows that the concentration of carbon dioxide equivalent (CO_{2eq}) emissions in the atmosphere has been growing in the past half-century and even faster in the last decade. The transportation sector is one of the most significant contributors to total emissions. According to the Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990–2017, transportation accounted for the largest portion (29%) of total U.S. emissions in 2017 with 83% of these transportation emissions are due to road transportation (*Sources of Greenhouse Gas Emissions*, 2019).
Thus, considering emissions in the classical vehicle routing problem (VRP) problem will ensure the sustainability of mother earth due to the dire results of the greenhouse gas emissions. Therefore, choosing the right selection of routes, that will meet ever-growing environmental concerns while still considering the economic aspect, is the main objective of the GVRP problem. Considering emissions may lead to quite different logistic plans for customer assignments, route selections, and schedules than the classical VRP. Although research in the field of classical vehicle routing problem (VRP) has been studied over the past decades, only after 2006, Green VRP (GVRP) became a hot topic in the field of research. Therefore, environmental dimension has been added to the economic dimension in the VRP, trying to find the right balance between these two targets. Green logistics activities include assessing the impact of the different distribution strategies on the environment, reducing the energy usage in logistics activities, and reducing waste and managing its treatment (Sbihi and Eglese, 2010).
According to an extensive survey of the GVRP problem by (Lin *et al.*, 2014), related studies on VRP from the perception of reducing emissions produced are rarely found. Furthermore, the traditional VRP objective of reducing the total distance is considered by most researchers since it is believed that routing decisions leading to minimizing total travel distance lead to a decrease in emissions and fuel consumption. (Lin *et al.*, 2014) also noted that variants of the classical VRP problem, since it was introduced in 1959, have been applied to the GVRP model to make it

comprehensive and more applicable to real-world problems. For instance the consideration of heterogeneous vehicles which may result in more reduction of fuel consumption and emissions by using different combination of vehicles.
In this work, development of a GVRP model that considers different classical VRP variants and aims to derive a set of routes with a heterogeneous set of capacitated vehicles to minimize carbon dioxide emissions and fuel consumption while satisfying a set of logical and relevant constraints such as fulfilling customer demand, vehicles capacity, and time windows. The work also considers a real-life problem that compares the routing decisions recommended by the developed model when using three different objective functions; namely, minimizing total distance traveled, minimizing the deviation from optimum travel speeds (that promises minimum emissions) on the amount of emissions produced, and minimization of total CO_2 emissions.
The remaining of this paper is as follows. Section 2 presents a brief review of the literature on different classes of GVRP and the different objectives used. The mathematical model is formulated in Section 3, and the real-life case study is presented in Section 4. Experimental results and analysis are summarized in Section 5. Finally, concluding remarks and direction for future research are drawn in Section 6.

2. Literature Review

This section covers an overview of GVRP related literature. It reviews different classes of GVRP and the various objectives considered while putting the environmental aspect into consideration. Also, a review of GVRP publications with emissions minimization objectives is addressed. Finally, a summary is provided to highlight the outcomes of this review.

2.1 Classes of Traditional VRP Problem Applied to GVRP

The elementary class of a classical VRP problem is capacitated vehicles (CVRP) where the capacity of each truck is explicitly considered and cannot be exceeded when distributing demand from depot to each customer. A more complicated case in the fleet size problem is to consider heterogeneous vehicles with different capacities.(Erdoĝan and Miller-Hooks, 2012) formulated a model with objective of minimizing distance while considering capacitated and heterogeneous fleets. (Li, Wang and Zhang, 2018) studied an emission-based capacitated heterogeneous fixed fleet vehicle routing problem by extending the traditional VRP by taking fuel and carbon emissions into account.
The Time-dependency constraint is another class of VRP (TDGVRP) in which the travel time between any two points depends on the distance or the time between the points. In (Xiao and Konak, 2015), the schedule of a vehicle is modelled using the total distance that the vehicle travels on each road segment in each time period, which is different from typical GVRP problems where the schedule of a vehicle is generally determined by the time points when the vehicle departs from each node on its route. In (Figliozzi 2010), GVRP was considered during design of routes in congested environments with time-dependent travel speeds.
Another class of VRP is the Multi-depot VRP (MDVRP), which considers more than one depot and each customer is visited by a vehicle that is assigned to one of these depots. (Markov, Varone and Bierlaire, 2016) presented a model for waste collection VRP (which is one of the GVRP types) that considered multiple dump sites for the collected waste flow, and they can be used when and as needed during a tour.
Another variant to the classical problem is adding the fuzzy logic in GVRP to formulate the ambiguous and vague elements. In (Wang et al., 2019) the fuel consumption and fuzzy travel time have been used in developing and solving FGVRP.
Finally, adding time windows to the VRP (VRPTW), where some customers force deadlines or the earliest time constraints on their deliveries. VRPTW has been a subject of intensive research efforts since it was first introduced, in (Kramer et al., 2015; Wang et al., 2016; Xiao and Konak, 2016; Yu et al., 2019) they incorporated the use of time windows while considering the environmental dimension to the VRP.
Some authors considered more than one VRP variant when developing their models. For example, (Çimen and Soysal, 2017) estimated the amount of fuel consumption and emissions produced while taking time dependency, capacitated vehicles and stochasticity of the vehicle speeds into account. (Xiao and Konak, 2016), defined a new mixed-integer linear programming model while considering heterogeneous vehicles, time-varying traffic congestion, customer and vehicle time window constraints, the impact of vehicle loads on emissions, and vehicle capacity constraints in the GVRP.
Based on the review of (Toro O., Escobar Z., and Granada E., 2016), most of the authors considered minimizing the total distance travelled in the objective function of the classical VRP, such as the multi-depot VRP model proposed by (Stodola, 2018) that aims to minimize the total distance travelled by all vehicles originating from multiple depots, and (Erdoĝan and Miller-Hooks, 2012) who formulated a mixed-integer linear programming model with the objective of minimizing distance claiming that it is directly related to distance traveled. (Liang and Liu, 2013) propose the VRP with Multiple Time Windows (VRPMTW), in which part of the objective function is to minimize the operating cost

by minimizing the total mean travel time. Minimization of total cost by reducing vehicle count and traveled distance has been addressed in literature by (Everett, Pizarro and Crocket, 2016). Although different objectives were considered, however incorporating sustainability was not a priority.

2.2 GVRP Objectives

Focusing on the objective functions presented in the literature that studies the VRP from a green perspective, it was evident that most objective functions included either fuel consumption or greenhouse gas emissions as a single objective or as part of a multi-objective function. A VRP with alternative stop points was introduced by (Lang et al., 2014) to minimize fuel consumption by constructing a bi-directional road network that allows for alternative stops depending on the package size and walking distance of deliveryman to customer location. Also, (Kancharla and Ramadurai, 2018) included load, speed, and acceleration in fuel consumption estimation using driving cycles for vehicle routing problems, and studying its effect on total fuel consumption estimates and route selection.

In (Erdoĝan and Miller-Hooks, 2012), mixed-integer linear programming model was developed to support vehicles in solving complications that exist as a result of limited refueling infrastructure. In (Koç and Karaoglan, 2016), service time at the customer node and refueling time at fuel station node are considered with all fuel stations having unlimited capacities and no limitation on the number of stops for refueling.

Considering emissions minimization to ensure sustainability has been covered in the following publications. (Xiao and Konak, 2016) formulated a new mixed-integer linear programming model that considered various VRP constraints in GVRP and its effect on emission minimization. (Stellingwerf et al., 2018) developed a model to optimize routing decisions while taking into account total emissions including refrigeration emissions in temperature-controlled transportation systems. (Yu et al., 2019) formulated a heterogeneous fleet GVRP model to minimize carbon emissions produced and suggested an improved branch-and-price algorithm to solve the model. (Xiao and Konak, 2015) presented a GVRP problem covering general time-dependent traffic conditions with the primary objective of minimizing emissions and weighted tardiness. (Ehmke, Campbell and Thomas, 2016) developed a model that considered the impact of traffic on travel speed and load of vehicles with an objective of minimization of emissions while assuming that each vehicle will visit multiple customers over a day.

Other publications formulated more comprehensive multi-objective functions that optimize economic costs and environmental costs to meet efficiency objectives and green criteria simultaneously. (Li, Soleimani and Zohal, 2019) have developed a multi-depot green vehicle routing problem by maximizing revenue and minimizing costs, time and emission and have solved the problem by an improved ant colony optimization algorithm.

2.3 Outcome of Review

Our brief literature review shows that, (i) there is a growing attention paid to sustainable VRP decisions with the objective of minimizing emissions, (ii) the relationship between traditional VRP objective of reducing the total distance and environmental pollutant emissions and fuel needs to be directly assessed using more accurate formulations, and (iii) most models presented in literature are either theoretical models or models tested using some dataset found in literature and used for benchmark purposes. Hence, there is a big gap between research in the GVRP area and implementation; where, very few research papers included any case studies.

This work aims to minimize emissions produced and fuel consumption by deriving a set of routing decisions with heterogeneous set of capacitated vehicles while conforming to a set of constraints within time windows and applying it to a real-life case study. Moreover, the relationship between distance traveled, velocity and emissions produced are studied.

3. Model Development

In this section, the mathematical model will be covered explicitly along with the list of assumptions needed to build the model and emissions calculations. A depot and a number customers who are located in different locations and having demands that must be fulfilled are given. In order to complete the routing operation, a fleet of heterogeneous vehicles is scheduled for delivery taking into consideration specific problem requirements and constraints related to the route traversed. The model presented in this work is a mixed-integer programming problem that aims to find the optimal route(s) from the depot to the customers that will minimize CO_2 emissions under a set of constraints. The model does not consider the stochasticity and dynamic nature of the input variables such as demand, travel time, and service time. The following assumptions are made to facilitate model development.

- A single depot.
- Each vehicle begins its journey at the depot and returns to that depot at the end of the journey.
- The fleet of vehicles is heterogeneous with known capacity of each vehicle's type.

- The effect of partial delivery is ignored in CO_2 and fuel consumption calculations.
- The speed from any source to any destination is constant.

Notations

The model is implemented using the below parameters is a single objective model.

i, j	index of nodes, $i = 0,1,2, \dots, n$
n	total number of nodes
N	set of nodes including the depot
N'	set of nodes including the depot, $N' = N\{0\}$
A	set of arcs formed by all pairs of nodes, $A = \{(i,j): \forall\, i \in N, j \in N, i \neq j$
D_{ij}	distance of arc (i,j)
s_i	service time of customer i
$[S_i, E_i]$	time-window for starting to service customer i
v_{ijk}	travel speed on arc (i,j) in period k
h	index of vehicle, $h = 1,2, \dots, q$
H	set of vehicles, $h \in H$
q	total number of vehicles, $q = \lvert H \rvert$
$[F_h, T_h]$	available time window for vehicle h
u	index of vehicle type, $u = 1,2, \dots, \lvert U \rvert$
U	set of vehicle types
w_{hu}	$\{0,1\}$ value indicating whether vehicle h belongs to type u
Υ_u	Inverse optimum traveling speed for the vehicle type u
k	index of period, $k = 1,2, \dots, m$

Parameters and continuous variables of the model are defined as follows:

X_{ij}	$\{0,1\}$ variable indicating whether arc (i,j) is traversed (1) or not (0)
y_{ijh}	$\{0,1\}$ variable indicating whether arc (i,j) is traversed by vehicle h (1) or not (0)
d_{ijh}	Continuous variable indicating the traveled distance of arc (i,j) by vehicle h
τ_{ijh}	Continuous variable indicating the time spent on arc (i,j) by vehicle h
v_{ij}	Continuous variable indicating the average travel speed used on arc (i,j)
l_i	Continuous variable indicating the departure time from node i
a_i	Continuous variable indicating the arrival time (or service starting time) at node i

Decision Variable

x_{ijh}	$\{0,1\}$ variable indicating whether arc (i,j) is traversed by vehicle h (1) or not (0)

Objective Function

The emission model of the Heavy-Duty Vehicle (HDV) based on the "Methodologies for estimating air pollutant emissions from transport" (MEET) model has been adopted, which is developed by (J. Hickman, D. Hassel, R. Joumard, Z. Samaras, 1999) and widely used in literature. The emission rate function was derived in MEET for four classes of HDV and has been used and multiplied by the vehicle load correction factor for zero gradients. The coefficients of the emission rate function given in Eq.1 are $c_{xu}: x = 0,1, \dots, 6;\ \forall\, u \in U$) and the coefficients of the emission rate function ε_{lu} given in Eq.2 after being multiplied by the vehicle load correction factor, are $f_{yu}: y = 0,1, \dots, 4;\ \forall\, u \in U$). We have adopted coefficients for the four classes of HDV from (J. Hickman, D. Hassel, R. Joumard, Z. Samaras, 1999). As stated, the objective of this work is to minimize to total amount of emissions produced from a set of heterogeneous capacitated vehicles as stated in Eq.3.

$$\varepsilon_u = c_{0u} + c_{1u} v_{ij} + c_{2u} {v_{ij}}^2 + c_{3u} {v_{ij}}^3 + \frac{c_{4u}}{v_{ij}} + \frac{c_{5u}}{{v_{ij}}^2} + \frac{c_{6u}}{{v_{ij}}^3} \tag{1}$$

$$\varepsilon_{lu} = \varepsilon_u \cdot \left(f_{0u} + f_{1u} v_{ij} + f_{2u} {v_{ij}}^2 + f_{3u} {v_{ij}}^3 + \frac{f_{4u}}{v_{ij}} \right) \tag{2}$$

$$Min\ Z = \sum_{h \epsilon H} \sum_{(i,j) \epsilon A} \sum_{u \epsilon U} X_{ijh} \cdot\ d_{ijh} . \varepsilon_{lu} \tag{3}$$

Constraints

The constraints developed by (Xiao and Konak, 2016) are used to model a heterogeneous fleet. The first three constraints (4)-(6) are related to the route. Constraints (4) and (5) ensure that the sub-distances traveled sum up to the total distance on arc (i,j). Constraint (6) prevents more than one vehicle to travel on the same arc (i,j).

$$d_{ijh} \leq D_{ij} \cdot x_{ijh} \quad \forall (i,j) \in A, h \in H \tag{4}$$

$$y_{ijh} \geq x_{ijh} \quad \forall (i,j) \in A, h \in H \tag{5}$$

$$X_{ij} = \sum_{h=1}^{q} y_{ijh} \quad \forall (i,j) \in A \tag{6}$$

Constraints (7)-(10) are related to the heterogeneous fleet. Constraint (7) ensures that a single vehicle departs the depot on a single arc. Constraint (8) and (9) are balancing constraints ensuring that a vehicle enters a node from a single arc and leaves the node on a single arc. Constraint (10) ensures that the vehicle that has entered a node leaves this same node expect for the depot. Constraint (11) ensures that the total distance is equal to the distance between the source i and destination j. Constraint (12) links the time taken to travel in each period to the traveling speed.

$$\sum_{j=1}^{n} y_{0jh} \leq 1 \quad \forall h \in H \tag{7}$$

$$\sum_{j=0}^{n} X_{ij} = 1 \quad \forall i \in N' \tag{8}$$

$$\sum_{i=0}^{n} X_{ij} = 1 \quad \forall j \in N' \tag{9}$$

$$\sum_{i \in N, i \neq j}^{n} y_{ijh} = \sum_{i' \in N, i' \neq j}^{n} y_{ji'h} \quad \forall\, h \in H, j \in N' \tag{10}$$

$$\sum_{h=1}^{q} d_{ijh} = X_{ij} D_{ij} \; \forall (i,j) \in A \tag{11}$$

$$\tau_{ijh} = 60 \cdot d_{ijh} / v_{ij} \quad \forall (i,j) \in A, h \in H \tag{12}$$

Constraints (13) and (14) ensure the arrival time a_i at node i is not violated and that the departure time l_i from node i will not affect the arrival at the next node. Note that $x_{ijh} = 0$ is arc(i,j) not traveled by vehicle h.

$$a_i + s_i \leq l_i \quad \forall\, i \in N' \tag{13}$$

$$S_i \leq a_i \leq E_i \quad \forall\, i \in N' \tag{14}$$

Finally, constraint (15) and (16) define the ranges of the decision variables.

$$X_{ij} \in \{0,1\}; y_{ijh} \in \{0,1\}; x_{ijh} \in \{0,1\}; \; \forall i,j,h \tag{15}$$

$$d_{ijh} \geq 0; \tau_{ijh} \geq 0; a_i \geq 0; l_i \geq 0 \tag{16}$$

Classical VRP objectives

The HCGVRPTW model described in the previous section aims to minimize CO_2 emissions. However, the traditional VRP objective of distance minimization and minimizing velocity deviation from optimum velocity can also experiment as an objective function of this model. The solutions found from three different objective functions are compared to demonstrate to what extent CO_2 emissions and fuel consumption can be reduced at the expense of longer travel distances or different traveling velocities. The classical VRP objective of minimizing distance is shown in equation (17).

$$Min\ Z = \sum_{h \epsilon H} \sum_{(i,j) \epsilon A} \sum_{u \epsilon U} X_{ijh} \cdot d_{ijh} . \varepsilon_{lu} \tag{17}$$

Figure 1 shows the effect of changing the travel speed and HDV class on the emission rate. The emission rate is at minimum for certain traveling speeds depending on the vehicle type. Also, the heavier the vehicle (notice the different HDV classes), the more emissions are expected.

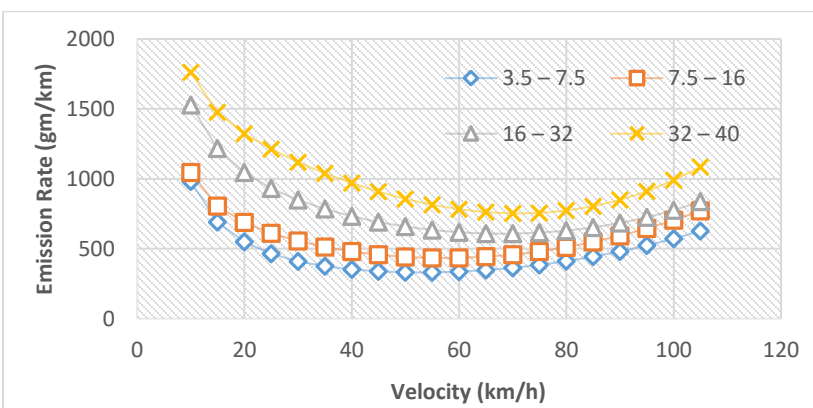

Figure 1. The Emission Rate Function ε_{lu} versus traveling speed.

Hence, the relationship between emission rates and travel speed is not linear (Figliozzi, 2010) and the general notion of "reduction in total distance will in itself provide environmental benefits due to the reduction in fuel consumed and the consequent pollutants" is not valid; unless, fuel consumption and resultant pollutants are measured explicitly or emphasized. Therefore, minimizing the velocity shift from the optimum velocity will be tested and compared with the other two objectives of minimizing distance and emissions produced. At the optimum speeds v_u^* for each HDV class, if the vehicle travels at this speed, it will result in least amount of emissions. So the objective of minimizing deviations from this speed will result in lower values of emissions. In Eq.18, for each active route (X_{ijh}) by a vehicle (h) and belonging to an HDV type (u), the speed (V_{ijh}) is multiplied by the inverse optimum travelling speed (Υ_u) for the corresponding HDV type (u) used.

$$Min\ Z = \sum_{h\epsilon H} \sum_{(i,j)\epsilon A} \sum_{u\epsilon U} X_{ijh} \cdot |V_{ijh}\, W_{hu} \Upsilon_u - 1| \qquad (18)$$

4. Case Study

This section covers the case study as an illustration of the heterogeneous capacitated GVRP with time windows. All the data reported in this section is used in the implementation of the mathematical model given in the previous section. The model is implemented on LINGO 17, results and analysis of the output data will be discussed in the next section. Part of the dataset is used to verify and validate the LINGO implementation of the mathematical model.

4.1 Data Collection

The case study presented in this work is a small-to-medium enterprise (SME) in the food industry. All products are distributed to the local market exclusively in branches allocated in different locations and owned by the SME. Daily schedules of a fleet of vehicles, which is also owned by the company, are generated to distribute their products. The manufacturing facility, where all products are produced, is considered as the depot. Although the SME owns a considerable number of branches, only 12 branches are included in this study as shown in Figure 2. These branches are considered as the customers and fall within an area of 97 kilometers from the depot. These customers are served by seven vehicles of different sizes and capacities. Compared to similar studies, 12 nodes are considered sufficient. (Kim, Yang and Lee, 2011) used 14 destinations for the log-trucks in the model, (Stellingwerf *et al.*, 2018) had nine supermarket chains in the Netherlands.

Figure 2. Customer locations and the Depot at Node 0

A vehicle must serve at least one customer and can serve more customers as long as the total demand of customers served by a single vehicle does not exceed the capacity of that vehicle (C_h). Additionally, the arrival time of a vehicle at each customer (a_i) is restricted by a time window; where, a vehicle cannot arrive earlier than a minimum arrival time (E_i) or later than a maximum arrival time (S_i). Once a vehicle arrives within the time window, customer service begins in a time (s_i), which is basically the time needed to unload the product and revise the order being delivered. The ability of a vehicle to arrive within the time window of the customer is affected by the time needed to traverse the route assigned to that vehicle (τ_{ijh}). This time depend on the distance between any two nodes along the route (D_{ij}) and the velocity of the vehicle (V_{ij}). Finally, all vehicles must leave the depot and return back to the depot after serving all customer(s).

Customers

Data related to each of the 12 customers are determined and collected (provided in Table 1). Each customer has a pre-determined demand in units that must be delivered daily by the assigned vehicle and service time spent at each node in minutes. The vehicles leave the depot starting from 7 AM, where the time windows provided since time of leaving the depot.

Table 1: Customers' Related Data.

Customer Number	Demand (units)	Service Time (min)	Time Window (min)	
			Minimum	Maximum
1	70	54	17	51
2	292	17	20	60
3	89	29	35	105
4	97	13	26	78
5	54	14	28	84
6	119	13	42	126
7	38	22	32	96
8	54	19	38	114
9	118	50	64	192
10	348	20	65	195
11	133	20	140	420
12	70	10	170	510

Vehicles

Seven heterogeneous vehicles are considered in this study, each with a given capacity in units, as shown in Table 2. The weights of the first three vehicles fall under the first HDV class 3.5 – 7.5 tons and are classified as Class 1 vehicles. The remaining four vehicles fall under the second HDV class 7.5 – 16 tons.

Table 2: Vehicles' Related Data

Vehicle	1	2	3	4	5	6	7
Capacity (units)	144	232	232	292	292	420	600
Vehicle Weight (Tons)	4.3	6.9	6.9	8.7	8.7	7.4	9.9
HDV Vehicle Type	Class 1	Class 1	Class 1	Class 2	Class 2	Class 2	Class 2

Routes Data

All possible distances between any pair of locations are retrieved from Google Maps at three different time phases with different congestion levels, and it is repeated for all pairs of locations. Table 3 shows the distance matrix in kilometers between the 13 different locations considered in this work and at the least congested time phase; where Location 0 is the Depot (the manufacturing facility), and locations 1 to 12 are the 12 customers.

Table 3: Distance Matrix in Kilometers between Depot and Customers at Least Congested Time Phase

		To Location												
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
From Location	**0**	0	5.5	6.6	11.5	8.3	9.2	14.1	13.4	12.7	23	20.8	50.1	66.4
	1	22.9	0	1.5	4.3	3.8	6.3	6.9	8.3	7.8	14.4	13.7	37.2	53.5
	2	24.1	1.2	0	4.1	5.7	7.6	6.7	9.9	9.2	14.2	13.5	37.1	53.5
	3	26.4	3.1	2.3	0	1.4	5.6	4.7	7.9	7.1	12.1	11.5	35	51.3
	4	25.2	3.9	3.5	1.5	0	3.2	3	5.1	4.7	11.5	10.8	34.4	50.7
	5	26.6	5.3	5.1	2.9	1.7	0	1.3	3	2.8	7.6	10.8	34.3	50.6
	6	27.1	5.8	5.3	3	2.1	1	0	2.7	2.6	7.4	8.8	32.3	48.6
	7	28.9	6.5	6.4	4.1	2.9	1.5	1.8	0	1.7	7.2	9.9	28.4	44.7
	8	27.5	8.2	9	5.8	4.6	3.2	3.5	1.7	0	5.8	7.9	27.1	45.5
	9	33.5	13.3	12.5	10.3	9.8	6.7	7.8	5.2	5.2	0	3.7	25	41.2
	10	37	13.4	12.6	10.3	9.9	8.6	7.8	7.7	9	5.6	0	18	38.1
	11	47.3	34.2	33.4	31.1	30.7	29.4	28.6	26.4	27.8	21.5	17	0	19.4
	12	66.9	53.8	53	50.7	50.3	49	48.2	46	47.5	41.1	42	23.9	0

It should be noted that all distances retrieved are the ones recommended by Google Maps, which are for the fastest routes between any two locations and not necessarily the shortest ones. So, three different distance matrices were retrieved; one for the least congested period, the other for the moderate congestion, and the third one for the highly congested time-period.

After defining the different locations included in the study and the distances between them, travel times are retrieved also using Google Maps. If more than one route is available between any two locations, travel time selected is on the shortest route while reporting average of trip duration. Table 4 shows the average time in minutes between all nodes when considering the least congested time phase. The three scenarios regarding vehicles' departure time from factory and all locations are D1, D2, and D3. The departure schedule for each scenario is as follows:

1. Departure 1, least congestion (D1): 06:00 - 07:00 AM
2. Departure 2, moderate congestion (D2): 07:00 - 09:00 AM.
3. Departure 3, maximum congestion (D3): 09:00 - 11:00 AM.

Velocity is calculated by dividing distance in km by the average travel times in hours.

Table 4: Average Trip Duration Matrix between Depot and Customer at Least Congested Time Phase

		To Location												
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
From Location	**0**	0.0	10.0	14.0	19.0	18.0	23.0	24.0	29.5	26.0	30.5	32.0	50.0	50.0
	1	22.0	0.0	6.5	11.5	10.0	15.0	18.0	19.0	16.0	28.5	24.0	55.0	55.0
	2	23.0	6.0	0.0	7.0	11.0	14.0	13.0	17.0	16.0	24.0	20.0	50.0	50.0
	3	32.5	6.5	4.5	0.0	9.0	11.0	9.5	15.0	13.0	20.0	17.0	45.0	47.5
	4	30.5	10.0	9.5	7.0	0.0	9.5	12.0	13.0	10.5	21.0	20.0	47.5	50.0
	5	30.5	11.5	11.0	6.5	5.0	0.0	7.0	8.0	6.0	17.0	18.0	47.5	50.0
	6	39.0	13.0	12.5	9.5	6.5	4.0	0.0	8.0	5.5	15.0	15.0	45.0	47.5
	7	42.5	13.0	12.5	9.5	6.5	4.0	7.0	0.0	6.0	19.0	18.0	47.5	47.5
	8	30.5	17.0	19.0	13.0	11.0	8.0	12.0	5.0	0.0	16.0	17.0	42.5	42.5
	9	29.5	24.0	22.0	17.0	16.0	13.0	16.0	10.0	11.0	0.0	9.0	34.0	34.0
	10	54.0	23.0	21.0	17.0	18.0	17.0	15.0	16.0	15.0	12.0	0.0	35.0	37.5
	11	45.0	50.0	47.5	45.0	45.0	45.0	42.5	37.5	40.0	34.0	37.5	0.0	21.0
	12	50.0	55.0	52.5	50.0	50.0	50.0	47.5	42.5	42.5	37.5	40.0	29.5	0.0

5. Results and Analysis

Three sets of experiments are conducted using the developed model and driven by the full dataset of the SME presented in the previous section. The purpose of these experiments is testing the effectiveness of the mathematical model developed for the HCGVRPTW to find an optimum route that would ultimately reduce emissions and fuel consumption of the fleet of vehicles. In this section, we compare the solutions found with three different objective functions, namely minimizing the total distance traveled, minimizing the velocity deviation from the optimum velocity, and minimizing the total CO_2 emissions produced. LINGO 17 has been used to solve the model with the three objective functions defined above.

The three experiments report total distance traveled by all vehicles from and to depot in km, total trip duration in hours, total velocity deviation of all vehicles from the optimum velocity, total amount of CO_2 emissions produced in grams, and total emission rate. The experiments will also report the amount of fuel consumed in liters. Provided the fact that fuel consumption rate (FCR) is interrelated with the amount of CO_2 emissions emitted on traversed routes, the FCR can be calculated as FCR = ε_{lu}/2640 (2640 g of CO_2 emissions are emitted in the process of consuming one liter of diesel) (Toro O., Escobar Z. and Granada E., 2016).

5.1 Distance Minimization

The first experiment set aims at minimizing the total distance regardless of the velocities of vehicles for the routes selected. It is the solution of the classical VRP objective of minimizing fuel consumption and total travel time. This experiment was executed for three different time-periods. Table 5 shows the data results of distance minimization model. It is clear from the results that the total distance traveled by all vehicles is kept at its minimum value of 340.6 km regardless of the time period, as shown in Table 5. Furthermore, as the time-period moves from D1 to D3, trip duration increases due to higher traffic; hence, velocities along all arcs decreases leading to higher velocity deviations from the optimum travel speed. Shifting to D3, the velocity deviation increases by 29%. The same distance but with

vehicle velocity shifting away from the optimum speed increases the amount of carbon dioxide equivalent emissions produced per km by 14%, and total amount of emissions and fuel consumed by 7%.

Table 5: Summary of Results of Distance Minimization Experiment

Departure Time	D1	D2	D3	Departure Time	D1	D2	D3
Total Distance Travelled by vehicles (km)	340.6	340.6	340.6	% Change in Total Distance	0%	0%	0%
Trip total duration (hrs)	8.4	9.7	10	% Change in Trip Duration	0%	15%	19%
Average Velocity (km/ hr)	41.5	36.9	35.7	% Change in Average Velocity	0%	-11%	-14%
Velocity Deviation	6.75	8.3	8.7	% Change in Total Deviation	0%	23%	29%
Total Emission Rate (g/km)	11146	12166	12716	% Change in Emission Rate	0%	9%	14%
CO_{2eq} Emissions (g)	183388	194777	196473	% Change in Total Emissions	0%	6%	7%
Fuel consumption (liters)	69.45	73.8	74.4	% Change in Fuel Consumed	0%	6%	7%

5.2 Velocity Deviation Minimization

The relationship between emission rates and travel speed analyzed in section 3 indicates that not only the distance traveled affect the amount of emissions produced but also traveling at speed lower or higher than optimum speed for each vehicle class increase the amount of emissions produced. Therefore, the second experiment is to minimize velocity deviation and analyze its effect on performance measures. Table 6 shows the effect of shifting time-periods with different levels of congestion on Experiment 2. Although, in D3 distance increase by 7%, but it does not retain the average velocity near the optimum value. In D1 the average velocity is 47 km/hr which is near the optimum of 57 km/hr, however in D3 it reaches 41 km/hr with 37% increase in velocity deviation. This is mainly attributed to the fact that shifting to other time-periods results in slower velocities on all possible routes. Due to longer travel times with lower speeds in D3, the amount of emissions produced per km increases by 15%, and consequently the total amount of emissions and fuel consumed increases by 7% compared to the results in D1.

Table 6: Summary of Results of Velocity deviation Minimization Experiment

Departure Time	D1	D2	D3	Departure Time	D1	D2	D3
Total Distance Travelled by vehicles (km)	423.05	440.6	451.15	% Change in Total Distance	0%	4%	7%
Trip total duration (hrs)	9.05	10.4	11.55	% Change in Trip Duration	0%	15%	28%
Average Velocity (km/ hr)	47.85	44.55	40.8	% Change in Average Velocity	0%	-7%	-15%
Velocity Deviation	4.55	5.6	6.25	% Change in Total Deviation	0%	23%	37%
Total Emission Rate (g/km)	9671.5	10426	11138	% Change in Emission Rate	0%	8%	15%
CO_{2eq} Emissions (g)	214067	222690	229145	% Change in Total Emissions	0%	4%	7%
Fuel consumption (liters)	81.05	84.35	86.8	% Change in Fuel Consumed	0%	4%	7%

5.4 Emissions Minimization

The third experiment objective is to minimize CO_{2eq} emissions produced as it will keep total distance traveled at its minimum value while having a minimal velocity deviation with the right combination of vehicles. Experiment 3 results are shown in Table 7 . The total distance traveled increases so the time-period moves to D3 since the shorter paths become more crowded. However due to higher traffic in D3, the amount of emissions produced per km increases, which leads to higher amount of emissions and fuel consumed by 8%.

Table 7: Summary of Results of Emissions Minimization Experiment

Departure Time	D1	D2	D3	Departure Time	D1	D2	D3
Total Distance Travelled by vehicles (km)	358.45	366.5	370.05	% Change in Total Distance	0%	2%	3%
Trip total duration (hrs)	7.2	7.35	7.35	% Change in Trip Duration	0%	2%	2%
Average Velocity (km/ hr)	49.7	49.85	47	% Change in Average Velocity	0%	0%	-5%
Velocity Deviation	5.4	6.05	6.7	% Change in Total Deviation	0%	12%	24%
Total Emission Rate (g/km)	9739.1	10385	11179	% Change in Emission Rate	0%	7%	15%
CO_{2eq} Emissions (g)	168071	175704	181178	% Change in Total Emissions	0%	5%	8%
Fuel consumption (liters)	63.7	66.55	68.65	% Change in Fuel Consumed	0%	4%	8%

5.5 Comparison of the Three Experiments

The average results of the performance measures on the three time-domains are shown in Figure 3. Since the third objective considers both distance and velocity deviation minimization, it does not choose the shortest congested route of (340.6 km with average velocity 38 km/hr) nor the longest less congested route of (438.3 km with average velocity 49 km/hr) but it puts both objectives into consideration by choosing a longer route than experiment 1 by an average of 7% and a less congested route than experiment 3 with average velocity less by 10%. Therefore, the total deviation decreases from the distance minimization experiment by 23% but increases by 15% when compared with the velocity deviation minimization experiment. Therefore, it decreases total carbon dioxide equivalent emissions and fuel consumed by 15% than the first experiment and by 21% than the second experiment.

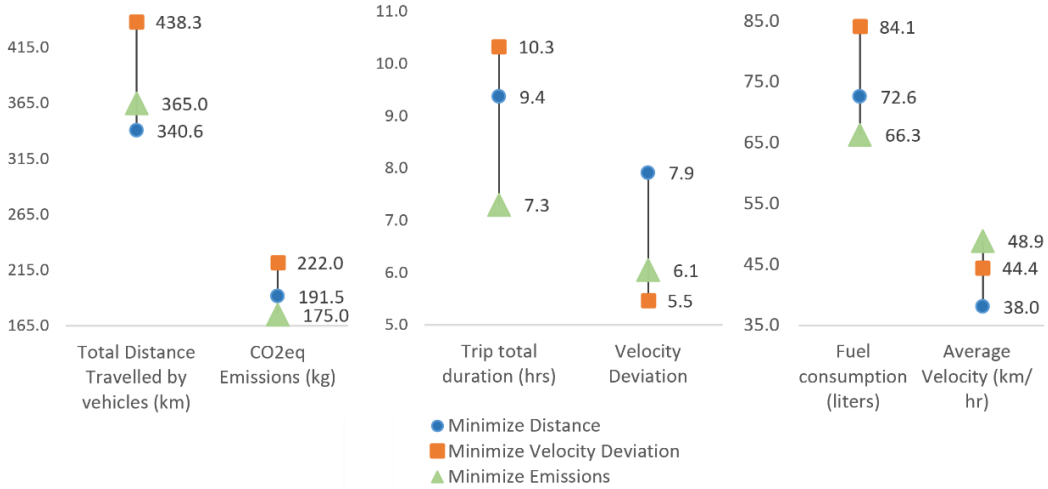

Figure 3: Comparison between Experiment 3 and Experiment 1 and 2 average results.

6. Conclusions

In this paper, we present a comprehensive mixed-integer linear programming model for heterogeneous, capacitated green vehicle routing and scheduling problem with time windows in order to minimize CO_{2eq} emissions and fuel consumed. Distance minimization, velocity deviation minimization and directly minimizing the emissions produced are the three objectives studied in this work. Distance minimization experiment generates routes of minimum total distance; however, this routing decision making leads to the selection of routes with more significant deviations from the optimum traveling speed. On the other hand, velocity deviation minimization model results in the longest routes with vehicle velocities closer to the optimum, regardless of the distances associated with these routes. However, emissions minimization model considers distance and velocity by choosing an intermediate route, longer and less congested than distance minimization model where the vehicle can travel on a speed near optimum and still shorter than velocity deviation minimization model resulting in the least travel time, emissions and fuel consumed. Comparing the three objectives shows that there is a trade-off between the total distance traveled and vehicle velocity. The experiments prove that minimizing distance objective does not always achieve optimum results. Therefore, managing trade-off is crucial to achieving least amount of emissions and fuel consumed. The model generated is implemented on a real-life case study, where feasible and optimal routes for the different model objectives are generated, proving the applicability of the developed mathematical model and its usefulness in proving implementation ready solutions to decision-makers. Results of all experiments show that shifting departure times to more congested time-periods decreases traveling velocities on all possible routes, increasing the deviation from the optimal travel speeds and, consequently, increasing both emissions and fuel consumed compared with departure times at less congested time-periods. In future work, developing better estimates for fuel consumption rate rather than being merely a linear function of the emission rate might be considered. Also, investigating whether the emissions caused by refrigeration should be taken into account in temperature-controlled transportation and whether will it affect the routing decisions.

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Biographies

Hagar H. Amer is an M.Sc. student at the Department of Industrial and Management Engineering, Arab Academy for Science, Technology, and Maritime Transport (AASTMT). Hagar received her BSc. in Industrial and Management Engineering from AASTMT in 2017. She joined the Department of Industrial and Management Engineering as soon as she graduated.

Hala A. Farouk is currently an Assistant Professor at the Department of Industrial and Management Engineering, Arab Academy for Science, Technology, and Maritime Transport (AASTMT). Dr. Farouk holds a Ph.D. degree in Electronics and Electrical Communication Engineering from Cairo University, Egypt. Dr. Farouk has published and reviewed several journal and conference papers. Her research interests include security hardware design and its adoption in industry, vehicle routing problem optimization, operating room scheduling problems, and Internet of Things (IoT).

Khaled S. El-Kilany is a Professor of Industrial Engineering at the Department of Industrial and Management Engineering at the AASTMT, which is accredited by the Engineering Accreditation Commission of ABET since 2010. The department offers both B.Sc. and M.Sc. degrees in Industrial and Management Engineering. Prof. El-Kilany is currently the head of the department since February 2009. He is a senior member of the IISE and is a reviewer of several journals, conferences, and textbooks. He has received his Ph.D. in Mechanical and Manufacturing Engineering from Dublin City University, Ireland, where his research work included modeling and simulation of automated material handling system of Intel's wafer fabrication facility Fab24, which was the second wafer fabrication facility in the world that produces 300mm wafers. His research interests lie in the analysis and improvement of manufacturing systems performance; specifically, material flow, production planning and scheduling, and WIP management using discrete-event systems simulation and optimization techniques.