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Green last-mile route planning for efficient e-commerce distribution

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ABSTRACT
This study aims to design vehicle routes based on cost minimisation and the minimisation of greenhouse gasses (GHG) emissions to help companies solve the vehicle routing problem with pickup and delivery (VRPPD) via particle swarm optimisation (PSO). An effective metaheuristics search technique called particle swarm optimisation (PSO) was applied to design the optimal route for these problems. Simulated data from Li and Lim (2001) were used to evaluate the PSO performance for solving green vehicle routing problems with pickup and delivery (Green VRPPD). The findings suggest that green vehicle routing problems with pickup and delivery should be used when distributing products to customers living in a specific area called a cluster. However, the design of vehicle routes by Green VRPPD costs more when used to distribute products to customers living randomly in a coverage service area. When logistics providers decide to use Green VRPPD instead of VRPPD, they need to be concerned about possible higher costs if an increase in the number of vehicles is needed. PSO has been confirmed for solving VRPPD effectively. The study compared the results based on the use of two different objective functions with fuel consumption from diesel and liquefied petroleum gas (LPG). It indicates that solving VRPPD by considering the emissions of direct greenhouse gases as an objective function provides cleaner routes, rather than considering total cost as the objective function for all test cases. However, as Green VRPPD requires more vehicles and longer travel distances, this requires a greater total cost than considering the total cost as the objective function. Considering the types of fuels used, it is obvious that LPG is more environmentally friendly than diesel by up to 53.61 %. This paper should be of interest to a broad readership, including those concerned with vehicle routing problems, transportation, logistics, and environmental management. The findings suggest that green vehicle routing problems with pickup and delivery should be used when distributing products to a cluster. However, the design of vehicle routes by Green VRPPD costs more when used to distribute products to customers living randomly in a coverage service area. When logistics providers decide to use Green VRPPD instead of VRPPD, they need to be concerned about possible higher costs if an increase in the number of vehicles is needed.

KEY WORDS
last-mile, routing, green, particle swarm optimisation, e-commerce

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Introduction

Environmental concerns are a serious issue in most developed countries. Transportation is one of the primary sources of GHG emissions. The Inventory of US Greenhouse Gas Emissions and Sinks under the United Nations Framework Convention on Climate Change (UNFCCC) is issued annually. According to Greenhouse Gas Emissions and Sinks 1990–2017 (EPA 2019), light-duty vehicles were the largest category source of GHG emissions in the

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transportation sector, followed by medium-duty and heavy-duty trucks with about 59 % and 23 %, respectively. The GHG emissions created by the transportation sector include carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). These emissions result from fossil fuel combustion.

In the last decade, the e-commerce business growth rate has increased significantly in most parts of the world. Online retail markets have changed rapidly. The US was the largest e-commerce market in the world before it was overtaken by China in 2013. In today's fiercely competitive business environment, online sellers need to adapt to outperform their business competitors. The literature on e-commerce generally considers issues addressing the interrelations between e-commerce companies and logistics providers, investigating solutions and measures in the e-commerce environment, and evolutionary applications in solving e-commerce problems (Zhang et al., 2020; Tsang et al., 2021; Mutinda Kitukutha, Vasa & Oláh, 2021; Al-Tit, 2020; Federko et al., 2018; Florek-Paszkowska, Ujwary-Gil & Godlewska-Dzioboń, 2021; Gulc, 2021). E-commerce for logistics service providers has faced the challenge of delivery service reliability that can serve the customised requirements of larger e-commerce enterprises while maintaining low-cost operations (Yu et al., 2020). Liu, Zhang, Chen, Zhou, and Miao (2018) suggested that logistics initiatives are among the main factors e-commerce businesses can use to leverage operational performance. Logistics initiatives have accelerated the speed with which order volumes move both up and down the supply chain. Numerous researchers have focused on topics related to online shopping behaviour (Fu et al., 2019; Rita et al., 2019; Zhou et al., 2020), customer experiences (Lemke, 2016; Yuen et al., 2019; Chen & Yang, 2021), online marketing (Gregory, 2017), the design of smart locker banks (Faugère & Montreuil, 2018), and last-mile delivery (Vakulenko et al., 2019; van Lopik et al., 2020; Qin et al., 2021). Researchers have focused on these topics because good products and efficient services are essential factors driving demand and, therefore, boosting revenue in e-commerce businesses. E-commerce businesses generate revenue for online businesses and also create opportunities for other service businesses in the supply chain. One type of supply chain business is known as a last-mile delivery service. The Capgemini Research Institute (2018) reported that 74 % of satisfied customers intended to increase their spending by 12 % with preferred retailers that provide great last-mile delivery service.

The purpose of a last-mile delivery service is to deliver products to customers as fast as possible. Therefore, various technologies have been developed to enhance the efficiency of last-mile delivery services. Examples of such technologies include drones, autonomous vehicles, delivery by car, and self-service lockers or smart lockers. The use of such varied technologies implies that last-mile delivery has become another key customer expectation in this era. However, last-mile delivery also impacts the environment due to increased GHG emissions.

Although many researchers have published studies on the concept of last-mile delivery, the optimal green route design for last-mile delivery has not been addressed. The last-mile delivery concept coupled with green route optimisation can transform ordinary last-mile delivery to be a much more efficient delivery method. The main idea of green route optimisation is to minimise total GHG emissions, delivery cost, and delivery time by considering several factors, such as the location of the depot and customers, the vehicles' capacity and number.

Subsequently, this study aims to propose an optimisation search technique called particle swarm optimisation (PSO) that can be used to design optimal green routes for the delivery of products to online shoppers. The remainder of this paper is organised into four sections. Theory and experimental research are presented in Section 2. This section describes a PSO algorithm used to solve green vehicle routing problems with pickup and delivery. Computational results and discussion are presented in Sections 3 and 4, respectively. Lastly, conclusions and future research recommendations are discussed in Section 5.

1. Literature review

The vehicle routing problem (VRP) is a generalisation of the travelling salesperson problem (TSP). The VRP is considered a combinatorial optimisation and integer programming problem. It is an NP-hard problem that is time-consuming when solved using exact algorithms, such as branch and price, branch and cut, and branch price and cut methods (Yu et al., 2019). However, such problems could be solved using metaheuristics approaches. Simulated annealing (SA) and genetic algorithm (GA) were applied to green vehicle routing with a heterogeneous fleet, including reverse logistics in the form of collecting returned goods. The experimental results showed that the proposed algorithms were able to find the near-optimal solutions for large instances. SA achieved relatively better results in terms of solution quality, while GA spent less computational time for all-sized test problems (Foroutan et al., 2020). A hybrid genetic algorithm (GA) was successfully developed to determine multi depot capacitated vehicle routing problem with split delivery and vehicle selection (Mehlawat et al., 2019). A hybrid genetic algorithm with variable neighbourhood search was developed to solve the problem multi-depot vehicle routing problem under the time-varying road network. It was found that the Hybrid genetic algorithm was effective for solving VRP (Fan et al., 2021).

The green vehicle routing problem with pickup and delivery is an extended version of the vehicle routing problem with a time window (VRPTW). Vehicle routes are commonly designed to visit each location on the route that requires pickups and deliveries, and the addition of this requirement transforms the VRPTW problem into the vehicle routing problem with pickup and delivery. Practical applications of VRPPD include postal deliveries, school bus routing, and urban newspaper distribution (Créput et al., 2004; Gupta et al., 2021). VRPPD can also include the problem of on-demand delivery service where customers pick up a product at a specific location (e.g., a convenience store or smart locker). A solution to the VRPPD problem involves designing a set of routes by minimising total routing cost while meeting the following requirements:

- Each route starts and ends at the depot.
- A pickup, and its corresponding delivery customer, is visited by exactly one vehicle.
- The total demand of any vehicle route does not exceed the capacity of the vehicle assigned to the route.
- The total duration of any route does not exceed the pre-set route duration bound.
- Time windows specified by the customer are satisfied.

PSO is one of the most famous optimisation search techniques for solving NP hard problems. PSO was inspired by the social behaviour of animals, such as bird flocking and fish schooling (Shi and Eberhart, 1998). Numerous researchers have successfully adopted PSO to solve the VRPs (Belmecheri et al., 2013; Goksal et al., 2013; Chen et al., 2016; Norouzi et al., 2017; Lagos et al., 2018; Zhu et al., 2019; Harbaoui Dridi et al., 2020; Bansal & Wadhawan, 2021).

The concept is to determine the solution by letting each particle search for the solution randomly. The solution of each particle is then compared with its own neighbour. The velocity and position of each particle is then updated according to its own best experience and the global best experience to reach the best solution.

The PSO algorithm consists of the following steps:

- The PSO algorithm starts by initialising an array of particles with random position and velocities on d dimensions.
- Initialise the inertia weight.
- Evaluate the objective function. [The objective function is to determine vehicle routing problems with pickup and delivery requests by minimising the emissions of greenhouse gases including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) in d variables.]
- Compare the particle's fitness evaluation with the particle's pbest (previous best). If the current value is better than pbest, then set the pbest value equal to the current value and set the pbest location equal to the current location in d-dimension space.
- Compare the fitness evaluation with the population's overall previous best. If the current value is better than gbest (global best) then set gbest to the current particle's array index and value.
- Adjust the velocity and position of the particle according to Equations (20) and (21), respectively.
- Loop back to step 2 until a stopping criterion is met. A stopping criterion is usually a sufficiently good fitness or a maximum number of iterations (generation).

2. Research methods

The following section presents a mathematical model for VRPPD, including the input parameters and variables used in the model.

Input parameters consist of the set of pickup nodes and delivery nodes. These nodes are defined as $P = \{1, \dots, n\}, D = \{n+1, \dots, 2n\}$, respectively, where n is the number of requests.
H_i represents the penalty cost when request i is not served.
$i \in P, K$ represents the set of all vehicles $|K| = m$. C_k denotes the capacity of the vehicle $k, k \in K$. f_k is the fixed cost of the vehicle $k, k \in K$ if it is used. τ_k is the start node of the vehicle $k, k \in K$. τ'_k is the end node of the vehicle $k, k \in K$.

All nodes are set as $V = N \cup \{\tau_1, \dots \tau_m\} \cup \{\tau'_1, \dots \tau'_m\}$. A denotes the set of arcs from node i to node $j(i,j)$ $i,j \in V$. While d_{ij} is the nonnegative distance from node i to node $j, i,j \in N$, t_{ij} represents the nonnegative travel time from node i to node $j, i,j \in N$. In cases where travel time is included, the travel time must satisfy the triangle inequality where $t_{ij} \leq t_{il} + t_{lj}$ for all $i.j.l \in V$. S_i is service time spent for loading and unloading vehicles at node i. The time windows are represented by $[a,b]$ for node i, and a visit to node i can only occur in this time interval. The quantity of goods loaded onto a vehicle at node i is represented as q_i when $i \in P$ and $q_i = -q_{i-n}$ for $i \in D$. Lastly, an emissions factor for each GHG is represented as ε where ε_{CO_2} denotes the emissions factor for CO_2, ε_{CH_4} represents the emissions factor for CH_4, and ε_{N_2O} refers to the emissions factor for N_2O.

Decision variables are explained below.

$x_{ijk} = \{1\ if\ edge\ between\ node\ i\ and\ j\ is\ used\ by\ vehicle\ k;\ 0\ otherwise.$

S_{ik} is a nonnegative integer that represents the service start time of the vehicle k at the location $i \in V, k \in K$.

Q_{ik} is a nonnegative integer that represents the upper bound on the amount of goods on the vehicle k after servicing node i where $i \in V, k \in K$.

$z_i = \{1\ if\ the\ request\ is\ placed\ in\ the\ request\ bank;\ 0\ otherwise, i \in P.$

According to the assumptions above, green VRPPDP can be explained with a mathematical model as follows:

Minimise

$$\alpha \sum_{k \epsilon K} \sum_{(i,j)} d_{ij} x_{ijk} (\varepsilon_{CO_2} + \varepsilon_{CH_4} + \varepsilon_{N_2O}) \quad (1)$$

Subject to

$$\sum_{k \in K} \sum_{j \in N_k} x_{ijk} + z_i = 1 \forall i \in P \quad (2)$$

$$\sum_{j \in V} x_{ijk} - \sum_{j \in V} x_{j\,n+i\,k} = 0 \forall i \in K, \forall i \in P \quad (3)$$

$$\sum_{j \in P \cup \{\tau'_k\}} x_{\tau_k jk} = 1 \forall k \in K \quad (4)$$

$$\sum_{i \in D \cup \{\tau_k\}} x_{i\tau'_k k} = 1 \forall k \in K \quad (5)$$

$$\sum_{i \in V} x_{ijk} - \sum_{i \in V} x_{jik} = 0 \forall k \in K, \forall j \in N \quad (6)$$

$$x_{ijk} = 1 \Rightarrow S_{ik} + s_i + t_{ij} \leq S_{jk} \forall k \in K, \forall (i,j) \in A \quad (7)$$

$$a_i \leq S_{ik} \leq b_i \forall k \in K, \forall j \in V \quad (8)$$

$$S_{ik} \leq S_{n+i\,k} \forall k \in K, \forall j \in V \quad (9)$$

$$x_{ijk} = 1 \Rightarrow Q_{ik} + q_i \leq Q_{jk} \forall k \in K, \forall (i,j) \in A \quad (10)$$

$$Q_{ik} \leq C_k \forall k \in K, \forall i \in V \quad (11)$$

$$Q_{\tau_k k} = Q_{\tau'_k k} = 0 \forall k \in K \quad (12)$$

$$x_{ijk} \in \{0,1\} \forall k \in K, \forall (i,j) \in A \quad (13)$$

$$z_i \in \{0,1\} \forall k \in P \quad (14)$$

$$S_{ik} \geq 0 \forall k \in K, \forall i \in V \quad (15)$$

$$Q_{ik} \geq 0 \forall k \in K, \forall i \in V \quad (16)$$

The goal of green VRPPD is to design a vehicle route by minimising three GHG emissions (CO_2, CH_4, and N_2O) from the transportation vehicle, as presented in Equation (1). This minimisation ensures that the pickup and delivery orders are performed by the same vehicle, and the orders are implemented in Equations (2) and (3). The confirmations for the conditions that each vehicle departs from its starting terminal and stops at its ending terminal are performed in Equations (4) and (5). Equation (6) ensures that consecutive paths between τ_k and τ'_k are used for each vehicle. Equations (7) and (8) guarantee that S_{ik} is set correctly along the paths within a particular time window. Further, these two equations are used to make sure that sub-tours will not be generated. Equation (9) ensures that each pickup takes place before the corresponding delivery. Equations (10) to (12) confirm that load variability is precisely set along the path and confirm the use of vehicle capacity constraints. Lastly, the nature of the decision variables is set up in Equations (13) to (16).

Various researchers have studied the alternative fuel for Green VRP by considering the GHG emission (Xu et al., 2019; Bruglieri et al., 2019; Sruthi et al., 2019). GHG emissions are calculated by multiplying fuel consumption by the emissions factor of GHG for each fuel type. The distance travelled is one of the most significant influencing factors for calculating GHG emissions. Consequently, GHG emissions are calculated by multiplying the travel distance by a distance-based emissions factor. The emissions factor for CO_2 relies on several factors such as fuel heat content, fraction of oxidised carbon in the fuel, and the carbon content coefficient, which is somewhat difficult to obtain. Therefore, only vehicle travel distance (distance-based approach) is applied for calculating GHG emissions in this study. The calculations of GHG emissions are divided into two main processes. In the beginning, data is collected for travel distance, in terms of freight distance (e.g., ton-

Tab. 1. Approximation of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions factors for a 10-ton capacity truck

State of vehicle	Weight laden (%)	Fuel consumption (litre/100 km)	CO_2 fuel conversion factor for diesel (kg CO_2/ litre)	CO_2 fuel conversion factor for LPG (kg CO_2/ litre)	CH_4 fuel conversion factor for diesel (kg CH_4/ litre)	CH_4 fuel conversion factor for LPG (kg CH_4/ litre)	N_2O fuel conversion factor for diesel (kg N_2O/ litre)	N_2O fuel conversion factor for LPG (kg N_2O/ litre)	CO_2 emissions factor for diesel (kg CO_2/km)	CO_2 emissions factor for LPG (kg CO_2/km)	CH_4 emissions factor for diesel (kg CH_4/km)	CH_4 emissions factor for LPG (kg CH_4/km)	N_2O emissions factor for diesel (kg N_2O/km)	N_2O emissions factor for LPG (kg N_2O/km)
Empty	0	29.6							0.786442	0.45291	0.000266	0.000207	0.005654	0.000533
Low Load	25	32							0.850208	0.489632	0.000288	0.000224	0.006112	0.000576
Half Load	50	34.4	2.6569	1.5301	0.0009	0.0007	0.0191	0.0018	0.913974	0.526354	0.00031	0.000241	0.00657	0.000619
High Load	75	36.7							0.975082	0.561547	0.00033	0.000257	0.00701	0.000661
Full Load	100	39							1.036191	0.596739	0.000351	0.000273	0.007449	0.000702

mile), for different vehicle types, sizes, and types of fuel used. The approximated freight distance is then converted into GHG emissions. The GHG emissions are determined by multiplying the freight distance by a distance-based emissions factor, as explained in the equations below:

$$CO_2\ Emissions = Distance\ Travelled\ \times \times\ Emissions\ Factor\ for CO_2 \tag{17}$$

$$CH_4\ Emissions = Distance\ Travelled\ \times \times\ Emissions\ Factor\ of\ CH_4 \tag{18}$$

$$N_2O\ Emissions = Distance\ Travelled\ \times \times\ Emissions\ Factor\ of\ N_2O \tag{19}$$

The energy consumption (in litres/100 km) is approximated according to Ubeda et al. (2014). However, the fuel conversion factor for diesel and LPG (kgCO_2/litre) is obtained from DEFRA (2013). The approximation of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions factors for diesel and LPG are presented in Table 1.

2.1. The particle swarm optimisation (PSO) algorithm for green VRPPD

The PSO algorithm is initialised with random position, velocity, and inertia weight. The velocity is constantly adjusted according to the particle's experience, and its group's experience, to move towards the better solution, as described in the following equations:

$$v_{id} = w^{*}v_{id} + C_1 rand(\ )^{*}(p_{id}-x_{id}) + C_2 rand(\ )^{*}(p_{gd}-x_{id}) \tag{20}$$

$$x_{id} = x_{id} + v_{id}{}^{*}\Delta t \tag{21}$$

where

v_{id} is the velocity of the i^{th} particle in the d^{th} dimension.

w is the inertia weight.

p_{id} is the best previous position (the position giving the particle's best fitness value) of the i^{th} particle in the d^{th} dimension.

p_{gd} is the best previous position (the position giving the swarm's best fitness value) of the i^{th} particle in the d^{th} dimension.

x_{id} is the position of the i^{th} particle in the d^{th} dimension.

C_1, C_2 is equal to 2.

$rand(\ )$ is a uniform random number generated within (0,1).

As shown in Equation (21), the velocity of the i^{th} particle in the d^{th} dimension consists of three terms. The first term is the momentum of the part of the particle. The inertia weight (w) represents the degree of the momentum of the particle's previous velocity. It is a control parameter used to control the influence of the previous velocity on the current velocity of the particle. A larger inertia weight would pressure the movement of particles towards global exploration (searching for a new area) because the particle can fly in large areas. In contrast, a smaller inertia weight would move the particle in a smaller search area. The suitable selection of the inertia weight should provide a balance between the global and local search areas.

The computation of PSO depends on population size, inertia weight, maximum velocity, maximum and minimum positions and a maximum number of iterations. The initial population size was chosen so that it was large enough to cover the search space within the iteration limit based on the trial runs and literature. The population size of 50 was then selected. The maximum number of iterations and other parameters were also initialised by using the same rationales. They should ensure that the search spaces are never violated and the solutions obtained are always valid. The same parameter settings were used for all datasets.

In this experiment, the performance of PSO for solving Green VRPPD based on a different value of inertia weight with the range from 0.1 to 0.9 and the inertia weight started from 0.9 and gradually decreased to 0.4 to balance the global and local exploration based on a linear function of time (iteration) for improving convergence rate (Kennedy, 1997) were tested and compared. It was found that when inertia weight is set to be a large value, it is difficult for particles to perform global exploration during the beginning of the search process. Then, the inertia weight value is gradually decreased so that the good region found can be found by the search process to provide the best searching performance.

The second term in Equation (21) is called the "cognition part" because the distance between the particle's previous best and current position $(p_{id}\text{-}x_{id})$ would provide a path for the particle to return to its best value achieved so far. The third term in Equation (21) is called the "social part" because the difference between the swarm's previous best and current position $(p_{gd}\text{-}x_{id})$ provides a path for the swarm to return to their best value.

C_1 and C_2 are positive constants called "acceleration coefficients". They are used to determine the relative "pull" of *gbest* and *pbest*. The higher the constant, the greater the acceleration toward the position it is multiplying. In this case, C_1 and C_2 are set to 2 for all PSO runs to balance the impact of its own trajectory with its neighbours' trajectory.

Also, *rand( )* is a random number uniformly distributed within the range (0,1). *rand( )* makes the system less predictable and more flexible so that each particle is stochastically accelerated towards its own previous position and the global best position.

Furthermore, v_{id} is limited to keep the computer from overflowing. This limit makes it more realistic to simulate the incremental changes of human learning and attitude change. The limit also determines the search of the problem space. Next, v_{id} is set to be within the boundary of $[-v_{max}, v_{max}]$ so that the search space of each particle is limited, and the particle cannot move out of this range. If v_{id} is greater than v_{max} , then set v_{id} equal to v_{max}. But, if v_{id} is less than $-v_{max}$, then set v_{id} equal to $-v_{max}$. The v_{max} parameter is important because it determines the resolution with which the regions around the current solutions are searched. If v_{max} is too high, then the PSO facilitates a global search, which means that particles might fly past good solutions. However, if v_{max} is too small, then the PSO facilitates a local search, which means that particles may not explore beyond locally good regions. In case of maximum and minimum positions of the variables in each dimension, they were chosen to represent the suitable search space, which is problem dependence.

The positions of particles in the equation are updated based on their movement over a discrete-time interval (Δt), with Δt usually set to 1 as depicted in Equation (21).

3. Research results

The experiment was conducted by using simulated data from Li and Lim (2001). One hundred task instances were used as a benchmark to evaluate the performance of the PSO for solving green vehicle routing problems with pickup and delivery. Each task is either for a pickup or a delivery. Four different types of datasets (LC1, LC2, LR1, LR2) were used to test the proposed model. The first set of problem instances (LC problems) represent customers located in clusters that are distributed in the coverage service area. This kind of distribution is similar to customers located in a town or in a city. Numerous people stay in certain areas forming clusters. The second set of problem instances (RC problems) represents customer locations that are randomly distributed in the coverage service area. This kind of distribution is similar to customers that live in rural areas. The LC1 and LR1 problems have a long scheduling horizon, while LC2 and LR2 problems have a shorter scheduling horizon. Next, the PSO parameter settings of the experiment are explained. The acceleration coefficients (C1 and C2) were equally set at 2 to balance the impacts of exploratory and exploitative learning experiences. The inertia weight (w) was set to linearly decrease from 0.9 to 0.4. This decrease allowed the particles to perform global searches at the beginning of the search and then gradually decrease the scope of the search space to the good region. The population size and the maximum number of iterations were set at 50 and 500, respectively. These parameter settings

Tab. 2. Comparison of results from two different objective functions for the cluster-distributed customer dataset

Instance	Minimising cost		Minimising GHG emissions		Distance increase (%)
	Distance	NV	Distance	NV	
LC101	828.94	10	989.91	12	19.42
LC102	828.94	10	828.94	10	0
LC103	827.86	10	827.86	10	0
LC104	861.95	9	903.85	9	4.86
LC105	828.94	10	828.94	10	0
LC106	828.94	10	828.94	10	0
LC107	828.94	10	828.94	10	0
LC108	827.61	10	827.61	10	0
LC109	827.82	10	827.82	10	0
LC201	591.56	3	591.56	3	0
LC202	591.56	3	591.56	3	0
LC203	591.17	3	591.17	3	0
LC204	590.60	3	590.60	3	0
LC205	588.88	3	588.88	3	0
LC206	588.29	3	588.49	3	0.04
LC207	588.29	3	588.29	3	0
LC208	588.32	3	588.32	3	0
				Average	**1.43**

Tab. 3. Comparison of results from two different objective functions for the randomly distributed customer dataset

Instance	Minimising cost		Minimising GHG emissions		Distance increase (%)
	Distance	NV	Distance	NV	
LR101	1543.38	17	1650.80	19	6.96
LR102	1361.93	13	1555.64	17	14.22
LR103	1071.23	10	1329.99	13	24.16
LR104	1013.99	9	1080.51	10	6.56
LR105	1295.14	12	1393.35	14	7.58
LR106	1221.29	12	1293.30	12	5.90
LR107	1174.83	11	1257.08	12	7.00
LR108	1085.18	10	1204.41	11	10.99
LR109	1263.96	12	1563.00	13	23.66
LR110	1135.66	10	1224.67	12	7.84
LR111	1156.54	11	1179.63	11	2.00
LR112	1151.38	11	1159.13	11	0.67
LR201	1266.25	4	1266.57	4	0.03
LR202	1162.40	4	1316.46	4	13.25
LR203	934.53	3	1153.83	3	23.47
LR204	912.40	2	1025.59	3	12.41
LR205	1118.70	3	1248.82	4	11.63
				Average	**10.49**

were set based on trial-and-error methods. The algorithms were coded using the C# version of Visual Studio 2019. The comparison of the results based on cost minimisation and GHG emissions minimisation for the LC and LR problems are presented in Tables 2 and 3, respectively.

Table 2 presents the results of the PSO for designing vehicle routes from 17 benchmark instances where customers are cluster-distributed. The PSO was applied to design vehicle routes by considering the minimum total cost as the objective function (VRPPD). The PSO was then applied to design the optimal route by considering the minimum GHG emissions as the objective function (Green VRPPD). The results from the two different objective functions were compared using the per cent increase of distance. The reason is that the travel distance is directly proportional to the total cost. The results reveal that designing the vehicle routes by using VRPPD and Green VRPPD are comparable when customers are cluster-distributed. The number of vehicles used for delivering products to customers using VRPPD or Green VRPPD is the same in most cases. However, the percentage difference of benchmark instance LC101 is 19.42, which is quite high when compared to two other benchmark instances: LC104 and LC206. On average, the Green VRPPD requires a travel distance that is 1.43% greater than that of VRPPD. It is suggested that Green VRPPD should be used for designing vehicle routes in the last mile of delivery when customers' locations are cluster-distributed.

Vehicle routes were designed by the PSO using 17 benchmark instances for problems where customers are randomly distributed. In this case, the location of customers is randomly dispersed around the service area. The experimental results in Table 3 show that vehicle route planning based on minimising GHG emissions requires a greater number of vehicles and greater travel distances than route planning based on minimum total cost as the objective function in most cases.

These results reveal that Green VRPPD requires travel distances that are 10.49% greater than those required by VRPPD on average. Furthermore, 11 out of 17 cases require a greater number of vehicles to deliver products to customers. Tables 4 and 5 presents the comparison of the results from the best-known solution and PSO for the cluster-distributed customer dataset and randomly distributed customer dataset, respectively. It found that the results from PSO are comparable to the best-known solution for LC1, LC2, and RC1. However, the results of PSO for solving RC2 problems are not as good as the best-known solution.

Tab. 4. Comparison of results from the best-known solution and the results from PSO for the cluster-distributed customer dataset

Instance	Minimising cost		Best-known solution		References	Deviation of distance (%)
	Distance	NV	Distance	NV		
LC101	828.94	10	828.94	10	Li & Lim (2001)	0.00
LC102	828.94	10	828.94	10	Li & Lim (2001)	0.00
LC103	827.86	10	1035.35	9	Bent & Van Hentenryck (2003)	-20.04
LC104	861.95	9	860.01	9	Hasle & Kloster (2007)	0.23
LC105	828.94	10	828.94	10	Li & Lim (2001)	0.00
LC106	828.94	10	828.94	10	Li & Lim (2001)	0.00
LC107	828.94	10	828.94	10	Li & Lim (2001)	0.00
LC108	827.61	10	826.44	10	Li & Lim (2001)	0.14
LC109	827.82	10	1000.6	9	Bent & Van Hentenryck (2003)	-17.27
LC201	591.56	3	591.56	3	Li & Lim (2001)	0.00
LC202	591.56	3	591.56	3	Li & Lim (2001)	0.00
LC203	591.17	3	591.17	3	Bent & Van Hentenryck (2003)	0.00
LC204	590.6	3	590.6	3	Bent & Van Hentenryck (2003)	0.00
LC205	588.88	3	588.88	3	Li & Lim (2001)	0.00
LC206	588.29	3	588.49	3	Li & Lim (2001)	-0.03
LC207	588.29	3	588.29	3	Li & Lim (2001)	0.00
LC208	588.32	3	588.32	3	Li & Lim (2001)	0.00

Tab. 5. Comparison of results from best-known solution and the results from PSO for the randomly distributed customer dataset

Instance	Minimising cost		Best-known solution		References	Deviation of distance (%)
	Distance	NV	Distance	NV		
LR101	1543.38	17	1650.8	19	Li & Lim (2001)	-6.51
LR102	1361.93	13	1487.57	17	Li & Lim (2001)	-8.45
LR103	1071.23	10	1292.68	13	Li & Lim (2001)	-17.13
LR104	1013.99	9	1013.39	9	Li & Lim (2001)	0.06
LR105	1295.14	12	1377.11	14	Li & Lim (2001)	-5.95
LR106	1221.29	12	1252.62	12	Li & Lim (2001)	-2.50
LR107	1174.83	11	1111.31	10	Li & Lim (2001)	5.72
LR108	1085.18	10	968.97	9	Li & Lim (2001)	11.99
LR109	1263.96	12	1208.96	11	Hasle & Kloster (2007)	4.55
LR110	1135.66	10	1159.35	10	Li & Lim (2001)	-2.04
LR111	1156.54	11	1108.9	10	Li & Lim (2001)	4.30
LR112	1151.38	11	1003.77	9	Li & Lim (2001)	14.71
LR201	1266.25	4	591.56	3	Li & Lim (2001)	114.05
LR202	1162.4	4	591.56	3	Li & Lim (2001)	96.50
LR203	934.53	3	591.17	3	Hasle & Kloster (2007)	58.08
LR204	912.4	2	590.6	3	Hasle & Kloster (2007)	54.49
LR205	1118.7	3	588.88	3	Li & Lim (2001)	89.97

Tab. 6. Comparison of GHG emissions from both diesel and LPG fuel

Instances	Diesel emissions	LPG emissions	Difference of GHG emission (%)
LC101	101.43	58.55	53.61
LC102	97.84	56.48	53.60
LC103	103.4	59.69	53.60
LC104	93.27	53.84	53.61
LC105	69.23	39.96	53.61
LC106	49.98	28.85	53.61
LC107	181.23	104.62	53.60
LC108	86.5	49.93	53.61
LC109	125.58	72.49	53.61
LC201	119.93	69.23	53.61
LC202	92.72	53.52	53.61
LC203	301.41	173.99	53.61
LC204	202.55	116.92	53.61
LC205	117.44	67.8	53.60
LC206	162.08	93.56	53.61
LC207	187.54	108.26	53.60
LC208	148.5	85.72	53.61
LR101	51.85	29.93	53.61
LR102	105.24	60.75	53.61
LR103	79.31	45.78	53.61
LR104	47.13	27.2	53.63
LR105	61.39	35.44	53.60
LR106	150.54	86.9	53.61
LR107	143.72	82.96	53.61
LR108	147.21	84.98	53.60
LR109	124.78	72.03	53.60
LR110	139.27	80.4	53.60
LR111	74.23	42.85	53.60
LR112	114.39	66.03	53.61
LR201	300.71	173.58	53.61
LR202	97.76	56.43	53.61
LR203	580	334.81	53.60
LR204	181.81	104.95	53.61
LR205	473.12	273.11	53.61
LR206	260.5	150.37	53.61
LR207	342.92	197.95	53.61
LR208	536.67	309.8	53.60
LR209	226.6	130.81	53.60
LR210	249.36	143.94	53.61
LR211	312.26	180.25	53.61
		Average	**53.61**

Considering greenhouse gases emissions, the results indicate that the use of liquefied petroleum gas (LPG) fuel is more environmentally friendly than the use of diesel fuel. Table 6 presents the comparison of GHG emissions from both diesel and LPG fuels. The data show that LPG fuel emits 53.61 % less GHG emissions than does diesel fuel.

4. Discussion of the results

Particle swarm optimisation (PSO) was applied to determine optimal vehicle routes based on two different objective functions. The first objective function is to design vehicle routes by minimising the total cost. Next, then PSO was applied to design vehicle routes by minimising GHG emissions as the objective function. Three main GHGs were considered in this study: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). Two different types of customer locations were tested. The first type of customer location is cluster-distributed, where the location of customers in the coverage service area are clustered in villages, towns, or cities. The results reveal that vehicle route design based on Green VRPPD is comparable to that of VRPPD, as presented in Table 2. Only three out of seventeen cases show that designing vehicle routes by considering GHG emissions requires more travel distance than by considering minimum total cost as the objective function. The results for Green VRPPD instance LC101 require 19.42 % more travel distance than the results for VRPPD. The increased travel distance is because the computational result from Green VRPPD requires two more vehicles to deliver products to customers. The average difference in travel distance is equal to 1.43 %, which does not have much effect on the total cost. Therefore, Green VRPPD is recommended for designing vehicle routes when the location of customers is cluster-distributed in the coverage service area.

The second type of customer location is randomly distributed around the coverage service area. The results presented in Table 3 show that Green VRPPD requires more travel distance compared to VRPPD. The average travel distance difference is equal to 10.43 %. Green VRPPD for three instances, LR103, LR109, and LR203, require 20 % more travel distance compared to VRPPD. When considering GHG emissions, most of the instances require more vehicles to service customers than when considering the total cost as the objective function. The implication is that environmental concerns would cost 10.49 % more for transportation. Fuel selection is another option that companies can use to provide more environmentally friendly transportation. The computational results indicate that the use of LPG fuel emits 53.61 % less GHGs than does diesel fuel.

The results reveal that Green VRPPD is suitable for the situation that the customer location is clustered. Generally, cluster-distributed customer location can save both transportation costs and time for the delivery of the product to the customers. Further, this would lead to the reduction of GHG from transportation. It also causes less local air pollution to use LPG as the fuel rather than using petrol gasoline or diesel. However, Green VRPPD is suitable for designing the route of vehicles in some cases when the customer location is randomly distributed around the coverage service area because it would require more travel distance to be travelled.

Conclusions

The purpose of this study is to design a green last-mile route that supports efficient e-commerce distribution. A metaheuristics approach called particle swarm optimisation (PSO) was applied to design the route for last-mile delivery. This study used 34 benchmark instances from Li and Lim (2001) to test the performance of the search technique. First, the PSO was developed to solve VRPPD for transportation cost minimisation. Then, the PSO was applied to design vehicle routes based on GHG emissions minimisation (Green VRPPD).

Two different types of customer location distributions were evaluated. The LC datasets contain clusters of customers, whereas the LR datasets contain customers that are randomly distributed. The results of this study reveal that the use of Green VRPPD is very suitable for LC problems because the total distances and the number of vehicles used are the same whether considering GHG emissions or minimum total cost as the objective function in most cases. For RC problems, the decision of vehicle routing should depend on the logistics provider's situation because a design based on Green VRPPD is more expensive and requires more vehicles than a design based on VRPPD in most cases.

This study also looks at the use of two different fuel types. The study compares GHG emissions from LPG fuel and diesel fuel. It was found that using LPG appears to be more environmentally friendly than using diesel fuel.

The limitations of this work are the problem instances. It would be more realistic to use real data from third-party logistics providers. However, it is somewhat difficult to get such data because most logistics companies consider this data to be confidential information. Suggested future research would be to improve the metaheuristics technique used to design routes for delivering products to customers.

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