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Green vehicle routing problem: introduction of electric and limited capacity vehicles to the fleet

1 Introduction

The transportation sector accounts for around 27% of global greenhouse gas (GHG) emissions and is responsible for the majority of the global growth in emissions alongside power generation (IEA, 2019). A significant part of these emissions is associated with burning fossil fuels for freight road vehicles (Figure 1). Therefore, finding ways to decarbonise energy use in freight transportation is crucial to mitigating climate change. For many businesses, reduction of emissions throughout their supply chain is already a key target. Green logistics allow companies to comply with legal constraints as well as reduce operational costs and appeal to environmentally conscious customers (Çimen and Soysal, 2017).

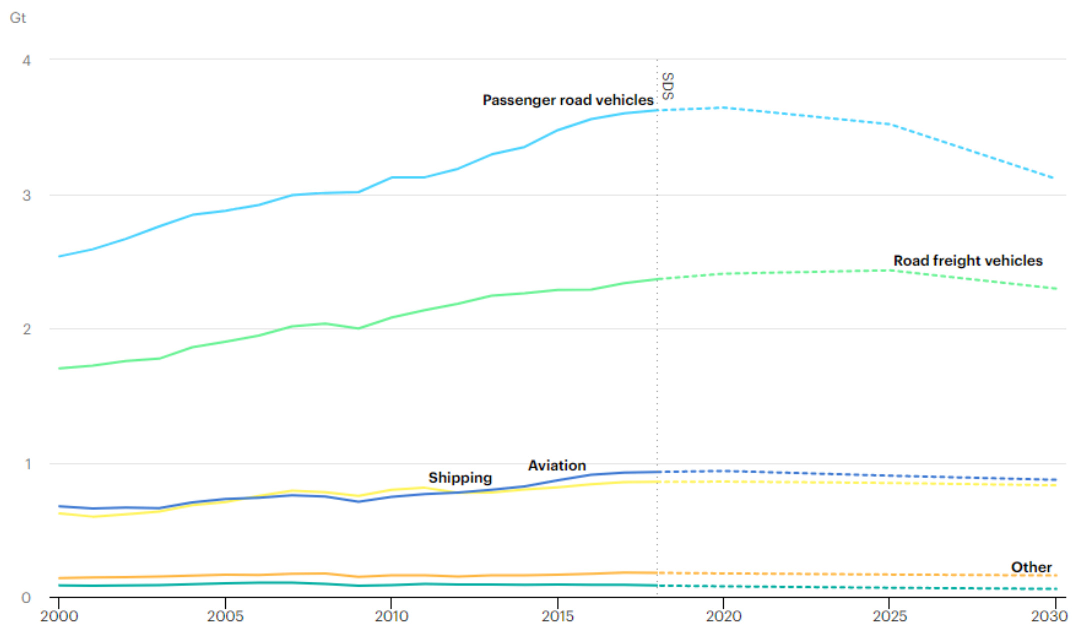


Figure 1. CO_2 emissions in the transport sector by mode (IEA, 2022)

Vehicle routing problem (VRP), first introduced over 60 years ago (Dantzig and Ramser, 1959), is a combinatorial optimisation that is a generalisation of the Traveling Salesman Problem (TSP) and is considered one of the most prominent problems in transportation operations. VRP aims to find an optimal routing plan for a fleet of vehicles to serve a set of customers. Traditionally, the fleet in the problem is assumed to be homogeneous, each customer is visited once by just one vehicle, each route ends at the origin depot, and some side constraints are satisfied. However, many variations of VRP and its features have been developed over the years (Montoya-Torres et al., 2015; Braekers, Ramaekers and van Nieuwenhuyse, 2016). Particularly, the green vehicle routing problem (GVRP), which is an extension of VRP that considers environmental factors, was introduced in 2012 (Erdogan & Miller-Hooks, 2012). GVRP includes a broad range of problems that aim to reduce fuel consumption or employ alternative-fuel powered vehicles (AFVs). GVRP also takes into account disadvantages associated with the introduction of AFVs including limited range and re-fuelling infrastructure, making the routing problem more complex.

This study aims to evaluate the impact of introducing electric vehicles and limited capacity vehicles to a fleet of conventional trucks. A base scenario of VRP for one conventional truck is considered and compared to two heterogeneous fleet GVRP scenarios: one with an additional electric truck (ET) and one with an additional electric van (EV). As to replicate a real-life spatial distribution, Warburtons in Bolton, UK is selected as a depot and Morrisons supermarket chain in Bolton and part of the wider Greater Manchester area, the UK is selected as clients. The Warburtons company originates in Bolton and is the largest bakery producer in the UK, with almost 1000 trucks delivering 2 million products to 18,500 stores every day (Warburtons, 2022). Morrisons is one of the largest supermarket chains in the UK.

The paper is organised as follows. In Section 2, a short literature review is presented. Section 3 introduces the methodology, including the proposed formulation of CGVRP. Section 4 will present the results of the numerical experiment and sensitivity analysis. Finally, section 5 will conclude the study.

2 Literature review

The GVRP was first introduced as a problem of limited driving range of AFVs in conjunction with limited charging infrastructure (Erdogan & Miller-Hooks, 2012). It was formulated via Mixed Integer Linear Programming (MILP) and solved through two heuristic algorithms, the modified Clarke & Weight Savings and the Density-Based Clustering.

Since then, there has been extensive research on many variants of the problem, including time windows (Govindan et al., 2014; Xiao and Konak, 2015), multiple depots (Soleimani, Chaharlang and Ghaderi, 2018), split deliveries (Vornhusen and Kopfer, 2015) and, heterogeneous fleets (Kwon, Choi and Lee, 2013; Vornhusen and Kopfer, 2015). Capacitated GVRP (CGVRP) is another common variant of the problem, where load capacities of the vehicles in the fleet are also considered (Vidal et al., 2013).

A study by Pradenas et al. (2013) evaluates the decrease in GHG, considering the vehicle load, backhauls and time windows. Using scatter search, the study finds that operating costs and emissions decrease if different companies operate together. Another CGVRP with time windows study by Küçükoğlu et al. (2015) proposes a MILP model and a memory structure adapted simulated annealing meta-heuristic algorithm to reduce the fuel consumption and CO_2 emissions.

Kwon et al. (2013) determine routes for a heterogeneous fleet, that satisfies the load capacities and client demand. They employ a tabu search algorithm and find that carbon trading allows carbon emissions to be reduced significantly with no cost sacrifice.

A study on CGVRP by Zhang et al. (2018) uses an ant colony system and a two-phase heuristic to solve the CGVRP that also considers the fuel tank capacity and charging station availability. The study finds that employment of AFVs would result in economic sacrifices for benefit of the environment.

Qian & Eglese (2016) adopt a column generation based tabu search algorithm to a GVRP with time-dependent speed limits and limited vehicle capacities, finding that distance-based criterion determining paths for vehicles travelling at the speed limit allows for the reduction in fuel emissions.

Recent work by Xu et al. (2019) incorporates fuel consumption algorithm into MILP formulation, considering vehicle load and time-varying speed. The results show that the improved non-dominated sorting genetic algorithm outperforms the traditional modelling approaches.

Another recent study by Normasari et al. (2019) proposes a simulated annealing (SA) heuristic to solve the CGVRP formulated as MILP and minimise the distance travelled by AFVs, demonstrating that vehicle range and the number of customers influence the total distance.

Overall, the solution methodologies can be split into exact or heuristic and metaheuristic. Due to GVRP being computationally NP-hard, its exact solution is difficult to find for larger problems (Baldacci and Hadjiconstantinou, 2004; Oesterle and Bauernhansl, 2016). Hence, heuristic and metaheuristic approaches are often preferred to derive near-optimal solutions.

Figure 2 shows the predominant use of the metaheuristic approach in the literature. Moreover, due to local optima deficiency heuristics are often combined with other methods, which results in the small percentage of heuristic studies in Figure 2.

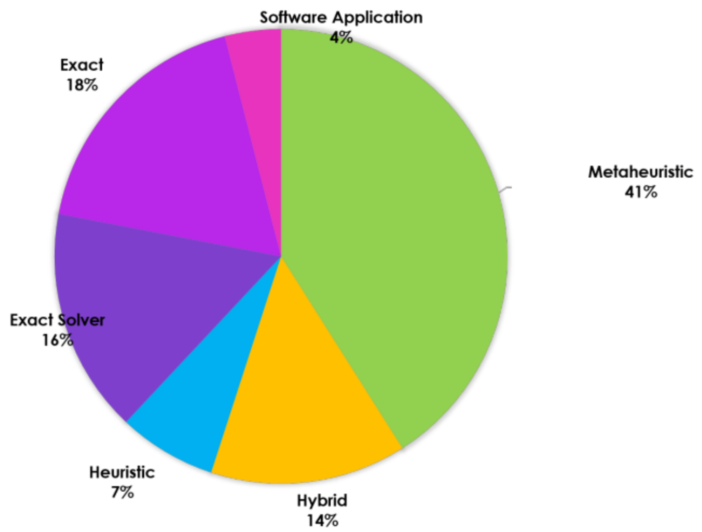


Figure 2. Distribution of solution methodologies in literature (Sabet and Farooq, 2022)

Heuristic methods use specific knowledge of the problem to resolve it and arrive at a suboptimal to a reliable solution (Demir, Bektaş and Laporte, 2012). Metaheuristics can be defined as higher-level heuristics designed to guide other heuristics. They require higher computation times but can consistently produce high-quality solutions (Cordeau et al., 2002).

This study will consider using delivery with AFVs alongside conventional trucks and formulate the CGVRP as MILP and attempt to minimise the total travelled distance with a Gurobi optimiser, which is a general exact Integer Linear Programming (ILP) solver (Gurobi, 2022).

3 Methodology

All of the code is written in Python and can be found here.

3.1 Data collection with Web Scraping

Obtaining real data allows for scenarios closer to real life and therefore a more accurate estimation. As such, location data for depot and clients was scraped using Google Places API (Google, 2022). Warburtons site was selected as the depot, and Morrisons supermarket chain was selected as the client in the area of Bolton and adjacent northern Greater Manchester in the UK.

A single query searching in the radius of one coordinate on Google Places only scrapes the most prominent results. Therefore, a grid search for Morrisons supermarkets was performed over the area.

After repeated results were removed a total of 42 supermarkets and one Warburtons depot were collected (Figure 4). A distance matrix was calculated from the locations of the depot and the clients (Figure 3).

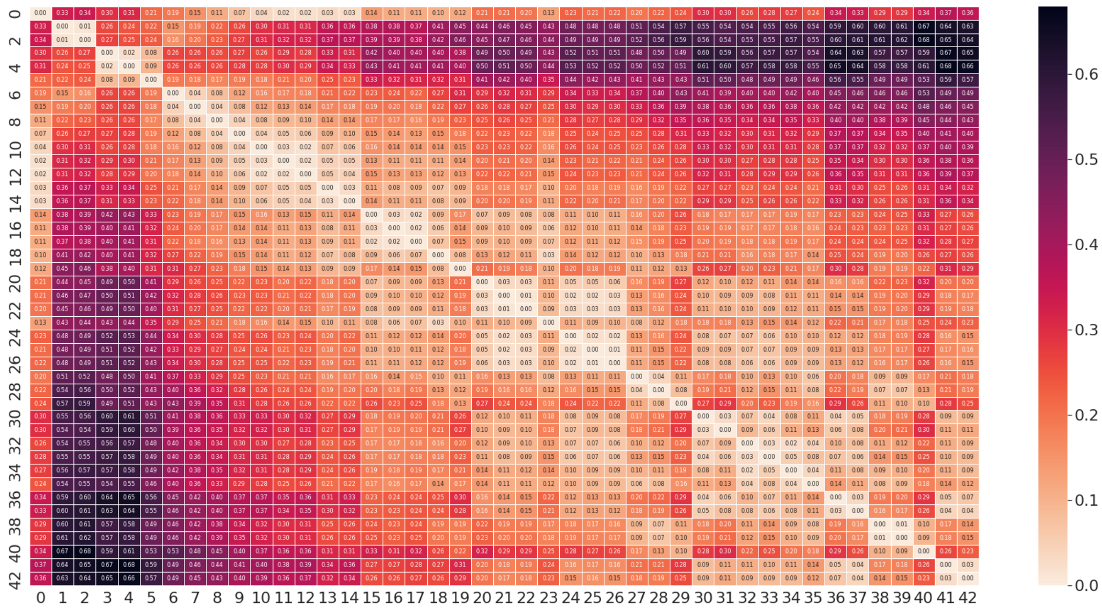
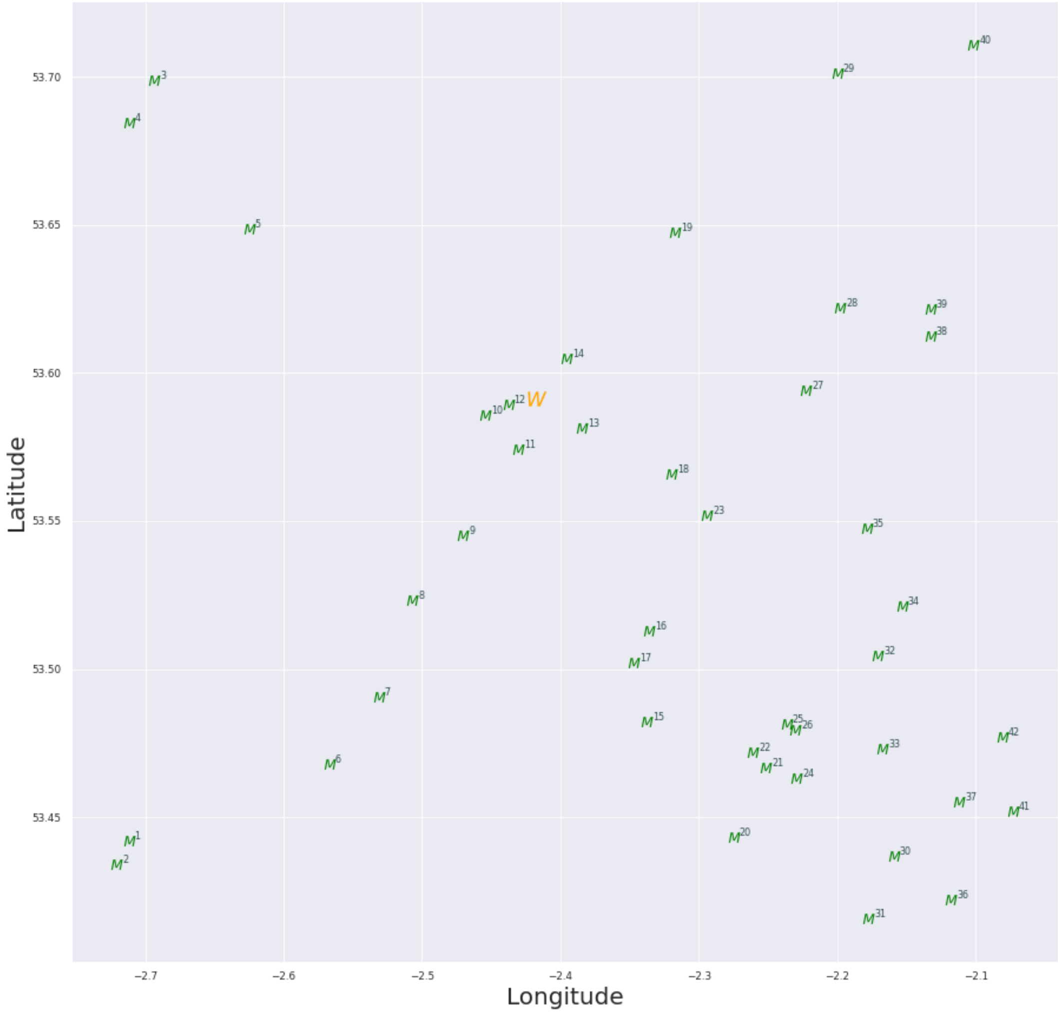


Figure 3. Distance matrix (in degrees coordinates) of the depot (0) and 42 clients.



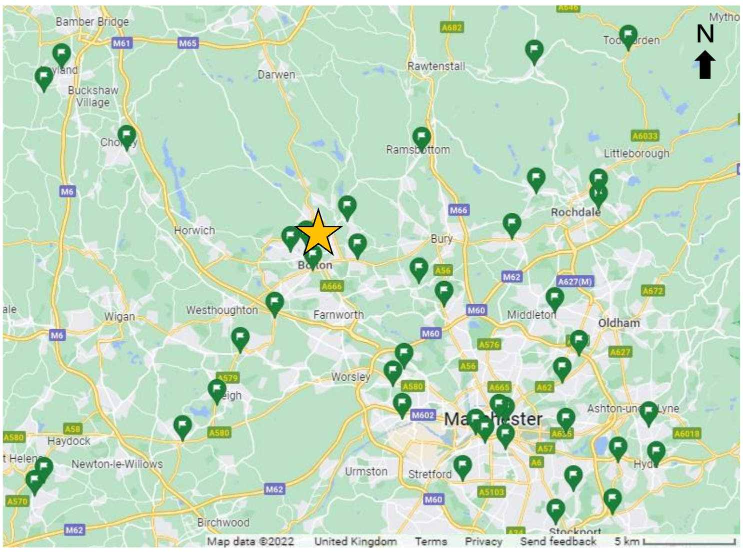


Figure 4. **Top**: distribution of clients (M) and the depot (W) plotted from collected data; **bottom**: same distribution on google maps (depot – star, clients – flags).

3.2 Problem definition, formulation and assumptions

Previously, the CGVRP has been defined by Zhang, Gajpal and Appadoo (2018). In this study, a MILP model is developed for the CGBRP that focuses on vehicle route determination by considering the employment of ET or EV, alongside CT and their maximum range as well as the vehicle loading capacity. The objective of the problem is to minimise the total distance travelled. The following constraints ad assumptions are considered:

1. Each vehicle starts and ends each tour at the depot;
2. Each client must be visited exactly once;
3. The total demand for each tour should be below the vehicle load capacity;
4. The total distance in each tour should be below the vehicle range;
5. CT is assumed to have an unlimited range;
6. EV and ET are recharged every time they return to the depot;
7. Charging infrastructure is assumed to be absent;

The formulation from (Erdogan & Miller-Hooks, 2012) can be adopted, defining the CGVRP as an undirected, complete graph $G = (V, E)$. Here V is a set of vertices (or nodes) that includes a set of clients $I = \{v_1, v_2, \dots, v_n\}$ and the depot v_0. The set of vertices is $V = \{v_0\} \cup I$ and $|V| = n + 1$. Moreover, $E = \{(v_i, v_j): v_i, v_j \in V, i < j\}$ is the set of edges that connect vertices V, where each edge is associated with a non-negative travel time t_{ij} and distance d_{ij}. The CGVRP can be defined as follows.

Sets

v_0: Depot

I: Set of customers, $\{v_1, v_2, \dots, v_n\}$

I_0: Set of customers and depots, $\{v_0\} \cup I$

V: Set of vertices, that is $V = \{v_0\} \cup I = \{v_0, v_1, \dots, v_n\}$

Parameters

Q: Vehicle load capacity

q_i: Demand of vertex i, set to zero if $i \notin I$

d_{ij}: The distance between vertices i and j

R: Maximum range of the vehicle

Decision Variables

x_{ij} : binary variable that is 1 if there is travel from vertex i to j, 0 otherwise

u_j: remaining loading capacity of a vehicle at vertex j

Mathematical Model

$$\min \sum_{i\in V',j\in V',i\neq j} d_{ij}x_{ij} \tag{1}$$

subject to

$$\sum_{j\in V',j\neq i} x_{ij} = 1, \qquad \forall i \in I \tag{2}$$

$$\sum_{i\in V',j\neq i} x_{ij} = \sum_{i\in V',j\neq i} x_{ij}\,, \qquad \forall j \in V' \tag{3}$$

$$\sum_{i\in V',j\in V',i\neq j} d_{ij}x_{ij} < R\,, \qquad \forall i \in I \tag{4}$$

$$u_j \leq u_i - q_i x_{ij} + Q\left(1 - x_{ij}\right), \qquad \forall i \in V', \quad j \in V'\{0\}, \quad i \neq j \tag{5}$$

$$0 \leq u_i \leq Q, \qquad \forall j \in V' \tag{6}$$

$$x_{ij} \in \{0,1\}, \qquad \forall i,j \tag{7}$$

The objective function (1) seeks to minimise the total distance travelled by the fleet. Constraints (2) guarantee that each client is visited exactly once. Constraints (3) are the flow conservation. Constraints (4) ensure that the tour distance is below the vehicle range. Constraints (5) find the remaining vehicle capacity at vertex j. Constraints (6) ensure that no vehicle can be overloaded. Constraints (7) guarantee binary integrality.

3.3 Solution of the CGVRP

The model is then solved in the following steps:

1. *Threshold distance is defined as half of the vehicle range.*
2. *Euclidean distance for all edges is computed and sorted in ascending order.*
3. *Minimum edges are naively selected from each node, beginning from the depot.*
4. *Step 3 is continued until the total distance covered reaches the defined threshold.*
5. *Separate graphs for CT and AFV are created by removing the accumulated nodes from the main graph.*
6. *Each graph is solved as a CVRP.*

4 Numerical experiment

4.1 Parameter setting

According to Warburtons (2022), the company produces 2 million products that are delivered to 18,500 stores every day. As such, the demand per client, q_i, is assumed to be 100. Moreover, Warburtons own nearly 1000 trucks which make the deliveries, which makes the load capacity of each truck $Q_t = 2{,}000$. For the electric vans, a quarter of the original load capacity, $Q_v = 500$ is assumed. Moreover, the electric trucks in the Warburtons fleet are reported to have a range of up to 150 km on a single charge, which Converted to degree coordinates equates to 1.35 degrees (USNA, 2019).

A linear relationship is assumed between the distance travelled by the CT and the amount of CO_2 emitted. 174 g/km conversion rate has been adopted, which is the number reported for the average petrol car in the UK (BEIS, 2021). The emissions from the AFVs are considered to be zero.

The model is solved using a Gurobi optimiser, with a computational time limit set to 300s and optimal solution tolerance of 5e-02.

4.2 Scenarios

Three scenarios have been evaluated including the base scenario.

Base scenario: the base scenario considers the routing problem with one conventional truck (Figure 5a). Although in this case the truck is assumed to have no maximum range, it is limited by its capacity to carry only 2,000 products. The model is solved with a 15% gap and the total travelled distance is found to be 299 km. The estimated emissions are around 52 kg CO_2.

ET scenario: this scenario employs a single electric truck alongside the conventional truck, with a 150 km range and load capacity of 2,000 products (Figure 5b). The model is solved with a 24.5% gap for CT and a 4.5% gap for ET. It is found that CT travels 194 km and ET travels 114 km, with the total travel distance of 308 km constituting only a 3% increase from the base scenario.

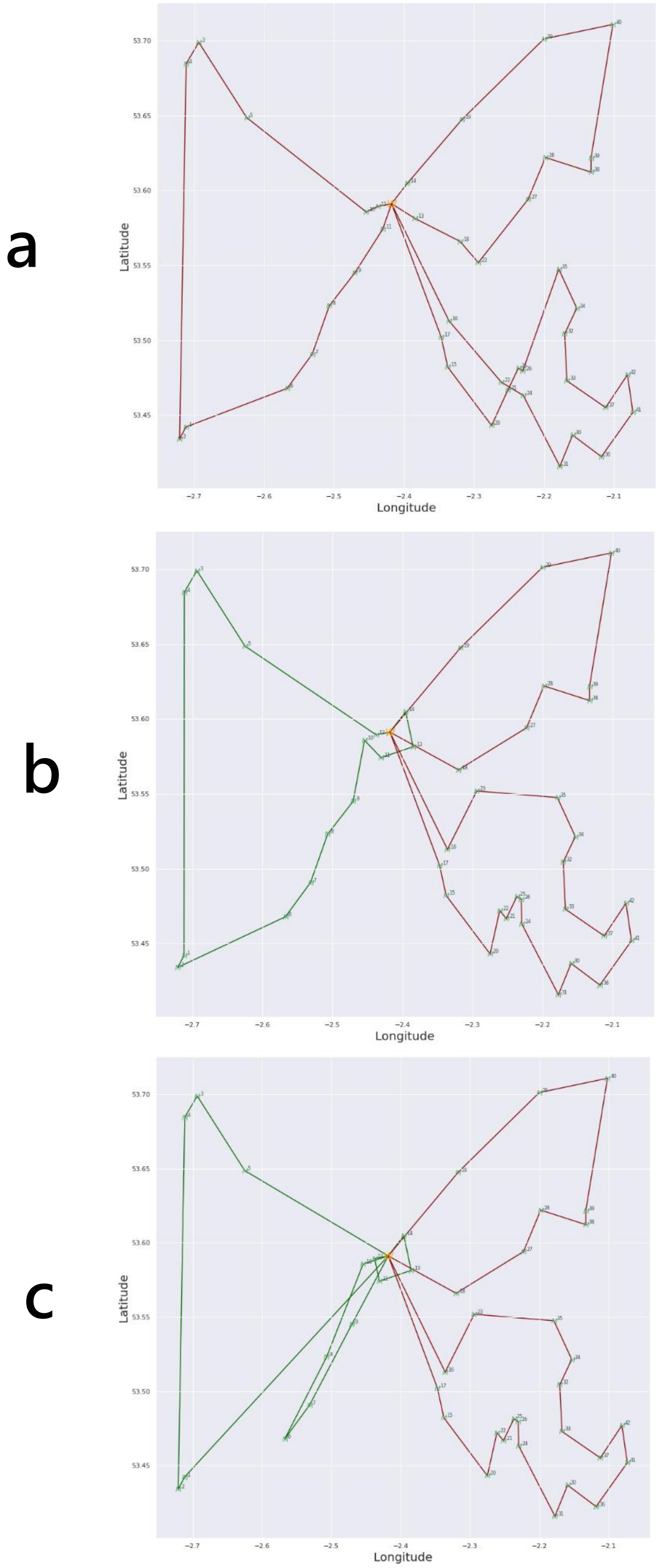


Figure 5. Plotted results of evaluated scenarios: **a)** base scenario; **b)** ET scenario; **c)** EV scenario.

EV scenario: this scenario employs a single electric van alongside the conventional truck, with a 150 km range and load capacity of 500 products. The model is solved with a 24.5% gap for CT and a 4.4% gap for ET. It is found that CT travels 194 km and ET travels 160 km, with the total travel distance of 354 km constituting only a 14% increase (Figure 5c).

In both ET and EV scenarios the optimal solution for the CT route remains the same, travelling 194 km. This equates to approximately 34 kg CO_2, which is a 35% decrease from the base case. Moreover, the ET scenario shows that introduction of the electric truck achieves the reduction with only a marginal increase in travelled distance. However in the EV scenario, limited loading capacity leads to a significant increase in travelled distance.

4.3 Sensitivity analysis

The effect of vehicle range and load capacity limit has been further explored, evaluating a mixed fleet model with 12 values of capacity and 8 values of the range.

The results of loading capacity testing show that the values for CT travel distance remain the same, and the change in total distance is controlled entirely by the variation in the route of the AFV. As such, the amount of emitted CO_2 also remains the same. Moreover, upon reaching the capacity of 1000 products, the change in the total distance becomes insignificant (Figure 6).

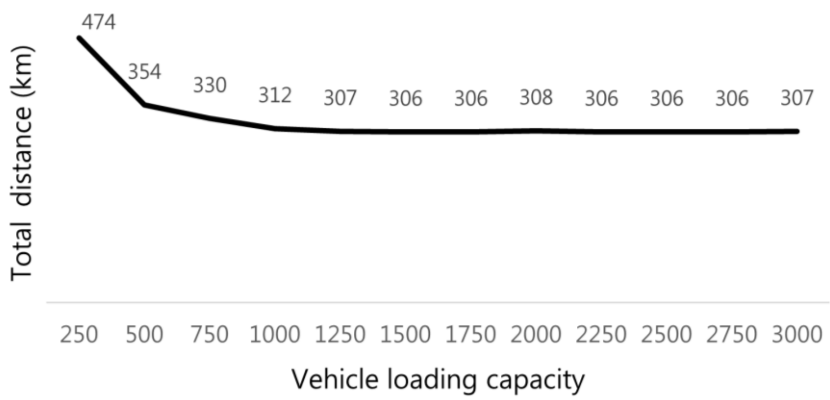


Figure 6. Impact of loading capacity on total distance.

Table 1 shows the impact of vehicle range variation on the distance travelled by the vehicles and the emitted CO_2. The total distance travelled by the vehicles increases until the route can be fully covered by the AFV when it drops to the base scenario value.

Table 1. Results of the vehicle range sensitivity testing.

Vehicle Range (degrees coordinates)	CT distance (km)	AFV distance (km)	Total distance (km)	CO_2 (kg)
0.5	225	102	328	39.15
1	202	103	305	35.14
1.5	191	137	328	33.23
2	137	171	309	23.84
2.5	127	209	336	22.10
3	109	264	374	18.96
3.5	82	296	379	14.27
4	0	295	295	0

However, the distance travelled by the CT and the associated CO_2 emission decrease as the AFV range increases Figure 7. Moreover, vehicle ranges of 1 degree (~111 km) to 2 degrees (~222 km) lead to only marginal increases in total distance, but significant decreases in carbon emissions.

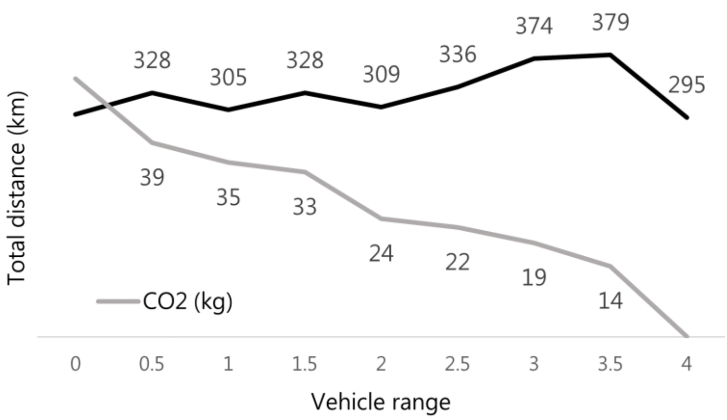


Figure 7. Impact of the vehicle range variation on the total distance and carbon emissions.

4 Conclusion

This study proposed and evaluated an intervention that involves the employment of AFVs alongside a conventional truck for delivery of Warburtons products to 42 Morrisons supermarkets across Greater Manchester. First, a mathematical formulation was given to the CGVRP model. Following that, techniques that aim to minimise the total distance travelled by the vehicles were proposed to solve the model.

Numerical experiments have shown that AFVs with a load capacity over half the capacity of the conventional truck can be introduced without incurring significant operational costs, but reduce the carbon emissions by at least 35%. Moreover, it was found that an increase in AFV range does not necessarily lead to a decrease in the total travelled distance, although significantly decreasing the distance travelled by CT and therefore the CO_2 emissions. However, it should be noted that the results of this study are representative of local scale operations and different results could be expected with sparser client distribution.

The study could benefit from improving the CGVRP model accuracy by additional assumptions and constraints, which would account for recharging time and infrastructure, as well as variations in vehicle speed, elevation and delivery time, among others. Another major improvement could involve incorporating emissions calculation into the objective function. Finally, consideration of fuel costs alongside carbon tax would greatly improve the study, allowing a cost-benefit analysis of the problem.

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