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DESIGNING MIXED-FLEET OF ELECTRIC AND AUTONOMOUS VEHICLES FOR HOME GROCERY DELIVERY OPERATION: AN AGENT-BASED MODELLING STUDY

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ABSTRACT

This paper proposes a hypothetical agent-based model of home grocery delivery operation using electric and autonomous vehicles. In the last-mile delivery context, agent-based modelling studies that consider the use of autonomous vehicles is lacking. The model in this paper can produce a mixed-fleet design that can serve a set of synthetic orders punctually. Through extensive computer experimentation, firstly, we investigate how infrastructure setup affects the fleet design. Secondly, we highlight the benefits of mixed-fleet over homogeneous fleet design. And thirdly, we evaluate the benefits of using autonomous vehicles in last-mile delivery operation.

1 INTRODUCTION

In 2021, about 16% of greenhouse gas (GHG) emissions in Europe came from the transportation sector (Eurostat 2021), of which light goods vehicles (LGVs) made a significant contribution. In the UK, 6% of carbon monoxide and 35% of nitrogen oxide emissions in 2018 were from LGVs (Department for Transport 2018). Electric vehicles (EV) can reduce fossil fuel consumption in the transportation sector (Al-Alawi and Bradley 2013). The UK government has set a target for all new car and van sales should be zero-emissions by 2040. The uptake of electric vans for delivery operations remains low due to factors such as range constraints, battery weight and and higher cost of ownership.

The driver's salary is a significant cost component, and shift length is a constraint to delivery efficiency. The use of autonomous vehicles (AVs) might thus become an option for reducing the cost of adopting EVs in delivery operations. Adopting battery-powered AVs may also reduce GHG emissions.

This paper is a part of a bigger project to analyse how logistics systems should be reorganized to better accommodate the use of EVs, considering LGVs, heavy goods vehicles (HGVs) and electric bikes among the potential mix. Using agent-based modelling (ABM), we have demonstrated how a real-world retailer in Manchester, UK, can replace all of its diesel LGVs with EVs. However, we highlighted a significant risk of degrading the service levels by about 30% (Utomo et al. 2019). The retailer can deliver the same number of orders, but the punctuality of the delivery may decline due to the time required for charging. We have also demonstrated that by introducing two opportunistic charging hubs outside the stores, about 20% of the service levels can be recovered while keeping the fleet size and profile fixed (Utomo et al. 2019). This research was followed up by investigating the charger power that should be installed at the retailer's stores, and how the vehicles should be charged to further increase the service levels without increasing the fleet size or the battery capacity (Utomo et al. 2021).

Our previous works in home grocery delivery focus on the infrastructure and design problems (Boysen et al. 2021), in which we aimed at optimally locating charging hubs, and choosing charger power by assuming that the retailer's fleet is fixed. This study will investigate the relationship between infrastructure and fleet design, and evaluate the benefits of using AVs in home grocery delivery. This paper presents a hypothetical ABM to explore those research questions.

The remainder of this paper is organized as follows. In section 2, we present the literature review to position our research in the context of ABM applications in last-mile delivery. The assumptions and process to develop our ABM are discussed in section 3. Sections 4 and 5 discuss the findings of this study, conclusion and potential future studies.

2 LITERATURE REVIEW

ABM has been widely applied to study last-mile delivery problems. Boysen et al. (2021) defined last-mile delivery as all logistics activities from a starting point in an urban area (*e.g.*, a central depot) and end when the shipment has successfully reached the customer's preferred destination. They also consider last-mile delivery and city logistics concepts to have some overlaps. City logistics is, however, a broader concept that also considers passenger transportation (Boysen et al. 2021). In this section, we summarize recent ABM applications that are relevant to the two concepts, but we only focus on freight transportation.

Following Utomo et al. (2018), we categorize the previous ABM applications into real and hypothetical case studies. Our review shows that most of the recent ABM applications use real case studies such as in Austria (Fikar et al. 2018; Fikar 2018), Netherlands (Anand et al. 2021; van Duin et al. 2021), Germany (Trott et al. 2021), Belgium (Mommens et al. 2018; Mommens et al. 2021; Kin et al. 2018), US (Castillo et al. 2022), UK (Utomo et al. 2021), Singapore (Sakai et al. 2020; Gopalakrishnan et al. 2020) and Denmark (van Heeswijk et al. 2019). Only Kim et al. (2021) present a hypothetical ABM. Both types of ABM are important. An ABM using a real case can be used to optimize the system being studied, while a hypothetical ABM can be used to derive theories that are applicable to many different cases.

Allen et al. (2018) suggested that last-mile delivery sectors can be classified based on the types of freight being transported *i.e.*, (i) grocery; (ii) parcels; (iii) large white and brown goods; and (iv) ready to eat meals (takeaways). Our review shows that grocery delivery is the most popular sector in recent ABM applications (Mommens et al. 2018; Utomo et al. 2021; Kin et al. 2018; Fikar 2018). Parcel delivery is the second most popular (van Duin et al. 2021; Trott et al. 2021; Castillo et al. 2022), followed by large white and brown goods (Anand et al. 2021; Kim et al. 2021) and ready to eat meals (Fikar et al. 2018). Some papers, however, model general freight that may include all of these sectors (Gopalakrishnan et al. 2020; Sakai et al. 2020; van Heeswijk et al. 2019).

Our review shows that the previous ABMs target different problem owners, which in some ABM applications is the government. For example, Anand et al. (2021) and van Heeswijk et al. (2019) tested policy concepts to encourage receivers and carriers to use urban consolidation centers instead of direct delivery. Gopalakrishnan et al. (2020) evaluated the impacts of changing parking supply for HGVs.

Other ABM applications target logistics operators; following Boysen et al. (2021), we classified previous ABM applications based on the decision problems owned by logistics operators in last-mile delivery into:

- **Setup or design of the infrastructure**: For example, Mommens et al. (2021) tested whether it is more beneficial to deliver or collect directly to the customers' house or to delivery hubs. Kim et al. (2021) tested the benefits of hyper-connected urban logistics for large-item delivery. Utomo et al. (2021) evaluated the impacts of charger power installed at a retailer's stores to the punctuality of the delivery done using a fleet of EVs.
- **Staffing and fleet sizing**: This type of problem is called fleet design in this paper. Within this category, Castillo et al. (2022) have evaluated a hybrid delivery system combining fleets owned by retail firms and crowdsourcing. Kin et al. (2018) evaluated payload consolidation scenarios to supply small stores.
- **Routing and scheduling**: For example, van Duin et al. (2021) presented a payload allocation and journey construction method based on an auctioning system. Trott et al. (2021) proposed a routing

heuristic to minimize emissions and delivery duration by considering parking bay availability. Mommens et al. (2018) evaluated the environmental impacts of night delivery to the supermarket. Fikar et al. (2018) proposed a method to minimize the total delay and travel distance in restaurant delivery operation. Fikar (2018) proposed a model to optimize inventory and delivery strategies in order to reduce food waste.

A variety of vehicle agents have been considered in the previous ABM applications. Van agents (Mommens et al. 2021; Trott et al. 2021; Utomo et al. 2021; van Duin et al. 2021; Kin et al. 2018) and truck agents (Mommens et al. 2018; Anand et al. 2021; Gopalakrishnan et al. 2020; Kim et al. 2021; van Heeswijk et al. 2019) are the most popular vehicle agent type. However small vehicles such as bicycles have also been considered (van Duin et al. 2021; Fikar et al. 2018). We also noted that most of the previous studies focus on conventional and diesel vehicles. To our knowledge, research modelling EVs in last-mile logistics is scarce and few sources are available, *e.g.*,Utomo et al. (2021). In addition, there is no previous ABM application that considers the use of AVs in last-mile delivery operation.

This literature review shows that most of the previous ABM applications focus on one problem owner and one type of decision problem. Little attention has been given to EVs and there is no previous attempt to analyze the benefits of AVs in last-mile delivery operation. The ABM presented in this paper also focus on one problem owner *i.e.*, a home grocery delivery operator. However, unlike previous ABM applications, we aim at understanding relationships between infrastructure design and fleet design problems when implementing EVs and AVs. More specifically, how the number and the location of stores influences the fleet size and battery profile within the fleet. Since our computational experiments also include the use of AVs, this model also contributes in understanding the impacts of using AVs in last-mile delivery operations. At this project phase, we aim at understanding general relationships, hence we chose to develop a stylized hypothetical model.

3 METHODOLOGY

We structure this section using the Strengthening The Reporting of Empirical Simulation Studies (STRESS) framework (Monks et al. 2019). The applicability of STRESS for ABM studies has been demonstrated, for example, by Onggo and Utomo (2021). We start by explaining the objectives of our ABM (subsection 3.1), followed by the logic or algorithm in our model (subsection 3.2), parameters to setup our model (subsection 3.3), experimentation (subsection 3.4) and model implementation (subsection 3.5).

3.1 ABM Objectives

Given a set of synthetic orders data, the ABM aims to produce the minimum number of vans required, so that all of the deliveries can be done punctually. Based on the distance travelled in all journeys done by a van, the model then decides the size of the battery that is appropriate for that particular vehicle.

3.2 Logic in the ABM

The model in this paper was developed based on the ABM proposed in Utomo et al. (2019) and Utomo et al. (2021). The main agent in this model is a retailer agent. It represents a home grocery operator in a hypothetical city. Its objective is to satisfy demand for grocery deliveries from its customers punctually and with the lowest possible cost. Hence, unlike in our previous works, the delivery time window is treated as a hard constraint. However, up to this phase of research, we do not estimate the cost in monetary value. Instead, we use the number of vehicles, the battery size, and the distance travelled as proxies of cost.

The retailer agent owns and operates a number of stores in the city. Each store agent owns and operates a number of van agents to carry out the delivery. In our previous works, we consider the number of vans owned by each store as inputs and are fixed throughout the simulation. In this paper, we assume each store is initiated with one van agent of a particular battery size, but when needed it can instantly purchase additional vans. By the end of the simulation a store may own several vans with different battery sizes.

Each day in the simulation starts by randomly generating a number of orders using a Poisson distribution. The mean of this Poisson distribution is set as an input. For each order, the quantity of product ordered (crates) is determined by sampling a truncated normal distribution with minimum value of zero and the result was rounded to the nearest whole number. The mean and standard deviation of this normal distribution is set as the model's input. The orders can come from customers who live anywhere in the simulated city with each cell having an equal chance to be selected. The cx_i and cy_i coordinate of the cell where the customer lives is recorded by the retailer agent.

Possible delivery time windows for orders are determined by considering the earliest delivery time (EDT), the store operational hour (OH) and the time window interval (TWI). All of those variables are used as model inputs. For instance, if EDT = 7:00 AM, OH is 16 hours and TWI is 4 hours, then there are four possible time windows for an order *i.e.*, 7:00 - 11:00 AM, 11:00 AM - 3:00 PM, 3:00 - 7:00 PM and 7:00 - 11:00 PM. The time window for each order is selected randomly from all possible time windows using a uniform distribution.

For each order, the retailer agent calculates the distance from the customer's location to each store agent. In common with van Duin et al. (2021), all of the distance calculations in this paper use the Euclidean distance formula multiplied by a correction factor of α (Equation 1). In Equation 1, sx_j and sy_j represent the x and y coordinate of store j. The α coefficient represents the road network topology (the minimum value of α is 1 and a road network with many junctions or one way traffic will have bigger α value).

$$dcs_{ij} = \alpha\sqrt{(cx_i - sx_j)^2 + (cy_i - sy_j)^2} \tag{1}$$

The retailer agent then evaluates whether the order is within the catchment area (CA) of the closest store agent (store with the smallest dcs_{ij}). If the customer's location is within the catchment area of the closest store then the customer can be served, otherwise the customer's order is excluded. In common with Delaney-Klinger et al. (2003), if an order can be served, it is then assigned to the closest store agent from the customer's location.

A store's catchment area determines the furthest customer's location that can be reached by its van agents and it is calculated using Equation 2. In this equation, DS denotes the driver shift in hours, v denotes the vehicle speed (km/hour), and $MaxR$ denotes the maximum vehicle range allowed in the system. DS, v and $MaxR$ are used as the ABM inputs, and they are divided by 2 to take into account the return journey.

$$CA = min\{(\frac{DS * v}{2}), (\frac{MaxR}{2})\} \tag{2}$$

Each store agent then allocates all of the customers' orders assigned to it into several vehicle journeys. The allocation process starts by sorting all of the customers' orders based on their delivery time windows, starting from the earliest to the latest. The assignment is then started from the customer with the earliest delivery time window. If there are more than one customer with the same delivery time window, then the customer to be evaluated first is selected randomly.

The next process is to calculate the distance and travel time from each van's last location (vx_k, vy_k) to the customer's location. The van's last location can be either the van's home store, or the customer location previously served by the van. Different from Utomo et al. (2019) and Utomo et al. (2021), there are two distance and travel time calculations in this paper *i.e., direct* journey and *via-store* journey. *Direct* journey means the van travels directly from its last location to the customer's location. The distance of a *direct* journey is described in Equation 3. In this equation dd_k denotes the total travel distance of a *direct* journey, dcv_{ik} denotes the distance between van k's last location and the customer's location, and dcs_{ij} is the distance between the customer and van k's home store (to take into account the return journey). The travel time of a direct journey (ttd_k) is then obtained by dividing dd_k with v (Equation 4).

$$dd_k = dcv_{ik} + dcs_{ij} \tag{3}$$

$$ttd_k = dd_k / v \tag{4}$$

A *via-store* journey means the van first visits the store before going to the customer's location. The total travel distance of a *via-store* journey (ds_k) is described in Equation 5. In this equation dsv_{jk} represents the distance between the van's last location and its home store. Similarly, the travel time of the a *via-store* journey (tts_k) is obtained by dividing ds_k with v (Equation 6).

$$ds_k = dsv_{jk} + 2 * dcs_{ij} \tag{5}$$

$$tts_k = ds_k / v \tag{6}$$

The following criteria are then applied to decide whether a van should serve the customer's order using *direct* or *via-store* journey.

- Vehicle capacity: Following Utomo et al. (2019) and Utomo et al. (2021) we assume that the vans used in home grocery delivery operation can carry up to 108 crates. Hence, if the remaining capacity of a van is lower than the number of crates ordered by the customer then the van should use *via-store* journey. Otherwise, it can use *direct* journey.
- Total journey time: The driver's shift constraints the duration of a van's journey. The typical driver's working shift is 8 hours, including 15 minutes breaks every 2 hours. Therefore, if under *direct* journey scenario, the additional working time to serve the customer and return to the van's home store means the driver's total shift exceeds 8 hours, then the van should use *via-store* journey.
- Maximum range: How far a van can travel is also constrained by the maximum vehicle range allowed in the system (*MaxR*). Hence, if under *direct* journey scenario, the additional journey length to serve the customer and return to the van's home store means *MaxR* is violated, then the van should use *via-store* journey.

The next step is to evaluate the eligibility of the vans. A van is considered to be eligible if it can arrive at the customer's location before the customer's delivery time window ends. The estimated time of arrival at the customer's location (arr) is calculated using Equation 7 if the van can use *direct* journey, and Equation 8, if the van should use *via-store* journey. In those equations dep represents the time when the van can depart form its last location. The tlc denotes the time required for reloading and charging. In diesel case the tlc value is 30 minutes. In electric vehicle case the tlc value is 1 hour (assuming that the van can be fully charged in 1 hour (known as the 1C rule)). If there is no eligible van, then a new van is instantaneously spawned by the store agent without any associated cost.

$$arr = dep + ttd_k \tag{7}$$

$$arr = dep + tts_k + tlc \tag{8}$$

A total score is then assigned for each van. A total score of zero is assigned to ineligible vans. While, for all eligible vans, the total score is obtained by averaging the score from three factors:

- Punctuality: A vehicle gets a score of 100 if it can arrive within the customer's delivery time window and gets score of zero if it arrives too early. This is because we assume that a delivery can only be made after the customer's delivery time window starts, hence it must wait if it arrives too early.
- Distance: The distance from the vehicle's last location to the customer's location, either dd_k or ds_k. The closest vehicle to the customer's location gets a score of 100 while the furthest vehicle gets a score of 0. The score for all other eligible vehicles is assigned between 0 and 100 using linear function.

- Maximum historical distance travelled: Distance travelled in this paper represents the journey length (in kilometers). This factor aims to prioritise the use of older vehicles and to keep the distance travelled of newly spawned vehicles low. The maximum historical distance travelled is obtained by taking the maximum value of distance travelled from all previous journeys that have been done by the vehicle. Vehicle with the longest distance travelled gets a score of 100 while vehicle with the lowest distance travelled gets a score of 0. The score for all other eligible vehicles is assigned linearly between 0 and 100. With regards to EVs, smaller battery pack can be assigned to vehicle agents with lower maximum historical distance travelled, and hence this factor can reduce the number of EVs with big battery.

Vehicle with the highest total score is selected to deliver the customer's order. There are two possible scenarios when incorporating the order into the vehicle's destination list:

- The selected vehicle can deliver the customer's order using *direct* journey: In this case the customer's order can be directly incorporated into the selected vehicle's destination list. The remaining capacity of the selected vehicle is then reduced by the quantity ordered by the customer. The remaining driver's shift is reduced by ttd_k (see Equation 4), and the remaining vehicle's range is reduced by dd_k (see Equation 3).
- The selected vehicle should deliver the customer's order using *via-store* journey: In this case the selected vehicle must first return to the store, and start a new journey. Its remaining capacity, driver's shift and remaining range are reset to their initial values. After that the customer's order is incorporated into the selected vehicle's destination list, and procedures in the *direct* journey case can be followed.

These steps are repeated until all orders in a day are served. The vehicle agents then deliver the customers' orders following their destination list. In this model we assume that there is no interaction between vehicles and traffic conditions. Hence the vehicle will always arrive at each destination as planned.

By the end of the simulation, the model assigns the battery size appropriate for each vehicle. This is done by evaluating the longest journey that was completed by a vehicle. For instance, even if we allow the vehicles in the system to travel up to 100 km ($MaxR$ = 100 km), but if historically the longest journey carried out by a particular vehicle is 75 km, then it can complete all of its journeys using 50 kWh battery.

3.3 Data

In addition to the values explained in subsection 3.2, our ABM uses several inputs, *i.e.*:

- City area: The size of the hypothetical city. The value is set to be 50km x 50km. This is representative for big cities in Europe such as, Paris, Moscow, Düsseldorf etc (Globalgeografia 2021).
- Number of stores: The number of stores owned by the retailer agent (used as scenario).
- Store location: The spatial distribution of the stores. There are two values for this parameter *i.e.*, *random* and *cluster*. *Random* means the stores are located randomly in the city. *Cluster* means the stores are located so that they become the center of the customer clusters. This parameter is also used as scenario.
- Average orders per day: The average number of orders received by the retailer agent (demand). This parameter is used as a scenario in the experiment.
- Mean and standard deviation of customer's order size (crates): For all scenarios the mean value is 4.82 and the standard deviation is 0.8 (Utomo et al. 2021).
- Driver shift: How long the vehicles can travel. For diesel and EV vans, the driver shift is set to be 8 hours. Assuming that AVs can travel as long as the store is open, the driver shift for AV vans is set to be 16 hours.
- Van speed: The speed of the vehicle. It is set to be 40 km/hour in all scenarios (Utomo et al. 2021).

- Dispatch time: The earliest time when the vans can leave the store (6:00 AM in all scenarios).
- Operational hour (OH): How long the store agents are operational in a day (16 hours in all scenarios).
- Earliest delivery time (EDT): The starting time of the earliest delivery time window (7:00 AM in all scenarios).
- Delivery time window: The duration of the delivery time window (used as scenario).
- Maximum range: The maximum range of the vehicles in the retailer agent's fleet. The value is set to be 500 km if the retailer agent uses diesel vehicles, 240 km for 120 kWh battery, 198 km for 99 kWh battery, 160 km for 80 kWh battery, and 100 km for 50 kWh battery (assuming the range per kWh is 2.5 km) (Watróbski et al. 2017). Please note that the final battery size for each vehicle is assigned based on its historical journeys. Hence even if the maximum range is set to be 240 km, the retailer agent may end up having several vehicles with 99 kWh, 80 kWh or 50 kWh.

Using these input data, the ABM produces several outputs *i.e.*, the number of customers that can be served, the fleet size, the total distance travelled (in km), and the battery size for each vehicle.

3.4 Experimentation

Experimentation using the ABM employs full a factorial design. Table 1 describes the factors and the corresponding levels explored in the experiments. In total there are 720 scenarios in one experiment set. Each scenario is run for 100 simulation days (initial runs showed that the system reach steady state after about 80 days) and replicated three times. The random seed was controlled so that scenarios in a replication used the same random seed, and hence serving exactly the same order set.

Table 1: Experiment table.

Factors	Levels
Number of stores	1, 4, 16
Store location	random, cluster
Average order per day	50, 100, 200, 400
Time window	1, 2, 3
Driver shift	8 hours including breaks (for Diesel and EVs), 16 hours (for AVs)
Maximum range	500, 240, 198, 160, 100

3.5 Implementation

The ABM is implemented in NetLogo 6.2.0. Its BehaviorSpace tool enables process parallelization that is useful for our experiment. The ABM uses fixed time steps of 10 minutes and all randomization in the model was handled using NetLogo built-in functions. In addition, NetLogo also randomizes the sequence of agents activation in each step to avoid bias. The experimentation was done on Intel(R) i5-8350U CPU @ 1.70GHz with 16 GB of physical memory.

4 EXPERIMENT RESULTS AND ANALYSIS

First we analyze the impacts of the number of stores and their location on the percentage of orders that can be served by the retailer agent. The experiment results show that regardless of the number and location of stores, the number of orders per day, and the time window, diesel vehicles can serve all orders received by the retailer agent. A fleet of EVs or AVs can also serve 100% of the orders if they are allowed to have 120, 99 or 80 kWh batteries.

However, this is not the case if the retailer agent limits the battery size of EVs and AVs fleet to 50KWh. Figure 1 shows how the average percentage of order that can be served change as the number of stores in the simulation increase. This figure shows that both EVs or AVs fleet can only serve 80.5 % of all incoming orders when the retailer agent only operates one store and is randomly placed in the hypothetical city. The percentage of orders that can be served can be increased to 98.5 % if the store is strategically located at the center of the customer cluster. However, if the retailer agent wants to serve all of the incoming orders, then it must operate more stores. This happens because the catchment area of the stores shrinks when the battery size is reduced (a consequence of Equation 2).

This experiment highlights the importance of understanding the relationship between infrastructure and fleet design. In a big city, when the number of stores is low, adding more vans might not be sufficient to serve all of the incoming orders. Hence it is better for the retailer agent to use vans with bigger battery. This is because the price of vehicles with big battery is generally cheaper than operating more stores.

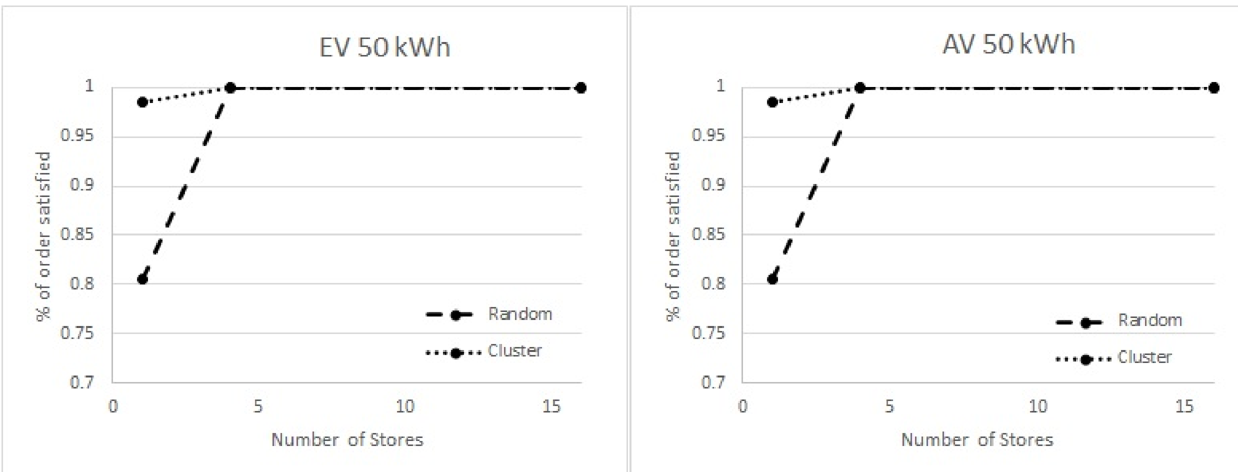

Figure 1: Percentage of order that can be satisfied using EVs and AVs with 50 kWh battery.

Next, we analyze the impact of the number of orders received on the size of the fleet required to serve all of these orders punctually. Figure 2 shows average fleet size required under a variety of demand scenarios. In this figure, EV120 represents scenarios in which the retailer agent allows the vehicles in its fleet to have battery with 120 kWh capacity at maximum. Similarly, AV120 represents scenarios in which the retailer agent uses autonomous vehicles with maximum battery size of 120 kWh. As a baseline, a line representing scenarios involving 100 % conventional diesel vehicles is also shown in Figure 2.

Figure 2 shows that regardless of the number of stores operated by the retailer agent, the average number of vehicles required increases as the number of orders increases. When the average order is 50 per day, the difference in fleet size across all vehicle type scenarios is not observable. But, when the number of orders is high (400 orders per day on average) the difference starts to become significant. The highest average fleet-size of 26.77 vans occurs when the retailer agent uses a homogeneous fleet with 50 kWh battery. The fleet size can be reduced if the retailer agent uses vehicles with bigger battery sizes.

Figure 2 also shows that both EVs and AVs scenarios produce exactly the same fleet size. However, we can still expect some savings from using AVs. This is because the retailer agent does not need to pay the driver's salary when it uses AVs.

We then analyze the total distance travelled from 100 simulation days. Figure 3 shows the total distance travelled under a variety of order levels, including from the baseline scenarios that involve 100% conventional diesel vehicles. This figure shows that the total distance travelled increases as the number of orders per day increases. However, Figure 3 also shows that the total distance travelled tends to decrease if the retailer agent deploys vans with bigger battery. This is because vans with bigger battery need to be charged less frequently. Hence reducing the distance of the return journey to the home store.

The saving from using AVs is not apparent in Figure 3. Table 2 shows that the savings from using AVs only occurs when the maximum battery size is 120 kWh and the average number of orders is 100 per day

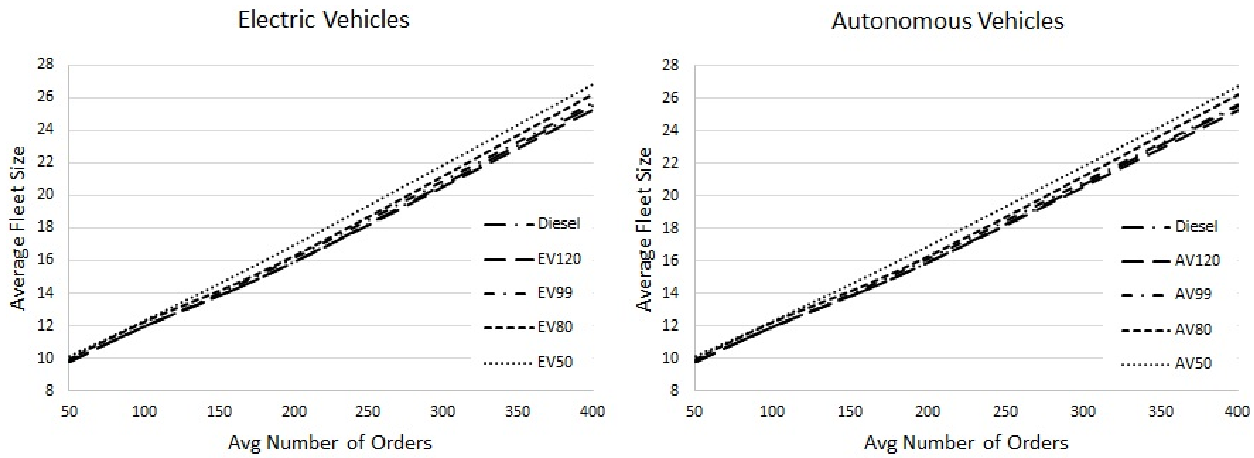

Figure 2: Impacts of the number of orders to fleet size.

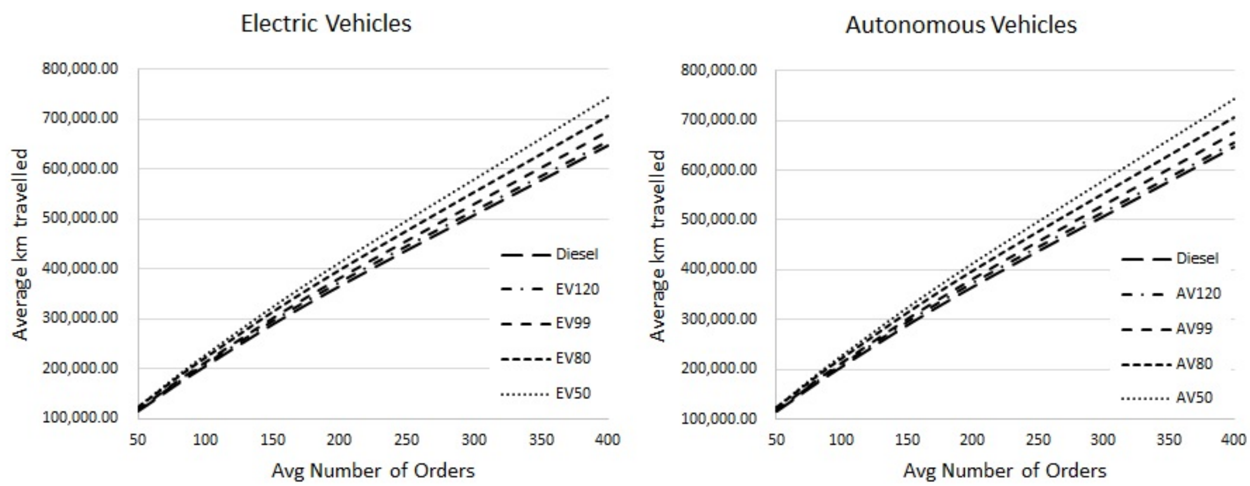

Figure 3: Impacts of battery size on the total distance travelled.

or higher. Table 2 indicates that when the number of order or the vehicle range is low, the driver's shift constraint is not fully utilized. Hence, relaxing it does not produce any effect. But when the order level and vehicle range are sufficiently high, using AV might reduce the need for the vehicles to return to the store to change driver.

Even though Figure 1, Figure 2, Figure 3 and Table 2 support the use of vehicles with big battery, it is not necessary for the retailer agent to operate a homogeneous fleet with big battery. Table 3 shows the average frequency of battery size from all scenarios with order level of 400 and maximum battery size of 120 kWh. This table shows that some of the vehicles can have battery smaller than 120 kWh. At the present time the price of the battery accounts for about 40% of the vehicle's price (König et al. 2021). Hence, deploying a mixed-fleet (*i.e.*, many large battery-sized vehicles and several small battery-sized vehicles) may reduce the initial investment required to purchase the vehicles. Furthermore, vehicles with smaller battery can be charged with less powerful chargers that are also cheaper to be installed.

Table 3 also show additional potential saving from using AVs. This table shows that AV fleet uses fewer vehicles with 120 kWh battery and more vehicles with 90 kWh and 80 kWh battery. One of the possible explanations is because relaxing the driver's constraint will allow the vans with 120 kWh battery

Table 2: Distance travelled by EVs and AVs fleet in scenarios with maximum battery capacity of 120 kWh.

avg. order per day	Km travelled EV	Km travelled AV	$EV - AV$
50	117,893.32	117,893.32	0
100	209,322.83	209,318.26	4.58
200	373,253.51	373,223.5	30.02
400	655,156.89	654,943.35	213.54

Table 3: Distribution of battery size of EVs and AVs fleet in scenarios with order level of 400 and maximum battery size of 120 kWh.

Fleet type	120 kWh	99 kWh	80 kWh	50 kWh
EVs	19.22	0.88	0.5	4.66
AVs	19.11	0.94	0.6	4.61

to utilize their range constraint more and incorporate more destinations into their journey. This makes the distance of the remaining journeys shorter and can be completed by vehicles with small batteries.

5 CONCLUSIONS, LIMITATIONS AND FURTHER RESEARCH

5.1 Conclusions

This study has proposed an ABM that can help to understand the relationships between infrastructure and fleet design problem when implementing EVs and AVs. We have also evaluated the benefits of mixed fleet and the use of AVs in home grocery delivery operations.

We have demonstrated that it is important to consider the battery sizing and store number as well as their spatial distribution together to optimize the fleet design. Providing that the design is robust and stress tested against randomly generated orders, a heterogeneous fleet consisting of vehicles with big and small battery is better than a homogeneous fleet design.

Introducing AVs into the fleet may yield some benefits. Firstly, AVs may reduce the operational cost by removing the driver. Secondly, AVs might increase the efficiency of the operation by reducing total distance travelled. This happens especially when some slack remains in the range constraint, while the shift constraint has been fully utilized using ordinary EVs. Thirdly, using AVs may reduce battery size for some vehicles in the fleet. This is beneficial because vehicles with smaller battery are generally cheaper and can be charged with less powerful chargers. Hence this may reduce the amount of investment required.

5.2 Limitations and Further Research

One of the limitations of this study is that we have not analyzed the financial impacts of the various design fleet produced by the experiment. To do this, we need to develop a cost model that is representative for the various types of EVs, AVs and chargers. Furthermore, even though in subsection 5.1 we mentioned that the cost to operate AVs might be cheaper because we can eliminate the driver's salary, AVs operations might involve other cost such as, *e.g.*, control system to manage the AV fleet. Unfortunately, information to estimate the cost structure for AVs is somewhat limited at present.

We assume the vehicles can only be charged at their home store and neglect the possibility of opportunistic charging; this capability could be very important in the future because vehicles that do not need to constantly return to their home store may incorporate more orders into their journey.

Six experimental design factors have been presented in this paper. Unfortunately, some have not been fully explored, for example, the number and location of the stores and the impact of different time windows. Having wider time windows for instance, may give the vehicles more opportunity to serve the orders punctually and may bring further reduction to the fleet size. Other factors that can also be explored in the future are such as, different speed, and different unloading time due to the fact that a customer would need to unload groceries from an AV themselves. Exploring the time required by a customer to unload his/her grocery or to understand their attitude and behavior toward AV delivery is also important. For this purpose, behaviour elicitation techniques such as scenario-based questionnaire (Utomo et al. 2022) or role playing game (Utomo et al. 2021) can be used. It is also important to explore the impact of the weights assigned to the three scoring factors in the heuristics. At present, those parameters are assumed to have equal weight. However, these weights can be optimised further, for example by using sensitivity analysis, to minimise the total cost or the total GHG emission.

The shortcomings from the modelling and simulation perspective might be the absence of the statistical analysis of the experiment outputs. To be able to do this, first we will ensure that we have sufficient replications from our experiments, for example, by applying convergent criteria (Hoad et al. 2010). Once sufficient experiment replications are obtained, confidence intervals of the experiment outputs can be established to generalize the results of this study. In addition to the confidence intervals, meta models of our experiment outputs can be developed to explore the impacts of independent factors e.g., driver shift and loading time, toward the system performance *e.g.*, distance travelled. All of this process will be carried out at the later phase of this project.

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