# Analysing charging strategies for electric LGV in grocery delivery operation using agent-based modelling: An initial case study in the United Kingdom

**Citation for published version:**
Utomo, DS, Gripton, A & Greening, P 2021, 'Analysing charging strategies for electric LGV in grocery delivery operation using agent-based modelling: An initial case study in the United Kingdom', *Transportation Research Part E: Logistics and Transportation Review*, vol. 148, 102269.
https://doi.org/10.1016/j.tre.2021.102269

**Digital Object Identifier (DOI):**
10.1016/j.tre.2021.102269



**Published In:**
Transportation Research Part E: Logistics and Transportation Review

Please cite as: Utomo, D. S., Gripton, A., & Greening, P. (2021). Analysing charging strategies for electric LGV in grocery delivery operation using agent-based modelling: An initial case study in the United Kingdom. Transportation Research Part E: Logistics and Transportation Review, 148, 102269. https://doi.org/10.1016/j.tre.2021.102269

# Analysing Charging Strategies for Electric LGV in Grocery Delivery Operation using Agent-Based Modelling: An Initial Case Study in the United Kingdom

This paper presents an agent-based simulation study aimed at evaluating the impact of different charging strategies on the performance of home grocery delivery operation using electric vans. In our previous work we established the quantity of orders that can be delivered using electric vans; in this paper we focus on the punctuality of the delivery. We present a baseline agent-based model imitating the operations of a real-world retailer. We then introduce electric vans into our model in order to ascertain how charging power and charging strategy influence the retailer's operations. Even though electric vans cannot match the performance of diesel vehicles using the same fleet size, our simulation experiments suggest that, by considering the quantity of orders and the geographical distribution of its customers, an operator can determine a suitable charging strategy that can minimise late delivery. Additionally, by employing a suitable charging strategy, an operator might avoid making unnecessary investments and reduce the barriers for electric vehicle adoption.

Keywords: agent-based modelling, electric vehicles, logistics operations

## 1. Introduction

In 2018, 28% of the UK's greenhouse gas (GHG) emissions came from the transportation sector (BEIS, 2020). Within road transportation, light goods vehicles (LGVs) represent 11% of the total vehicle mix (DVLA/DfT, 2020), and have contributed to approximately 6% of the UK's carbon monoxide and 35% of nitrogen oxides emissions (DfT, 2018b). The UK government's transport decarbonisation strategy has set a target that all new car and van sales are to be zero emissions by 2040 (DfT, 2018a). This target requires a substantial growth in the sales of battery electric vehicles (EVs). However, as of 2020 the uptake of electric vans for delivery operations remains low. Factors such as range constraints (approximately 100 km for a typical electric LGV), 5% to 15% payload reduction due to battery weight, and higher cost of ownership, cause limited fleet penetration within retail and parcel operations.

This paper is one of the strands of a bigger project aimed at analysing how logistics systems should be reorganised to better accommodate the use of EVs, considering LGVs, HGVs and electric bikes among the potential mix. In this strand, we focus on the use of electric LGVs for home grocery delivery in urban areas, using a case study in Manchester, UK. Using agent-based modelling and simulation (ABMS), we demonstrated in our previous paper that it is possible for a real-world retailer to replace all its diesel fleets with electric LGVs, albeit with a significant risk of degrading service levels (Utomo et al., 2019). More specifically, the retailer can deliver the same number of orders, but the punctuality of the delivery may decline due to the time required to charge the vehicles.

The objective of this paper is to establish the most appropriate and robust mix of charging infrastructure and charging strategies that enable the adoption of an EV fleet without any degradation of service levels. Firstly, we investigate the relationship between charging power and the punctuality of the delivery. Secondly, we investigate when and how much charge should be added into the battery to minimize late delivery.

The remainder of this paper is organised as follows. In section 2, we present the literature review to highlight the novelty of this paper i.e., the use of ABMS to propose necessary changes in operational decision as consequences of the adoption of EVs. In section 3, we describe the methodology that we employed in this study. In section 4, we discuss the findings from our modelling and simulation. And finally, we present the conclusion of this study and our plan for further research in section 5.

## 2. Literature Review

This section begins by discussing the importance of ABMS for the study of supply chain and logistics. We then discuss ABMS applications related to EVs and subsequently discuss interventions that have been proposed by the previous studies to support EVs adoption. We conclude this section by highlighting a lack of studies of how logistics operators will have to adapt their operations when replacing their diesel van fleet with an electric van fleet.

### *2.1. The applications of ABMS in logistics and supply-chains*

ABMS is now widely accepted as a powerful method for investigating complex systems. A logistics system is a complex system described by a multitude of interdependencies, degrees of autonomy, and tends to be non-linear, critically organised and therefore emergent (Janjevic et al., 2019). Such systems have large solution spaces and are best explored using high fidelity, large scale computer simulations that incorporate both macro and micro perspectives (Roorda et al., 2010).

Several papers (e.g., Oliveira et al. (2016); Utomo et al. (2018)) have shown the increasing popularity of ABMS as an operational research method to study logistics and supply-chain systems. Oliveira et al. (2016) show that within the supply-chain domain, 14% of simulation studies employed ABMS. The use of ABMS within the logistics domain is more prominent; Crainic et al. (2018) noted that 47% of simulation studies in this domain are ABMS. More recent examples are Firdausiyah et al. (2019) who proposed solutions to reduce environmental emissions in city logistics by modelling the behaviours of freight carriers around an urban consolidation centre, and Sakai et al. (2020) who analysed the impact of delivery time window regulation by using a multi-scale urban transportation ABMS.

However, we also note that very few ABMS incorporate electric commercial vehicles ; based on the titles in the reference list, we estimate commercial EV publications account for only about 3% of the sample presented by Crainic et al. (2018). In the next subsection we will explore in more detail how ABMS have been used in the study of EVs, both for commercial or private purposes, and for passengers or goods.

### *2.2. The applications of ABMS in studies regarding EV implementation*

ABMS has been widely applied to studies involving EVs. Based on the research purpose, these studies can be broadly partitioned into two groups: studies aimed at analysing the adoption process for EVs, and studies aimed at analysing how EVs interact with broader energy systems.

Within the first group, Eppstein et al. (2011) proposed a spatially explicit ABMS that explores the market penetration of private EVs. Their model considers spatial and social effects, as well as media influences on US consumers to establish factors that might affect the market penetration of personal plug-in hybrid EVs and potential policies to influence them. Shafiei et al. (2012) proposed an ABMS that can describe the evolution of the passenger vehicles market in Iceland, including EVs. They considered social influences and the market attractiveness of the vehicle (purchase price, fuel consumption, luggage capacity, etc) and found that market penetration is highly influenced by gasoline price, the EV price and the tax on imported EVs. Brown (2013) combined a mixed logistic regression model and ABMS to simulate the diffusion of private EVs in the Boston metropolitan area. The mixed logistic regression model in this study is used to relate consumers' demographic characteristics with the features of the vehicle they chose. Propfe et al. (2013) simulated the penetration of EVs to the German passenger car market. They suggested that the market success of EVs depends on factors that include purchase price incentives, rising oil prices, and low energy costs for hydrogen and electricity. Querini and Benetto (2014) focused on the use of EVs to substitute passenger cars in Luxembourg. They analysed the dynamics of EV adoption by combining ABMS and life-cycle-analysis. They concluded that it would be very difficult to achieve the targeted proportion of electric vehicles due to limited capacity to park and plug the car at home, and without sufficient deployment of charging infrastructure and incentives.

Some of the ABMS studies aim to analyse the interaction between EVs and energy systems. Lindgren and Lund (2015) used ABMS to model electric passenger cars in Helsinki. Their objective was to identify potential bottlenecks in the use of shared charging infrastructure. Olivella-Rosell et al. (2015) studied the behaviours of EV users in Barcelona, Spain. They described how EV charging demands influence the electricity network by simulating EV characteristics, user mobility needs, and charging processes required to reach their destination using ABMS. Tang et al. (2017) combined a non-deterministic polynomial model, ABMS and ANOVA to identify potential charging locations in Beijing that can minimise the total travel distance of passenger cars. By applying ABMS in a case study of Austin, Texas, Farhan and Chen (2018) suggested that ride-sharing system using EVs might decrease private vehicle ownership, vehicle miles travelled, urban greenhouse gas emissions, and energy use. Finally, Latifi et al. (2018) developed an ABMS based on game theory concepts to propose an EV charging scheduling system that can minimise cost and maximise grid efficiency.

This literature review shows that until recently ABMS has been mainly used to model passenger EVs. In addition, this literature review also shows that case studies in the UK context are limited.

### *2.3. Strategies to support EVs adoption*

Beyond ABMS, there have been many studies that aim to support EVs adoption, particularly by considering their interaction with electricity distribution network. Arias-Londoño et al. (2020) classified these studies as follows:

- Studies aim at estimating the impact of EV charging on the power network at various levels of EV adoption. An example of these studies is Rahman and Shrestha (1993) who emphasised the importance of sufficient electricity generation to support passenger EVs adoption without adverse effects on the electric grid.
- Studies that relate to the EV participation in electricity markets, energy price, and cost-to-benefit ratio. For example, Fele and Margellos (2019) who took into account price uncertainty in studying the decentralised charge scheduling problem for an EV fleet participating in a demand response scheme.
- Studies that analyse how financial incentives can encourage EV owners to reduce or shift their EV recharge during peak periods. For example Mallette and Venkataramanan (2010) explore the economic incentives that should be given to private EV owners so that they are willing to contribute on softening the load profile curve.
- Mathematical modelling studies that aim to minimise the operation and investment costs and/or maximising the number of EVs that can be plugged into the network, by considering constraints such as load factor, voltage limits, and EV owners' driving patterns. Lopes et al. (2009), as an example, proposed a mathematical model to maximize the number of private EVs plugged into electricity network, subject to voltage limits in residential areas and battery energetic requirements.

- Studies that analyse how EVs can provide signals to support power system. An example in this category is Doumen and Paterakis (2019) who analysed how the use of smart charging for passenger EV can potentially ease network imbalance and grid overloading issues.
- Studies regarding Vehicle-to-Grid (V2G) concept. Within this category, El Chehaly et al. (2009) provide an overview of the state of the art in battery technologies and charger requirements. They also discuss the advantages and requirement for V2G implementation for passenger EVs.
- Studies that address the planning of Electric Vehicle Charging Stations and Battery Swap Stations. For example, Tang et al. (2011) proposed an optimisation algorithm combined with Voronoi polygons to locate charging stations that can balance the electricity load.

In common with our conclusion in section 2.2, studies that consider private passenger vehicle are more prevalent. Moreover, the technological interventions and operational strategies proposed through these studies are more relevant to government, electric power companies or private EV owners than to logistics operators, especially those who run home delivery operation.

### *2.4. Contribution of this study*

The novelty in this study is the application of ABMS to model commercial EVs within a logistics system. Interaction in a logistics system tends to be more complex because it involves many diverse firms as well as consumers. To meet consumer needs, the firms must make many decisions related to operations, marketing, and supply chain management (Roorda et al., 2010). Unlike private vehicle owners, a firm also needs to consider strategies for payload allocation, payload consolidation and vehicle routing (van Duin et al., 2012). Furthermore, a logistics operation can be tightly coupled (Wu and

Chaipiyaphan, 2019). Unlike passenger EVs where small changes tend to have little effect, in a logistics operation small changes or disturbance may propagate through the system. Regarding the charging strategy, previous studies typically assumed that there is always enough time for charge a passenger EV until its battery is full (Farhan and Chen, 2018; Lindgren and Lund, 2015; Lindgren et al., 2014; Olivella-Rosell et al., 2015). This will typically not be the case for commercial EVs, especially when deployed on routes where total power requirements exceed that of a full battery, limiting opportunities to return to charge at the depot.

## 3. Methodology

This section begins by discussing the conceptual model and boundaries of the ABMS presented in this paper. After that, the processes to develop and validate the base ABMS are discussed. We then modify the base ABMS by introducing electric LGV. Finally, we describe the experiment to evaluate the operator's delivery performance under a variety of operational decision scenarios.

### *3.1. Conceptual model and model boundaries*

Our overall project aims to obtain robust solutions to decarbonize freight transport, in particular through EV adoption. Figure 1 describes our conceptual model of a logistics system.

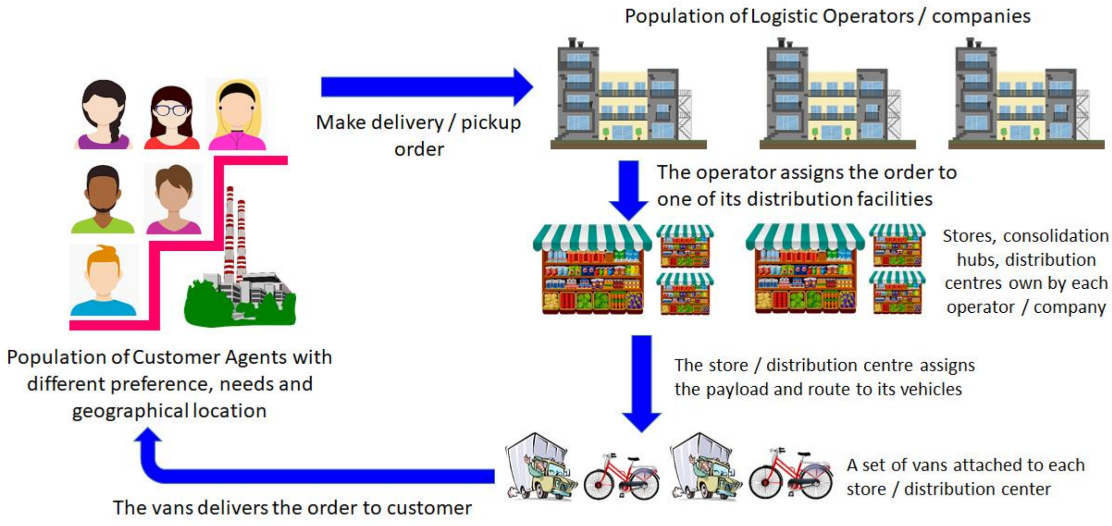


Figure 1 A conceptual model of a logistics system

In any logistics system there always a population of customers. These customers can be individual households or businesses. In this system, there is also a population of logistics operators. The processes within this system are initiated by a customer placing an order (either delivery or pickup) to one of the operators. The selected operator can act as a supplier for the customer, for example, a customer who is ordering groceries from a supermarket, or as an intermediary for the customer, for example, a postal service delivering mail for its customer.

Each customer has their own decision-rules in selecting which operator to place the order on, the order frequency, and the order quantity. A customer's decision to select the operator might be influenced by the customer's needs, their past experience with the operator, cost and the operator's reputation. For example, a customer may switch to another supermarket due to a poor previous delivery performance. Furthermore, a customer may influence another customer's perception towards an operator. The order frequency and quantity are also decided by the customers using a certain rule. For example, if the customer is a business then its decisions might be based on the economic order quantity principle. In the long term we will consider these complex decision-making processes in our project. However, at this phase, we simplify the customers' decision rules, by assuming that their decisions are always match the statistical distribution from the historical data. In addition, we also limit to model one logistics operator in this study, even though there are many logistics operators that can be chosen by the customers in real home grocery delivery operation.

A logistics operator may own and operate more than one warehouse, distribution centre, consolidation hub or store. Each of these facilities can own and operate several vehicles. These vehicles can be trucks, vans or bicycles. Each vehicle can also have different characteristics such as fuel type, range and operational cost structure.

Upon receiving the customers' order, the logistics operator must choose which facility (store) should serve the order. The operator's decision is also complex and is influenced by many factors, such as the distance from the store to the customer, the availability of the items being ordered by the customer and the warehousing capacity of the store. In this research phase, we assume that the items ordered by customers are always available in every store and each store has an unlimited capacity. The stores are only heterogeneous with respect to their location (therefore the distance to each consumer), and the number of vehicles they own.

Each store then selects the vehicle that will be used to serve each order, and assigns the route that should be used by each vehicle. In reality there are many commercial software packages that can be used to assist making this decision. In this paper we propose a heuristic that aims to minimize the vehicle travel distance while satisfying the delivery time window and the vehicle capacity constraints.

When delivering the items ordered by the customer, the vehicle also interacts with traffic conditions and congestion. However, at this research phase, we assume that the vehicle can travel without any interference and at a constant speed.

Macal (2016) defined four levels of ABMS complexity based on individuality, agent behaviours, interactions between agents, and agent's adaptability.

1. Individual ABMS: The model is composed of a population of agents who have diverse set characteristics. At this level, the agent behaviours are exogenously provided and not based on endogenous events during the simulation. The interaction among agents is limited and the agent have no capability for adaptation.
2. Autonomous ABMS: The model is composed of a population of agents who have diverse set characteristics. However, at this level the agents have autonomy. They can make independent decisions based on the state of the system at any time and to act without external guidance or prescription. The interaction among agents is limited and the agents have no capability for adaptation.
3. Interactive ABMS: In terms of individuality and agents' behaviours, autonomous and interactive ABMS are similar. However, at this level an agent has the capability to interact with other agents and the environment. For example, agents can diffuse information or spread infection through contact with other agents. Nevertheless, the agents cannot change their behaviours throughout the simulation (no adaptation).
4. Adaptive ABMS: In addition to the individuality, autonomy and interactions that are mentioned in the interactive ABMS, the agents in adaptive ABMS can adapt. They can change their behaviour by learning from their previous actions or other agents in the population.

Taking this categorisation into account, ABMS is an approach that fits the purpose of our overall project, because the system we are studying involves interactions between heterogeneous agents, who make their decisions autonomously and can adapt to the scenario. Indeed, we have mentioned that many simplifications are made at this phase of the project. However, the model we propose in this paper can still be considered as an

ABMS, at least between individual and autonomous levels. This is because it still involves heterogeneous agents, some of whom can make their decision autonomously while the others are driven by the data. Indeed, applying ABMS starting from the beginning of this project will ease us to incorporate the self-organising nature of the logistic systems later on.

### *3.2. Base ABMS description and validation*

The case study in this research is in Manchester, UK. Here, we justify the choice of test city by showing the similarity of its demographic to other cities in Great Britain. The Office for National Statistics (ONS) has classified each output area (OA) of around 100-200 households in Great Britain, based on the social classification of their residents (ONS, 2011). Figure 2 compares the distribution of each social classification between average cities in Great Britain and Manchester. We run a Wilcoxon sign rank test to decide whether the difference in social class proportion between the average city in Great Britain and Manchester is zero. The test result suggests retaining the null hypothesis with asymptotic 2 tailed value of 0.83 at 95% confidence interval. Assuming that social class has some influence on shopping patterns, we can judge that Manchester is a sufficiently representative sample of a city in Great Britain.

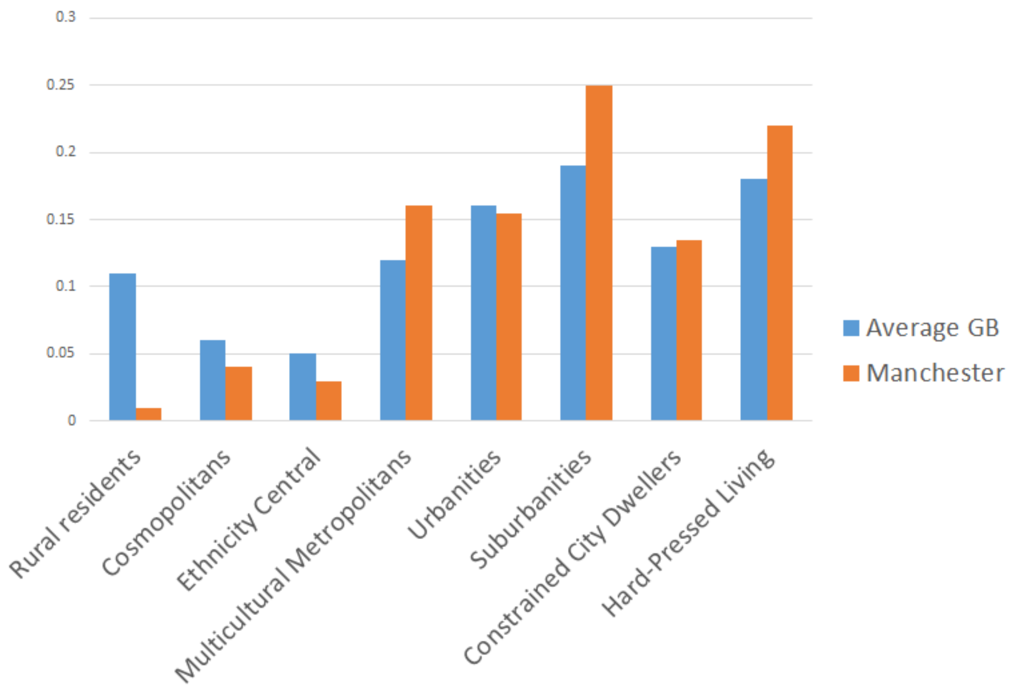


Figure 2 social class distribution of average city in Great Britain and Manchester

We based our ABMS upon a set of real data for home grocery deliveries provided by a home delivery supplier in Manchester, referred to hereafter as the *target retailer*. Based on Mintel (2016), we can consider the *target retailer* as a mid-tier home grocery delivery supplier in the UK in term of the size of operation. Because it is not significantly bigger or smaller than other grocery delivery operators, many other operators might run similar operations to the *target retailer*.

The dataset was recorded for 373 days between June 2018 and July 2019. This data set comprises several pieces of information including:

- The geographical distribution of the target retailer's customers;
- The order frequency and the quantity ordered by each customer;
- The distribution of delivery time windows selected by the target retailer's customers;
- The location of the target retailer's stores;
- The total number of vehicles operated by the target retailer;

- The number of journeys of each vehicle and the drop density in each journey.

Figure 3 provides a general overview of our ABMS.

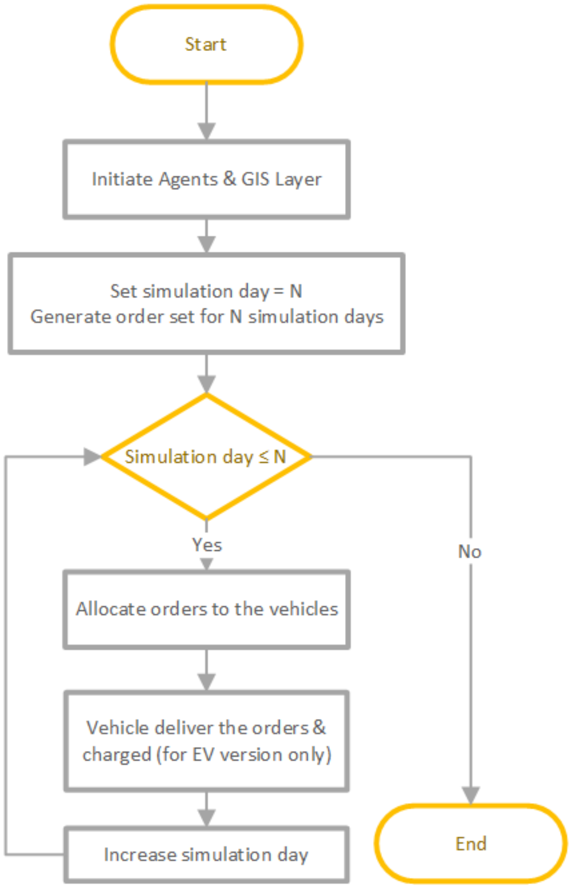


Figure 3 General overview of the ABMS model

Our ABMS begins by defining the agents and the environment. There are three types of agents in our ABMS: the retailer agent (1 agent), the store agents (5 agents, each representing stores in the Manchester area) and the vehicle agents (17 agents). To set up the simulation in AnyLogic®, we added the agent locations to a GIS layer obtained from OpenStreetMap (Open Street Map, 2019). We used a road network data provided online by Geofabrik GmbH (Geofabrik, 2019) from OpenStreetMap data. This road network data provides inter-point distances and the topology.

The second step is to set the simulation length and generate the order set that will be used throughout the simulation. Indeed, the empirical data regarding the number of order per day is available, but we do not want our analysis to be constrained to the empirical distribution in the dataset. Hence, we generalised the number of daily order distribution to one of the standard statistical distributions by using StatFit software. Using the result from this analysis, the number of orders that must be delivered on each simulation day is generated randomly using a normal distribution with parameters ($\mu_{order}$ = 113.3; $\sigma_{order} = 36.65$) and rounding to the nearest whole number. In this process we neglect seasonal and weekend patterns where the number of orders might be higher than usual.

Each of these orders is then assigned to a random customer based on the dataset's empirical distribution of each customer's order frequency. The delivery time window for the selected customer is then determined using the empirical distribution of time windows in the dataset (Table 1). The empirical distribution is used because the delivery time window distribution does not fit with any standard statistical distribution.

Table 1 Empirical distribution of the delivery time window

| No | Time window | Probability |
|---|---|---|
| 1 | 7 – 8 | 0.8% |
| 2 | 8 – 9 | 0.3% |
| 3 | 9 – 10 | 18.1% |
| 4 | 10 – 11 | 4.8% |
| 5 | 11 – 12 | 6.5% |
| 6 | 12 – 13 | 16.7% |
| 7 | 13 – 14 | 10.5% |
| 8 | 14 – 15 | 3.3% |

| No | Time window | Probability |
|---|---|---|
| 9 | 15 – 16 | 6.2% |
| 10 | 16 – 17 | 4.8% |
| 11 | 17 – 18 | 6.0% |
| 12 | 18 – 19 | 6.1% |
| 13 | 19 – 20 | 4.6% |
| 14 | 20 – 21 | 7.2% |
| 15 | 21 - 22 | 4.1% |

Each order can consist of ambient, chilled and frozen products. The correlations between the number of crates of each product are considerably low, hence we assume that they are independent. Similar to the number of orders per day, we use StatFit software to generalise the empirical distribution in our dataset. For each order, the quantity (crates) of each product category is determined by sampling a normal distribution and rounding to the nearest whole number, using the following parameters:

- Crates of ambient products ($\mu = 3.04$; $\sigma = 0.69$)
- Crates of chilled products ($\mu = 1.15$; $\sigma = 0.26$)
- Crates of frozen products ($\mu = 0.63$; $\sigma = 0.33$)

For each order, the retailer agent selects one of its stores to serve it based on the proximity between the store agent and the customer's location (Delaney-Klinger et al., 2003). When calculating the proximity, we did not rely on straight line distance, instead we consider the route topology in the OpenStreetMap road network dataset downloaded from GeoFabrik, using Dijkstra's Shortest Path algorithm (Cherkassky et al., 1996; Dijkstra, 1959) to perform wayfinding between each pair of points. We note that, using this algorithm, 88% of the time the retailer agent selects the same closest store as the target retailer did as shown in the data. Dijkstra's Shortest Path algorithm outperformed A* algorithm (another built-in algorithm in AnyLogic®) that can only predict the correct store 79% of the time. This level of accuracy shows that the validity of this process is sufficiently high, however it also indicates that the target retailer considers factors other than distance when selecting which stores should serve which orders.

The third step of the process is to allocate the generated orders into several vehicle journeys. This process is done iteratively on each simulation day. In the real world, this process is carried out using commercial software. We do not know how this commercial software works due to business confidentiality. However, our research only aims at establishing a system that strongly resembles the target retailer's operations and not to propose a more efficient routing algorithm. We also acknowledge that there are analytical approaches to routing (for example Cortés-Murcia et al. (2019); Murakami (2017)). However, the number of customers in our model is too large (more than 10,000 instances over 100 simulation days) to be solved using analytical approaches within a reasonable time. Hence in our ABMS, we rely on heuristics to obtain feasible solutions. Our heuristic is a modification of Nearest Neighbour heuristics, as explained by for example by Balakrishnan (1993). The main difference of our heuristic to the standard Nearest Neighbour heuristics is that we also try to accommodate the punctuality of the delivery. For instance, it might be preferable to send a vehicle that is further away from the customer's location but can deliver the orders on time, than to send the closest vehicle to the customer but will violate the delivery time window. In the later part of this section, we will explain a scoring system to calculate the combined payoff of these two factors. Figure 4 describes the algorithm we adopt to allocate the customer's orders to vehicle journeys, as executed by each store agent.

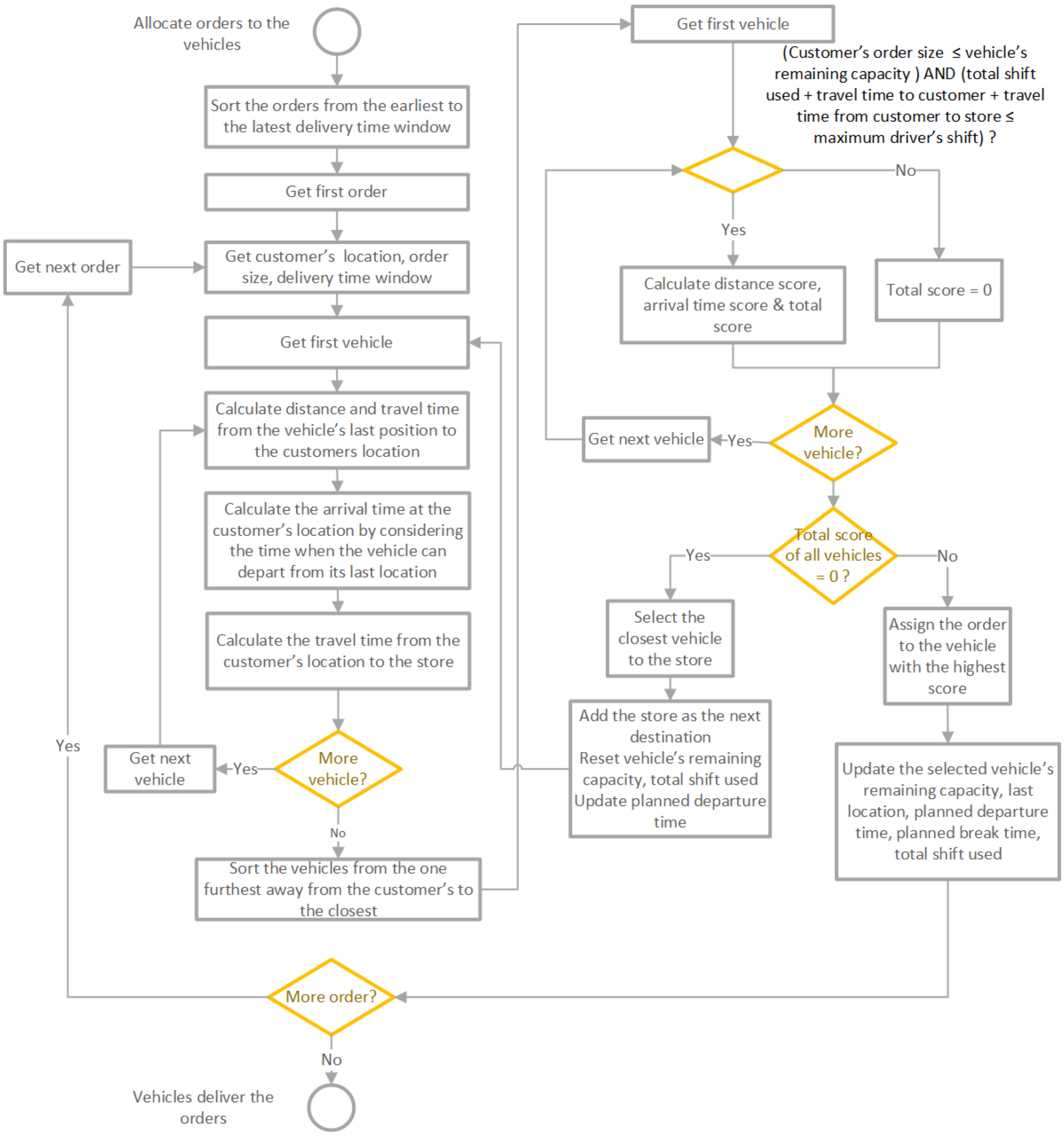


Figure 4 Algorithm to allocate the orders to the vehicles

In this heuristic we start by sorting the customers' orders based on their delivery time windows, starting from the earliest to the latest. The order allocation starts from the customer with the earliest delivery time window.

We then calculate the distance from each vehicle's last location to the customer's location. The vehicle's last location can be either the vehicle's home store, or the customer location previously served by the vehicle. We also calculate the distance between the customer's location and the vehicle's store, in order to account for the vehicle returning to its home store after potentially serving this order. The travel times for these journey legs are also calculated. In calculating the travel time, we assume that all vehicles move at the same constant speed. The data obtained from UK Department for Transport shows that the average vehicle speed around the Manchester area is 19.0 mph (30.5 km/h; 8.5 m/s) (Department for Transport statistics, 2017).

The next step in the heuristic is to filter the vehicles that are unable to deliver the customer's order. The following criteria are used in this filtering process:

- Vehicle capacity: According to a source from the target retailer, each vehicle can carry up to 72 ambient crates and 36 chilled and frozen crates. Hence, if the remaining capacity of a vehicle is lower than the number of crates (either ambient, chilled or frozen) ordered by the customer then the vehicle will be ineligible.
- Total journey time: The duration of a vehicle's journey is constrained by the driver's shift. The typical driver's working shift at the target retailer is 8 hours. Therefore, a vehicle will be ineligible if the additional working time to serve the customer under consideration and returning to its store means the driver's total shift exceeds 8 hours.
- For simulations involving electric vans, additional range constraints based on the battery are also implemented at this stage; these will be explained in a later section.

The total score for each vehicle is then calculated. A total score of zero is assigned to ineligible vehicles. The total score of all eligible vehicles is obtained by adding score from two factors:

- Punctuality: We consider whether the vehicle can arrive within the customer's delivery time window. The arrival time is obtained by adding the time required to reach the customer's location, to the planned departure time of the vehicle from its last location. A vehicle gets a score of 100 if it can arrive within the customer's delivery time window and gets a smaller score if it arrives too late or too early. A vehicle's punctuality score is set to zero if it arrives too late or too early by 1 hour, with a tapered linear score for violations of under an hour. The earliest possible departure time for a vehicle from the store to serve its first customer is 6 AM (the planned departure time variable = 6 AM). However, the planned departure time from the store can be relaxed as long as the vehicle can arrive before the customer's delivery time window starts. For instance, the delivery time window for the first customer that should be served by a vehicle starts at 8 AM, and it takes 30 minutes to travel from the store to the customer's location. Hence, instead of 6 AM the vehicle can set off from the store at 7.30 AM.

- Distance: The distance from the vehicle's last location to the customer's location. This is assigned relative to the distance of other vehicles to the customer's location. The closest vehicle to the customer's location gets a score of 100 while the furthest vehicle gets a score of 0, with a tapered linear score for all other eligible vehicles.

The order is then incorporated to the destination list of the vehicle with the highest total score. The remaining capacity of the selected vehicle is then reduced by the quantity ordered by the customer. The vehicle can leave the customer's location after unloading the order, which is assumed within the simulation to take 7 minutes of the vehicle's time, and if necessary, the driver takes a break, modelled as per health and safety regulations which require a 15-minute break every 2 hours (Driver & Vehicle Standard Agency, 2014). If the score of all vehicles is zero, then the closest vehicle to the store is asked to return. 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 simulation we assume that there is no interaction between vehicles and traffic conditions. Hence the vehicle will always arrive at each destination as planned.

For validation, we ran our base model for 100 simulation days and replicate the experiment five times due to constraints on computational power. However, this number still meets the minimum number of replications in a simulation study, namely three or five, as suggested by Law and McComas (1991). In addition, we evaluated whether the number of replications we use is sufficient using simple graphical method proposed by Robinson (1994). Following Hoad et al. (2010), we plot the cumulative average of number of routes per day, miles per route, travel time per route and percentage of timely delivery (punctuality) against the number of replications. Figure 5 demonstrates that on the fifth replication the cumulative average of these four parameters are converging to a single value.

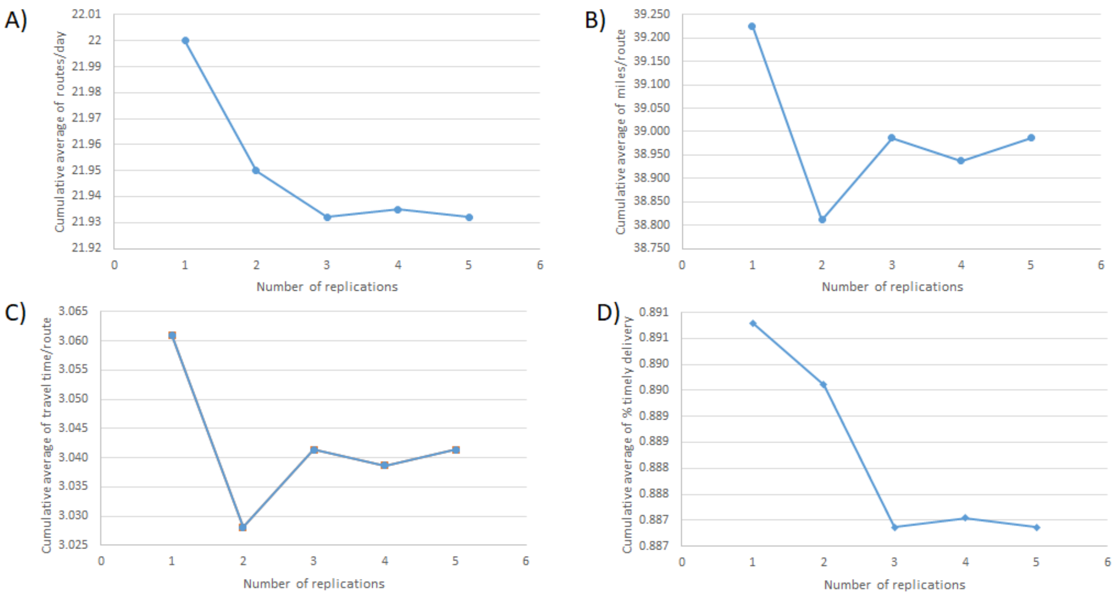


Figure 5 cumulative average of A) number of route per day; B) miles per route; C) travel time per route and D) percentage of timely delivery (punctuality)

With this small number of replications, the statistical power to carry out a hypothesis testing will be very low. Hence, we rely on analysing the error of the simulation output from the real data, as an alternative to measure the simulation validity (Balci, 1989). Following this approach, we measure the percentage error of the simulation outputs in each replication to the real data ($Error_i = \frac{\left(X_i^{simulation} - X^{real}\right)}{X^{real}}$). Table 2 shows the comparison between our simulation's outputs to the real data along with the mean percentage error of each parameter ($\overline{\%Error} = \frac{\sum Error_i}{5}$).

Table 2 Comparison between the base model outputs to the real data.

| Variable | $\bar{X}_{Sim}$ | $S_{Sim}$ | Real Data | $\lvert\overline{\%Error}\rvert$ |
|---|---|---|---|---|
| Average number of route / day | 21.93 | 0.063 | 17.8 | 23.2 % |
| Average order / route | 5.25 | 0.048 | 6.35 | 17.1 % |
| Average travel time / route (hours) | 3.04 | 0.029 | 3.52 | 13.5 % |
| Average distance / route (mile) | 38.98 | 0.382 | 48.02 | 18.8 % |
| Average number of order / day (customers) | 115.33 | 1.234 | 113.30 | 1.7 % |
| Average ambient crate / order (crates) | 2.89 | 0.010 | 3.04 | 4.9 % |
| Average chilled crate / order (crates) | 1.06 | 0.004 | 1.15 | 7.3 % |
| Average frozen crate / order (crate) | 0.84 | 0.009 | 0.63 | 32.3 % |
| % Timely delivery (%) | 88.8 | 0.44 | 0.96 | 7.6% |

In Table 2, the column labelled with $\bar{X}_{Sim}$ presents the average value of output parameters from 5 replications, while the standard deviation is presented in column $S_{Sim}$. For all output parameters, the standard deviation values from 5 replications are quite low which indicates a high internal validity due to the low stochastic variability in the model (Balci, 1989; Sargent, 1996). Table 2 also shows that in absolute terms the percentage error of most variables is below 20%, except for the average number of routes per day and the average frozen crates per order. Hence, descriptively we can judge that the retailer agent in the simulation carries out similar daily operations to the target retailer. Therefore, there can be a reasonable expectation that an intervention introduced to the retailer agents, such as incorporation of EVs, will influence the target retailer in a similar manner.

### *3.3. Incorporating electric LGV into ABMS*

Compared to its diesel counterpart, an EV has limited range and the time required to charge its battery pack is quite substantial. In addition, to maintain battery lifetime, it will typically not be fully utilised; best practice is to ensure the remaining power in a battery pack never falls below 20% of its capacity. We added several attributes to vehicle agents in our ABMS to capture these constraints, namely:

- Battery capacity (bc) (kWh): Power that can be stored in the vehicle's battery.
- Motive power consumption (mpc) (kWh/km): The amount of power consumed on each kilometre travelled by the vehicle.
- Refrigeration unit power consumption (rfc) (W): The amount of power consumed by the vehicle's refrigeration unit per hour.

We also introduce a new attribute to the store agent namely charger power (kW). This attribute represents the amount of power that can be added to the vehicle's battery when it is charged.

Figure 6 describes the modifications that are necessary to incorporate these attributes.

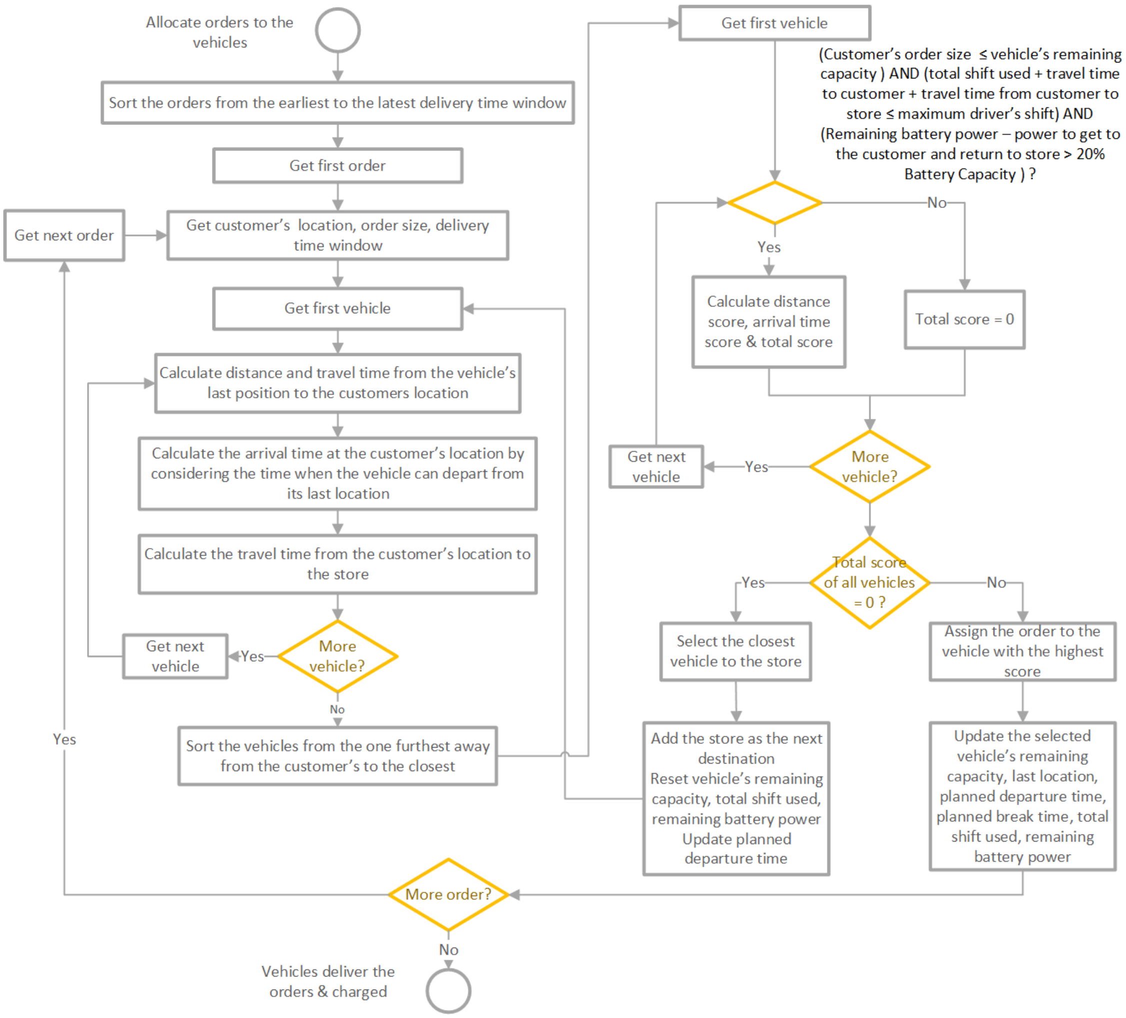


Figure 6 Algorithm to allocate the orders to the electric vehicles

The first modification is made when we are filtering the vehicles that are eligible to deliver the customer's orders. In addition to the vehicle's capacity and the driver's shift, to be eligible the remaining power in the vehicle's battery must be more than 20% if it serves the customer and return to the store.

The second modification is when the vehicle with the highest score is serving a customer. In addition to updating its remaining capacity, planned departure and the remaining driver's shift, the remaining power left in its battery is also calculated. This is done by using equation 1.

$$RB_{t+1} = RB_t - (d \times mpc) - \big((tt + wt + ut + bt) \times rfc\big) \qquad (1)$$

In equation 1 $RB_{t+1}$ denotes the remaining power in the vehicle's battery after serving the customer, while $RB_t$ denotes the battery state before the vehicle departs from its previous location. *d* represents the travel distance from the vehicle's previous location to the customer's location and *mpc* represents the motive power consumption. *tt, wt, ut, bt*, and *rfc* denote the travel time, waiting time (if the vehicle arrives too early), unloading time (7 minutes), break time and refrigeration power consumption respectively.

As with the diesel version, when the score of all vehicles is zero, then the closest vehicle to the store is asked to return. However, in the EV version, the vehicle should also be charged before it sets off to serve the customer. The time spent to charge the vehicle's battery will influence how long it should stay at the store and eventually its planned departure time. To calculate how long the vehicle should be charged, first we calculate the minimum power required to serve the customer from the store using equation 2.

$$PR = (2d \times mpc) + \big((2tt + wt + ut + bt) \times rfc\big) \qquad (2)$$

In equation 2 we double the distance (*d*) and travel time (*tt*) from the store to the customer's location, using the assumption that the vehicle should at least be able to serve one customer. Another factor that influences how long the vehicle should be charged is the mid-day (opportunistic) charging target strategy. This represents the target retailer's policy regarding the minimum power a vehicle should have before it departs from the store (e.g., a mid-day charging target of 60% means that a vehicle should at least set off with 60% of its battery capacity). The time required to charge the vehicle at the store is then calculated using equation 3. In this equation *ct* and *cp* denote charging time and charge power respectively.

$$ct = \begin{cases} \dfrac{PR}{cp} & if \quad PR > target - 0.2bc \\ \dfrac{target - RB_t}{cp} & if \quad PR \leq \ target - 0.2bc \end{cases} \tag{3}$$

The last modification is made after all vehicles complete their journey and return to the store. Upon their arrival, all vehicles are charged until their batteries are full. We assume that the number of chargers available at the store is equal to the number of vehicles. The time required to fully charge the vehicle at night influences when they can depart from the store in the next day. We use equation 4 to determine this.

$$ct = \frac{bc - RB_t}{cp} \tag{4}$$

The time interval of *ct* is then added to the vehicle's arrival time at the store to obtain the time when the overnight charging is completed. On the subsequent day, the model set the vehicle's departure time from the store by taking the biggest value, considering the typical vehicle's departure time, departure time relaxation due to the first customer's delivery time window and the time when the vehicle charging is finish.

For instance, a vehicle returns to the store at 8 PM on the first day, and the *ct* of the overnight charging is 5 hours. Hence, the overnight charging will finish at 1 AM on the second day. As we mentioned in section 3.2 a vehicle is typically sets of from the store at 6 AM. However, on the second day, the delivery time window of the first customer who is assigned to the vehicle starts at 10 AM, and the travel time to this customer it only 30. Therefore, the particular vehicle will depart from the store at 9.30 AM on the second day instead of 1 AM or 6 AM.

### *3.4. Experimentation*

In this section we explore how the *target retailer* should operate the electric LGV by running experiments using our ABMS. It is assumed that the *target retailer* replaces all its vans with EVs. We assume that each van has a battery pack capacity of 56 kWh, power consumption of 0.29 kWh/km and refrigeration unit power consumption of 500W.

Two operational decisions are evaluated through these experiments. First is the *target retailer's* charger power. EV chargers in the market can be classified into two types, i.e., slow chargers (3 kW, 7 kW, 22 kW) and rapid chargers ( > 50 kW) (Pod Point, 2020). IEA (2019) reported that up to 2018, 98.4% of the chargers that have been deployed are slow chargers. One common perception is that to be able to adopt electric LGV in a commercial operation, the operators should wait until rapid chargers become more available and with a more affordable price. In this study we attempt to show that by using the slow chargers that are more available nowadays, we can still replace diesel vans with electric LGVs, provided the correct operational strategy is followed. Therefore, we use three charger power scenarios *i.e.,* 3kW, 7kW and 22kW in this experiment.

The second operational decision is how the *target retailer* should charge the EVs. In the first scenario the *target retailer* solely relies on overnight charging. The EVs are only charged after all orders have been served until their battery is full. The EVs can be charged in the middle of the day if there are still orders to be served, but the remaining power stored in the battery is not enough to serve them. In the second scenario the EVs are charged up to 60% of their battery capacity if they return to the store in the middle of the day while there are still orders that must be delivered. Finally, in the third scenario the EVs are charged up to 80% in the middle of the day. In all three scenarios, if the charging plan cannot fulfil the next order (for example, to serve the next order and return to store, the van requires more than 80% battery capacity) then the van will be charged until at least it can take one more order. If this happens then the charging plan will have failed.

Table 3 Combinations of operational decisions evaluated in the ABMS experiments

| Scenario | Charger Power | Mid-day charging | Overnight Charging |
|---|---|---|---|
| 1 | 3 | 20% (No charging) | Full or until 9 AM the next day |
| 2 | 3 | 60% | Full or until 9 AM the next day |
| 3 | 3 | 80% | Full or until 9 AM the next day |
| 4 | 7 | 20% (No charging) | Full or until 9 AM the next day |
| 5 | 7 | 60% | Full or until 9 AM the next day |
| 6 | 7 | 80% | Full or until 9 AM the next day |
| 7 | 22 | 20% (No charging) | Full or until 9 AM the next day |
| 8 | 22 | 60% | Full or until 9 AM the next day |
| 9 | 22 | 80% | Full or until 9 AM the next day |

In every scenario the ABMS is run for 100 simulated days and each scenario is replicated five times. The random seed in each replication is controlled, this ensures that all scenarios within a replication use the same order set. We present and discuss the experiment results in the subsequent section.

## 4. Results and Discussion

The focus of our analysis is the punctuality, or percentage of timely delivery (%TD). The delivery punctuality is important for a retailer because it reflects the retailer's service level. In our simulation a delivery is late if the van arrives after the end of the customer's delivery time window.

Table 2 and Figure 8 show that even if the retailer agent uses diesel fleet some of the deliveries arrived late (about 11% on average). The real dataset also shows that 4% of deliveries by the *target retailer* using their diesel fleet were planned to arrive after the delivery time window closed. Indeed, the percentage of late deliveries produced by our simulations is higher. This is because the algorithm in our ABMS only aims at obtaining feasible solutions for payload and route allocation. Nevertheless, as shown in Table 2 the difference between the real dataset and the simulation outputs is acceptably small (7.2% on average).

In this section we evaluate whether there is an EV scenario that can match the punctuality of the delivery using a diesel fleet. Since we control the random seed, each replication in a scenario will correspond with the same replication in the other scenarios. For instance, the first replication in the diesel scenario uses the same order set with the first replication of scenario 1 in Table 3. This allows us to treat the simulation output from different scenarios as related samples. Unfortunately, the distribution of the difference between the punctuality of diesel scenario and those of the EV scenarios ($\%TD_{diesel} - \%TD_{EV}$) do not always follow the normal distribution, and are not always symmetrical. For example, Figure 7 shows the distribution obtained from scenario 4, scenario 8 and scenario 9 that demonstrate the most severe deviation from normality.

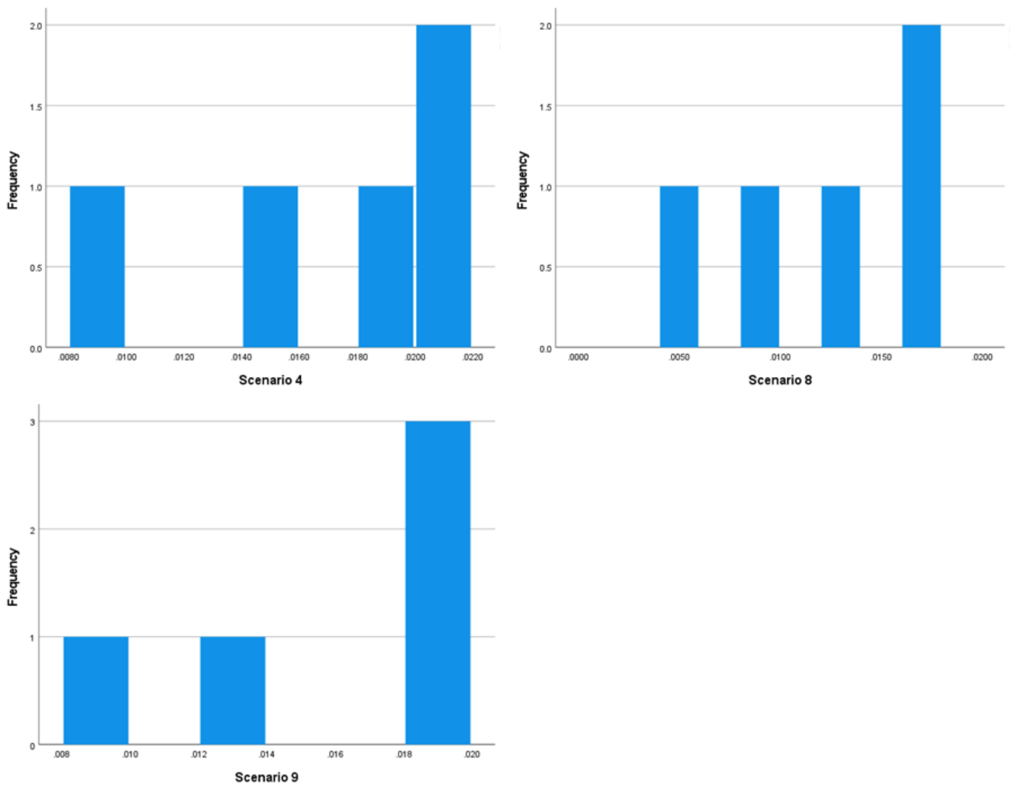


Figure 7 the distribution of the difference between the punctuality of diesel scenario and EV scenarios ($\%TD_{diesel} - \%TD_{EV}$)

The skewness of the output distribution prohibits us from using parametric tests e.g., t-test. Hence, we use a non-parametric test i.e., the Wilcoxon signed rank test, to infer whether the punctuality of diesel and EV scenarios are equal without the need to make a normality assumption. The null hypothesis in this test is "$H_0$: *The difference between the pairs is distributed symmetrically around zero*". If the null hypothesis is accepted then the punctuality of the delivery from both diesel and electric LGV are equal, and vice versa. Table 4 shows that at 95% confidence interval there is no EV scenario that can match the punctuality of diesel fleet's delivery (the 2-tailed asymptotic significance of all EV scenarios is below 5%).

Table 4 Wilcoxon signed rank test results to compare the percentage of timely delivery between diesel scenarios and various EV scenarios

| Charger Power | Mid-day charging | Asymptotic significance (2-sided test) | Conclusion |
|---|---|---|---|
| 3 | 0.2 | 0.043 | Reject the null hypothesis |
| 3 | 0.6 | 0.043 | Reject the null hypothesis |
| 3 | 0.8 | 0.043 | Reject the null hypothesis |
| 7 | 0.2 | 0.043 | Reject the null hypothesis |
| 7 | 0.6 | 0.043 | Reject the null hypothesis |
| 7 | 0.8 | 0.043 | Reject the null hypothesis |
| 22 | 0.2 | 0.043 | Reject the null hypothesis |
| 22 | 0.6 | 0.043 | Reject the null hypothesis |
| 22 | 0.8 | 0.043 | Reject the null hypothesis |

In addition to the statistical test results, it is also important to observe how the delivery punctuality changes depends on the charging power and the mid-day charging scenarios. The first pattern that can be observed in Figure 8 is that, using the same charger power, the delivery punctuality decreases as the mid-day charging target increases. This makes sense because with higher mid-day charging targets, the time spent to charge a vehicle before dispatch is longer.

The second observation is, under the same mid-day charging strategy, the delivery punctuality will increase if we use a more powerful charger. This is consistent with the finding in our preliminary study (Utomo et al., 2019). Of particular note is that when we replace the 3kW charger with a 7kW charger, the delivery punctuality increases significantly (about 7% on average). However, if charger power is further increased to 22kW then the delivery punctuality only increased by about 1% compared to the 7 kW option. This means that, given current order numbers and the spatial distribution of the customers, the use of 22kW chargers does not produce significant time savings when compared to 7kW chargers. Additionally, we can observe that the intersection between the areas representing the output of simulations using 7 kW and 22 kW charger power scenarios is quite big when the mid-day charging target is set between 20% and 60%. This indicates that under these mid-day charging strategies the performance of the delivery is almost equal.

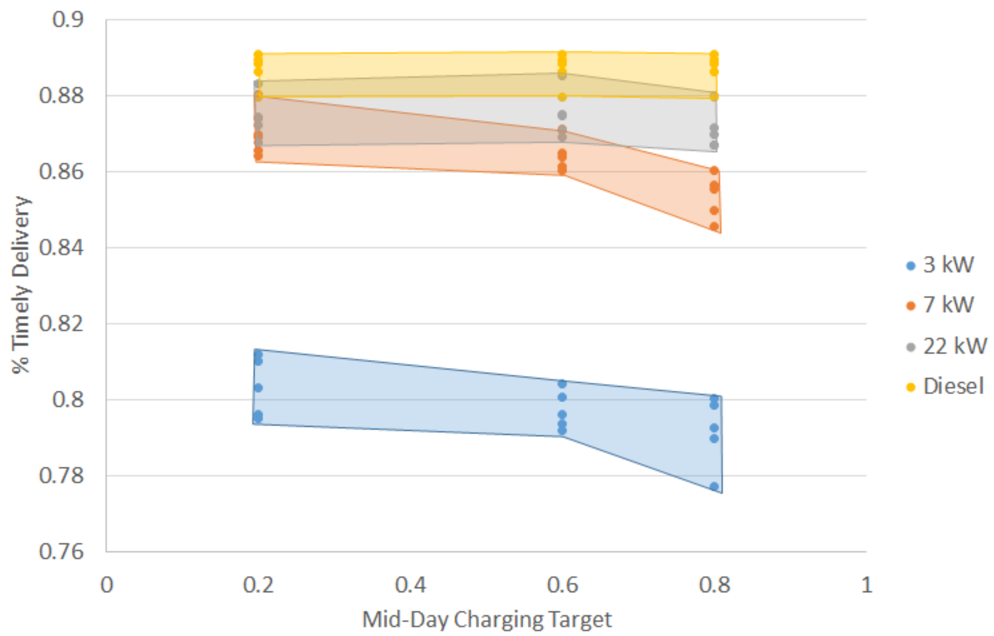


Figure 8 Relationship between the delivery punctuality and the mid-day charging target

The third observation is that under the same charging strategy, the variance of the delivery punctuality is much higher when the target retailer uses 3kW chargers. This indicates a higher uncertainty when we use a 3kW charger, which may be associated with the amount of charge that can be added to the battery when EVs are charged during the night.

To investigate this further we evaluate the average load from all stores under a variety of charger powers. Figure 9 shows the time of the day as the horizontal axis and the average load at the store as the vertical axis. Vertical axis value of zero indicates that all vehicles are fully charged at that particular time (as we have explained in section 3.2 and 3.3 this does not reflect when the vehicle can depart on the subsequent day). According to Figure 9, if the target retailer uses 22kW chargers then most of the vehicles will be fully charged after midnight, while if 7kW chargers are used then typically the charging process will be finished after 5 AM. Hence under both scenarios it is almost certain that the target retailer can serve the morning orders punctually, because the entire fleet can be used. In contrast, the charging process is spread fairly evenly throughout the day when 3 kW chargers are used. This may be a sign that the target retailer cannot use its entire fleet even to serve the morning orders.

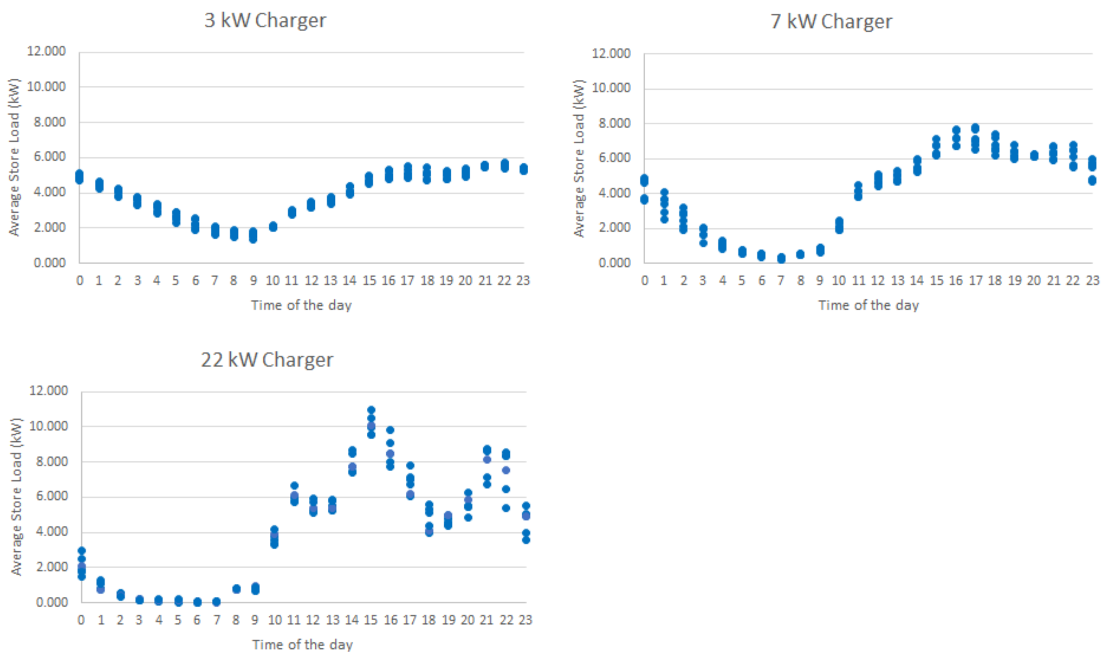


Figure 9 the average load from all stores during 100 days of simulation

The three patterns show that, in terms of delivery punctuality, there is a good chance that the benefits of using a 7 kW and 22 kW are roughly equal. This is important because installation of a set of 22 kW chargers is more likely to require electricity infrastructure to be reinforced, requiring the building of an expensive substation, the capital costs of which would be borne by the retailer.

Finally we investigate the robustness of each charging strategy. This analysis aims to answer whether the vehicles should always be fully charged to ensure that they can deliver the customers' orders and return to the store. Figure 10 shows the average success rate of each charging strategy, regardless the power of the charger being used.

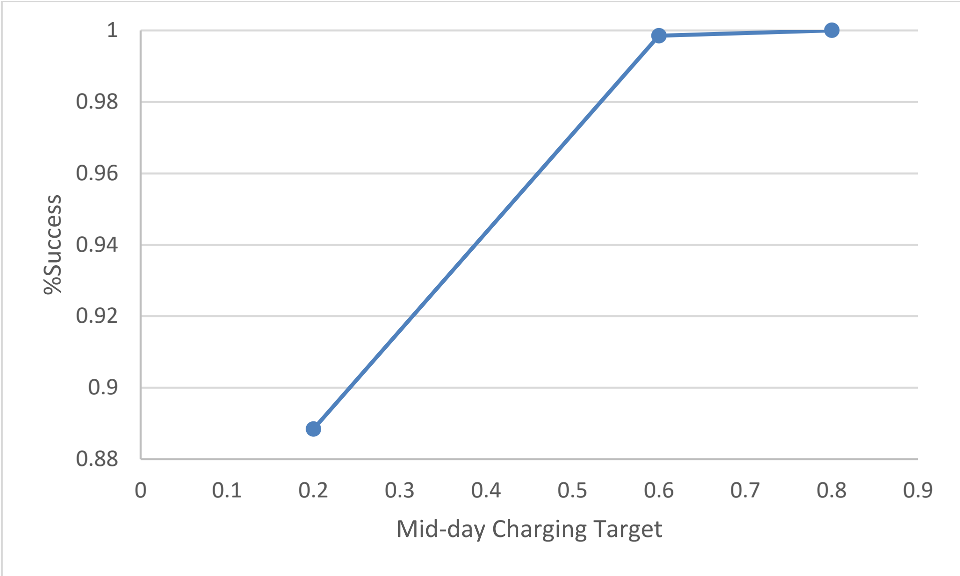


Figure 10 robustness of each charging strategy

Figure 10 shows that setting a target to charge the vehicle's battery up to 60% of its capacity is sufficient to ensure that customer orders can be delivered and the vehicle can return to the store 99.8% of the time. Therefore, for the target retailer it seems unnecessary to charge the battery beyond this threshold and sacrifice the punctuality of the delivery. This notwithstanding, the ideal threshold value will depend upon the quantity of orders and the geographical distribution of the customers.

We acknowledge that a smart charging system that is integrated with the payload allocation and routing system might be available in the near future. Such a system can estimate the amount of energy required and, if necessary, estimate how long a vehicle should be charged in the middle of the day. However, implementing such a system requires additional investment. The analysis as we present here can serve as a rule of thumb for operators to substitute smart charging systems during the early adoption of electric LGV. This will help reduce initial investment and barriers to adoption of electric LGV.

We have mentioned in section 3.2 that Manchester is a representative sample of typical cities in Great Britain, and that many other operators might run similar operation as the target retailer. Therefore, our proposal are also applicable to the other operators in Great Britain, especially those whose operation is bigger than the target retailer. This is because bigger operator tends to own more stores and hence virtually decrease the catchment area of each store. Because of this, the drop density of the vehicles tends to be higher and conversely the total miles per route tend to decrease. Therefore, it is very likely that the energy demand when a bigger operator charges their vehicle is much lower than the target operator's.

## 5. Conclusions and Further Research

### *5.1. Conclusions*

In this study we have proposed an agent-based model simulation (ABMS) of grocery delivery in urban settings using empirical data. We have modelled electric vehicles (EV) in our ABMS and analysed the delivery performance under a variety of operational decision scenarios (charger power and charging strategy). Our analysis focuses on the punctuality of the delivery, which is an important measure for a retail operator.

Our analysis shows that the punctuality of the delivery is strongly influenced by the charger power and how long vehicles are charged. Firstly, regardless of charger power, using the same fleet size it is unlikely that a fleet of electric LGV can match the punctuality of a diesel fleet. This is because of the time required to charge the vehicles.

Secondly, in principle an operator can increase the punctuality of the delivery by using more powerful chargers. However, the relationship between the charger power and punctuality is nonlinear, and it is influenced by the quantity of orders and the geographical distribution of customers. In our case study, the benefits from increasing the charger power from 7 kW to 22 kW is marginal when compared to increasing the charger power from 3 kW to 7 kW. This means that it is not necessary for the target retailer in our case study to use 22 kW chargers and making significant infrastructure investments to adopt electric LGV.

Thirdly, it is very unlikely that an operator can solely rely on overnight charging. The vehicles should be charged when they return to the store in the middle of the day while there are still orders to be delivered. However, it is unnecessary to fully charge these vehicles, because this might decrease the punctuality of the next delivery. For the target retailer in our case study, charging the vehicles up to 60% of their battery capacity is sufficient to ensure that the next customers can be served, and the vehicles can return to the store without violating the battery constraints.

The model and analysis presented in this paper can serve as a guidance for the operators to determine the necessary investment (e.g., fleet size and charger power) and the rules of thumb that they should bear in mind when adopting electric LGV.

### *5.2. Further research*

We continue to develop our ABMS so that it can become a robust and comprehensive decision support tool. There are several extensions we are implementing both with the model and the research methodology.

Firstly, this paper assumes that the customers' behaviour in making orders is fixed and always follows the pattern in the dataset. In reality, customers' behaviour may change due to changes in the retailer's service level. Customer churn to and from other retailers is also possible in reality. To understand how the customers' decision making might change, data related to their behaviour are required. Techniques to collect human behavioural data to develop ABMS, for example scenario-based questionnaires, vignette experiments, laboratory experiments or interviews (see for example An (2012); Utomo et al. (2020)), are in continuous development and might be useful in future study. In addition, we are also developing a Bayesian approach to understand the relationship between customers' demographic and how they make orders (e.g., to which supermarket, the order quantity, the order frequency).

Secondly, this paper assumes that there is no interaction between the vehicles and the traffic conditions, hence they can travel at constant speed. Currently we are also incorporating congestion models into our ABMS. These congestion models allow the vehicle agents to travel at different speeds depending on the time of day. Moreover, the vehicle's speed might have significant impacts on its energy consumption. In our future research we will also incorporate an energy consumption model in our ABMS, so that the energy consumption of a vehicle will vary depend on its speed, payload and the road gradient.

Thirdly, we are seeking to increase the models' complexity and analyse the benefits from a variety of new innovations. These innovations include combination of different transportation modes (e.g., between vans and bicycles), the use of shared charging hubs by multiple operators, autonomous vehicles, etc. Our objective is to find the least cost options for decarbonisation through the adoption of electric vehicles. However, as the complexity of the model increases, the time required to run the experiment will increase. We are tackling this problem by firstly developing an experimental design framework to explore solution spaces in logistics ABMS. In addition, we are establishing a specialised modelling environment for logistics ABMS, which we hope in future to be able to stream operation data from fleet operators in real time.

## References


An, L., 2012. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling* 229, 25-36.

Arias-Londoño, A., Montoya, O.D., Grisales-Noreña, L.F., 2020. A Chronological Literature Review of Electric Vehicle Interactions with Power Distribution Systems. *Energies* 13(11), 3016.

Balakrishnan, N., 1993. Simple heuristics for the vehicle routeing problem with soft time windows. *Journal of the Operational Research Society* 44(3), 279-287.

Balci, O., 1989. How to assess the acceptability and credibility of simulation results, *Proceedings of the 21st conference on Winter simulation*, pp. 62-71.

BEIS, 2020. 2018 UK Greenhouse Gas Emissions, In: Department for Business Energy & Industrial Strategy (Ed.), *Final UK greenhouse gas emissions national statistics: 1990 to 2018*, 4 February 2020 ed.

Brown, M., 2013. Catching the PHEVer: simulating electric vehicle diffusion with an agent-based mixed logit model of vehicle choice. *Journal of Artificial Societies and Social Simulation* 16(2), 5.

Cherkassky, B.V., Goldberg, A.V., Radzik, T., 1996. Shortest paths algorithms: Theory and experimental evaluation. *Mathematical programming* 73(2), 129-174.

Cortés-Murcia, D.L., Prodhon, C., Murat Afsar, H., 2019. The electric vehicle routing problem with time windows, partial recharges and satellite customers. *Transportation Research Part E: Logistics and Transportation Review* 130, 184-206.

Crainic, T.G., Perboli, G., Rosano, M., 2018. Simulation of intermodal freight transportation systems: a taxonomy. *European Journal of Operational Research* 270(2), 401-418.

Delaney-Klinger, K., Boyer, K.K., Frohlich, M., 2003. The return of online grocery shopping: a comparative analysis of Webvan and Tesco's operational methods. *The TQM Magazine*.

Department for Transport statistics, 2017. DfT Travel Time Data.

DfT, 2018a. The Road to Zero: Next steps towards cleaner road transport and delivering our Industrial Strategy. Department for Transport, London.

DfT, 2018b. Transport Statistics Great Britain 2018. Department for Transport, London.

Dijkstra, E.W., 1959. A note on two problems in connexion with graphs. *Numerische mathematik* 1(1), 269-271.

Doumen, S., Paterakis, N.G., 2019. Economic viability of smart charging EVs in the Dutch ancillary service markets, *2019 International Conference on Smart Energy Systems and Technologies (SEST)*. IEEE, pp. 1-6.

Driver & Vehicle Standard Agency, 2014. Staying Legal.

DVLA/DfT, 2020. Licensed vehicles by body type (quarterly): Great Britain and United Kingdom, In: Department for Transport (Ed.), *Vehicle Licensing Statistics*, 30 April 2020 ed.

El Chehaly, M., Saadeh, O., Martinez, C., Joos, G., 2009. Advantages and applications of vehicle to grid mode of operation in plug-in hybrid electric vehicles, *2009 IEEE Electrical Power & Energy Conference (EPEC)*. IEEE, pp. 1-6.

Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy* 39(6), 3789-3802.

Farhan, J., Chen, T.D., 2018. Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet. *Transportation Research Part C: Emerging Technologies* 93.

Fele, F., Margellos, K., 2019. Scenario-based robust scheduling for electric vehicle charging games, *2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*. IEEE, pp. 1-6.

Firdausiyah, N., Taniguchi, E., Qureshi, A.G., 2019. Modeling city logistics using adaptive dynamic programming based multi-agent simulation. *Transportation Research Part E: Logistics and Transportation Review* 125, 74-96.

Geofabrik, 2019. OpenStreetMap Data Extracts.

Hoad, K., Robinson, S., Davies, R., 2010. Automated selection of the number of replications for a discrete-event simulation. *The Journal of the Operational Research Society* 61(11), 1632-1644.

IEA, 2019. Global EV Outlook 2019. IEA, Paris.

Janjevic, M., Knoppen, D., Winkenbach, M., 2019. Integrated decision-making framework for urban freight logistics policy-making. *Transportation Research Part D: Transport and Environment* 72, 333-357.

Latifi, M., Rastegarnia, A., Khalili, A., Sanei, S., 2018. Agent-based decentralized optimal charging strategy for plug-in electric vehicles. *IEEE Transactions on Industrial Electronics* 66(5), 3668-3680.

Law, A., McComas, M., 1991. Secrets of successful simulation studies, *Winter Simulation Conference*. IEEE Computer Society, pp. 21-27.

Lindgren, J., Lund, P.D., 2015. Identifying bottlenecks in charging infrastructure of plug-in hybrid electric vehicles through agent-based traffic simulation. *International Journal of Low-Carbon Technologies* 10(2), 110-118.

Lindgren, J., Niemi, R., Lund, P.D., 2014. Effectiveness of smart charging of electric vehicles under power limitations. *International Journal of Energy Research* 38(3), 404-414.

Lopes, J.P., Soares, F.J., Almeida, P.R., 2009. Identifying management procedures to deal with connection of electric vehicles in the grid, *2009 IEEE Bucharest PowerTech*. IEEE, pp. 1-8.

Macal, C.M., 2016. Everything you need to know about agent-based modelling and simulation. *Journal of Simulation* 10(2), 144-156.

Mallette, M., Venkataramanan, G., 2010. Financial incentives to encourage demand response participation by plug-in hybrid electric vehicle owners, *2010 IEEE Energy Conversion Congress and Exposition*. IEEE, pp. 4278-4284.

Mintel, 2016. Online Retailing – UK, London.

Murakami, K., 2017. A new model and approach to electric and diesel-powered vehicle routing. *Transportation Research Part E: Logistics and Transportation Review* 107, 23-37.

Oliveira, J.B., Lima, R.S., Montevechi, J.A.B., 2016. Perspectives and relationships in Supply Chain Simulation: A systematic literature review. *Simulation Modelling Practice and Theory* 62, 166-191.

Olivella-Rosell, P., Villafafila-Robles, R., Sumper, A., Bergas-Jané, J., 2015. Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks. *Energies* 8(5), 4160-4187.

ONS, 2011. 2011 Residential-based Area Classifications In: Statistics, O.o.N. (Ed.).

Open Street Map, 2019. Planet OSM.

Pod Point, 2020. EV Charging Connector Types and Speeds, London.

Propfe, B., Kreyenberg, D., Wind, J., Schmid, S., 2013. Market penetration analysis of electric vehicles in the German passenger car market towards 2030. *International Journal of Hydrogen Energy* 38(13), 5201-5208.

Querini, F., Benetto, E., 2014. Agent-based modelling for assessing hybrid and electric cars deployment policies in Luxembourg and Lorraine. *Transportation Research Part A: Policy and Practice* 70, 149-161.

Rahman, S., Shrestha, G., 1993. An investigation into the impact of electric vehicle load on the electric utility distribution system. *IEEE Transactions on Power Delivery* 8(2), 591-597.

Robinson, S., 1994. *Successful simulation: a practical approach to simulation projects*. McGraw-Hill.

Roorda, M.J., Cavalcante, R., McCabe, S., Kwan, H., 2010. A conceptual framework for agent-based modelling of logistics services. *Transportation Research Part E: Logistics and Transportation Review* 46(1), 18-31.

Sakai, T., Romano Alho, A., Bhavathrathan, B.K., Chiara, G.D., Gopalakrishnan, R., Jing, P., Hyodo, T., Cheah, L., Ben-Akiva, M., 2020. SimMobility Freight: An agent-based urban freight simulator for evaluating logistics solutions. *Transportation Research Part E: Logistics and Transportation Review* 141, 102017.

Sargent, R.G., 1996. Verifying and validating simulation models, *Proceedings of the 28th conference on Winter simulation*, pp. 55-64.

Shafiei, E., Thorkelsson, H., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. *Technological Forecasting and Social Change* 79(9), 1638-1653.

Tang, M., Gong, D., Liu, S., Lu, X., 2017. FINDING KEY FACTORS AFFECTING THE LOCATIONS OF ELECTRIC VEHICLE CHARGING STATIONS: A SIMULATION AND ANOVA APPROACH. *International Journal of Simulation Modelling (IJSIMM)* 16(3).

Tang, X., Liu, J., Wang, X., Xiong, J., 2011. Electric vehicle charging station planning based on weighted Voronoi diagram, *Proceedings 2011 International*

*Conference on Transportation, Mechanical, and Electrical Engineering (TMEE)*. IEEE, pp. 1297-1300.

Utomo, D.S., Gripton, A., Greening, P., 2019. Modeling Home Grocery Delivery Using Electric Vehicles: Preliminary Results of an Agent-Based Simulation Study, *2019 Winter Simulation Conference (WSC)*. IEEE, pp. 1637-1648.

Utomo, D.S., Onggo, B.S., Eldridge, S., 2018. Applications of agent-based modelling and simulation in the agri-food supply chains. *European Journal of Operational Research* 269(3), 794-805.

Utomo, D.S., Onggo, B.S.S., Eldridge, S., Daud, A.R., Tejaningsih, S., 2020. Eliciting agents' behaviour using scenario-based questionnaire in agent-based dairy supply chain simulation. *Journal of Simulation*, 1-15.

van Duin, J.H.R., van Kolck, A., Anand, N., Tavasszy, L.ó.A., Taniguchi, E., 2012. Towards an Agent-Based Modelling Approach for the Evaluation of Dynamic Usage of Urban Distribution Centres. *Procedia - Social and Behavioral Sciences* 39, 333-348.

Wu, P.-J., Chaipiyaphan, P., 2019. Diagnosis of delivery vulnerability in a logistics system for logistics risk management. *The International Journal of Logistics Management*.