SIMULATING HOME GROCERIES DELIVERY USING ELECTRIC VEHICLES IN MANCHESTER: AN AGENT-BASED APPROACH

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A Unique Collaboration…

Technology
- Goodyear
- Firestone
- Volvo
- OPTRAK
- SIC
- SRF
- Haldex

Operations
- Wincanton
- Tesco
- TransdeK
- DHL
- John Lewis
- Denby
- Hargreaves Logistics
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Introduction & Motivation

- UK government: committed to target 80% reduction in greenhouse emissions by 2050 compared to 1990 levels – currently significant emissions from diesel road freight. NIC report recommends zero net carbon by 2050 (NIC 2019)

- Light goods vehicles (LGV) that represent 15% of the total vehicle mix (Department for Transport 2017) have contributed to approximately 16% of total UK greenhouse gas (GHG) emissions from road transport (Department for Transport 2018b).

- Significant reduction in GHG emissions can only be achieved if the existing LGVs are replaced with electric LGVs.

- Though the UK governments target of 100% new van sales of zero emissions by 2040, uptake of battery electric vehicles has remained low (Department for Transport 2018a).

- Within retail and parcel operations, range constraints (approximately 100 km for a typical electric LGV), 5 to 15% payload reduction due to battery weight and higher cost of ownership than diesel vehicles may responsible for the limited fleet penetration.
Objectives & Approach

Objectives:
- To investigate the impacts of electric LGVs to a fleet’s performance (measured in percentage of timely and untimely delivery).
- To investigate necessary changes to the retailer’s operations in order to maintain the fleet’s performance.

Approach:
- First we propose an agent-based simulation (ABS) that can imitate the operations of one of the major home grocery retailers in the Manchester area.
- Iteratively, we introduce electric vehicles into our model, to ascertain viability of routes.
- Finally, we evaluate how these technologies influence the target retailers operations.
Agent Based Simulation (ABS) is an approach to model complex systems that are difficult to simulate using deterministic means. It allows one to describe the behaviour of multiple system components and then allowing the components to interact within a simplified framework.

For example in this system orders or delivery jobs provide an input signal that agents at a depot, regional or fleet level can then select a response to (e.g. assigning vehicles, despatching them at certain times etc.)

ABS has been widely used to model passenger electric vehicles. The novelty from this research is the application of ABS to model commercial electric vehicles within a logistics system.

Interaction in a logistics system tends to be more complex because:
- It involves many diverse firms as well as the consumers.
- To meet the consumers needs, the firms must make many decisions including operational decisions, marketing decisions, and supply chain management decisions.
- Unlike the private vehicle owners, a firm also needs to consider strategies for payload allocation, payload consolidation and vehicle routing.
Step 1: Analyse empirical data from one of the UK’s retailers

Step 2: Develop an Agent-Based Simulation to imitate the retailer’s fleet (the baseline model)

Step 3: Introduce electric vans in the simulation (adding battery, range & charger power constraints)

Step 4: Identify potential locations (using facility location modelling) and optionally introduce remote charging hubs into the simulation

We analysed:

• The geographical distribution of the customers;
• The order frequency and the quantity ordered by each customer;
• The distribution of delivery time window selected by the customers;
• The location of the retailer’s stores and the number of vehicles available at each store (all diesel vehicles);
• The number of journeys of each vehicle and the drop density in each journey.
**Methodology**

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**Order generation module:**
Using the statistical distribution of each parameter we resample the customers’ order on each simulation day

**Branch selection module:**
We select the branch that must serve each order based on proximity

**Route & payload allocation module:**
We used heuristics to allocate the payload and route to each vehicle. Our heuristics considers the distance to each customer and the delivery time window
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The electric vehicle we are considering has the following characteristics:

- Battery capacity (kWh): 56 kWh
- Motive power consumption (kWh/km): 0.29
- Refrigeration unit power consumption (W/h): 500
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We used a heuristics i.e., centre of gravity concept.

From this analysis we found 2 locations that are at most 25 km away from each customer and the store.
Modelling Framework

A set of customers with different preferences, needs and geographical locations etc...

A set of companies

Place order

The company assigns the order to one of its stores

Retail Companies

A set of stores / distribution centres owned by each company

Parcel Companies

A set of vans attached to each store / distribution centre

The store assigns the order to one of its vans

The vans deliver the orders to customers

Note: The geographical information, demand, preferred delivery windows etc of Waitrose’s customers are initiated from the database. Currently, other companies’ customers are initiated hypothetically.
Agents in the ABS Environment

Van’s attributes:
• Capacity
• Type of fuel (diesel /electric)
• Power consumption (if electric)

Store’s attributes:
• Location
• Number of vans available

Consumer’s attributes:  
(for illustration purpose only 2 are shown)
• Location
• Order frequency
• Order size
Validation of the baseline model

We statistically compared the simulated diesel fleet operations with the data provided by the retailer. The result suggests that we can have a reasonable expectation that any intervention introduced in the simulation will influence the target retailer’s operation in a similar manner.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Real Data (N = 45 days)</th>
<th>Simulation (N = 7 * 45 days interval)</th>
<th>P-Value ( &gt; 0.05 indicates a valid model)</th>
<th>Valid?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Std. Deviation</td>
<td>Average</td>
<td>Std. Deviation</td>
</tr>
<tr>
<td>Number of order per day</td>
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<td>32.9</td>
<td>117.34</td>
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<td>Number of Ambient Order (crates)</td>
<td>346.31</td>
<td>104.7</td>
<td>351.12</td>
<td>12.25</td>
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<tr>
<td>Number of Chilled Order (crates)</td>
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<td>40.63</td>
<td>135.53</td>
<td>5.39</td>
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<td>Number of Frozen Order (crates)</td>
<td>72.09</td>
<td>22.58</td>
<td>73.32</td>
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<td>Number of Vehicles dispatched per day (Vans / day)</td>
<td>23.75</td>
<td>3.81</td>
<td>24.26</td>
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<td>Number of Delivery per Vehicle’s Journey (Delivery / Journey)</td>
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<td>2.58</td>
<td>4.9</td>
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<td>Km per journey (km)</td>
<td>49.20</td>
<td>28.74</td>
<td>50.21</td>
<td>3.67</td>
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<td>Time travelled per journey (hours)</td>
<td>1.51</td>
<td>0.9</td>
<td>2.34</td>
<td>1.09</td>
</tr>
</tbody>
</table>
After incorporating electric LGV into our simulation, we found that:

- Electric vehicles can deliver the same number of orders as diesel vehicles
- However, because the time necessary to charge the vehicles, there is a high chance that a fleet of electric vehicles will have higher percentage of untimely delivery, even after we incorporate remote charging hubs
Conclusions

- In this study we have proposed an ABS model of home grocery delivery performed by a fleet consisting of diesel vehicles, and used its results as a baseline from which to predict the effect of replacing diesel vehicles with electric vans in a range of charging scenarios.

- Using EVs, the fleet can still deliver the same number of orders, without adding the number of vehicles. This indicates that there are still quite a lot of slack in the target retailer’s diesel fleet operations.

- However, using EVs, both with and without charging hubs, is very likely that the fleet cannot satisfy the delivery time window. This is due to the time required to charge the vehicles. Nevertheless, we showed that the use of opportunistic charging hubs and more powerful chargers can significantly increase the percentage of timely delivery that can be done by the retailer agent using electric vans.

- To maintain its punctuality performance an operator can:
  - Increase the number of their electric vans or operate more charging hubs so that the vans can be charged closer to the customer locations (expensive alternative).
  - They can also try to negotiate the delivery time window with their customers (e.g., by offering a wider delivery time window, or by giving discount for each late delivery). However, they need to understand how the customers respond these changes.

- Although possible technological interventions exist, they can be very expensive or risky to be carried out unilaterally by an operator. Hence, in order to reduce carbon emissions at an reasonable cost, the urban delivery system must be reorganized. This reorganization process may require different fleet operators to operate more experimental strategies, such as collaboration or synchronization of order fulfilment.
Future Direction

- To incorporate multiple fleets in our simulation and evaluate the benefits of cooperation among operators. This requires us to collect more data from different operators.

- Sensitivity analysis using various combinations of technologies and demand pattern and propose a robust solution to enable the adoption of electric LGV. This requires us to understand the influences of each technology toward the vehicle’s performance.

- Finally, we are also working on incorporating better payload and routing algorithms in our modelling. Many algorithms have been proven to be able to minimize the distance travelled by the vehicles and optimizing vehicle utilization. Incorporating these algorithms may improve the feasibility of the electric vehicle deployment.
References


