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LONG HAUL LOGISTICS USING ELECTRIC TRAILERS BY INCORPORATING AN ENERGY CONSUMPTION META-MODEL INTO AGENT-BASED MODEL

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ABSTRACT

This paper presents the preliminary result of an Agent-Based Modeling Study (ABMS) that analyzes an electrification strategy for the UK's long haul logistics operations. Because long haul logistics is very energy intensive, the dynamics of the trailer's energy consumption must be taken into account. Engineering approaches are computationally expensive and inhibit us from modeling interactions within the entire fleet of trailers. This paper proposes an alternative approach to model the vehicle's energy consumption. Our model validation shows that the ABMS can replicate a real world operator's operations with sufficient accuracy. Subsequently we use our ABMS to evaluate the potential benefits of using electric trailers in the operator's fleet.

1 INTRODUCTION

This paper presents preliminary results from an ongoing project aimed at evaluating the feasibility and benefits of electrification (e.g., electric trucks and trailers, electric road system, etc) in reducing greenhouse gas (GHG) emissions, and analyzing necessary reorganizations in the UK's long haul logistics system through agent-based modeling and simulation (ABMS). The full scope of our project encompass how the operators interact with their customers and with other operators. For instance, adoption of new technology such as electric vehicles may influence an operator's delivery performance, and subsequently the customers may react by changing their order size or order frequency. Another example is, several operators may cooperate in operating and utilising a shared infrastructure such as a charging hub. This is our main reason for adopting ABMS. However, in this paper we only focus on the development of energy consumption module in our ABMS. We use electric trailers as a case study to demonstrate our approach.

Trailer operations are a critical part of supply chains in many of the world's developed economies. In the UK, it is estimated that long haul logistics contributes around 45% of all GHG emissions from road freight (DfT 2017). One way to reduce GHG emissions in this sector is by fitting a battery on the trailer to use as an energy source for the tractor unit. However, because long haul logistics is very energy intensive and would require batteries of considerable size and weight, the dynamics of the trailer's energy consumption must be taken into account in order to evaluate the feasibility and potential benefits of this intervention.

Engineering approaches enable us to simulate the amount of energy required by a single trailer to travel on a particular route. This approach can take into account, for example, changes in velocity, elevation and the trailer's weight. However, it is computationally expensive and inhibits us from modeling the interaction within the entire fleet of trailers (e.g., scheduling, "pony express" systems, payload consolidation). To

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overcome this barrier, innovation in energy consumption modeling is required. Hence, our objectives in this paper are:

- To propose a suitable approach for modelling representative energy consumption int an ABMS. We do this by developing a meta-model based on Goeke and Schneider (2015) to estimate the energy consumed by the tractor unit and the trailer per km.
- To evaluate the benefits of electric trailers for long haul logistics operations. This is done by incorporating the meta-model into an ABMS that represents the operations of a UK trailer operator.

2 LITERATURE REVIEW

We begin this section by discussing the roles of ABMS in studies relevant to long haul logistics. Subsequently, we review the applications of ABMS in studies about electric vehicle (EV) implementation, and highlight the importance of a representative energy consumption model.

2.1 Application of ABMS in Long Haul Logistics Studies

Crainic et al. (2018) illustrate that up to 46 % of the simulation studies focus on road transportation. The rest of the studies are split into multi-modal and inter-modal freight transportation. Furthermore, 30% of the total set of selected studies focus on studying road freight transportation in urban settings (Crainic et al. 2018). Only 5% of the total studies consider road freight transportation at a national or regional level (long haul logistics).

ABMS is one of the simulation methodologies that is considered suitable to model complex interactions within a logistics system (Roorda et al. 2010). These interactions involve many strategic, tactical and operational decisions that should be made by diverse firms to meet consumer needs. The benefits of ABMS are reflected in a review by Crainic et al. (2018) as 47% of the selected studies employed ABMS. Indeed there are also ABMS studies that are relevant to long haul logistics, i.e., Baindur and Viegas (2011), Burgholzer et al. (2013), Holmgren et al. (2012), Joubert et al. (2010), Liedtke (2009), Samimi et al. (2010), and Sirikijpanichkul et al. (2007). However, with the exception of a study described in Holmgren et al. (2012) all other ABMS of long haul logistics do not incorporate hybrid or EVs. Moreover, the discussion on how to model EVs within an ABMS is also considerably brief in Holmgren et al. (2012). This study will make a significant contribution to the extant knowledge concerned with the decarbonisation of long haul road freight and in particular the electrification strategies for road freight

2.2 Application of ABMS in Studies of EV Implementation

ABMS has been widely applied to study EVs, especially in analyzing: (i) the adoption process (market penetration) for EVs (Brown 2013; Eppstein et al. 2011; Shafiei et al. 2012; Querini and Benetto 2014); and (ii) to analyze how EVs interact with broader energy systems (Lindgren and Lund 2015; Olivella-Rosell et al. 2015; Tang et al. 2017). However, Utomo et al. (2019) noted that until recently ABMS is mainly used to model passenger EVs. Modeling commercial EVs using ABMS might be more challenging, because a firm also needs to consider strategies for payload allocation, payload consolidation and vehicle routing (van Duin et al. 2012).

The previous studies generally accounted for the energy consumed by the vehicle as a constant number, such as the maximum range of the vehicle (Brown 2013; Eppstein et al. 2011) or the average energy consumption per distance (or time) (Lindgren and Lund 2015; Shafiei et al. 2012). However, in reality, energy consumption is not a linear function of traveled distance or time, but also influenced by speed, gradients and payload (Goeke and Schneider 2015). Nowadays, the field of vehicle routing has started to incorporate more realistic energy consumption models (Bektaş and Laporte 2011). Hence, the use of a representative energy consumption model is also important when modeling a logistic system using ABMS.

Engineering models of the vehicle energy consumption are plentiful (Madhusudhanan and Na 2020) and have been parametrized and validated using empirical data. These models usually track the energy consumed by a single vehicle by time interval. This kind of approach is not suitable for ABMS that attempt to model the interactions within a fleet of vehicles, as it significantly increases the time required to run the simulation. Hence innovative approaches to incorporate a more representative model of energy consumption into ABMS of logistics systems are required.

The novelties of this study are: (i) we propose an approach to incorporate a more representative energy consumption into an ABMS, without significantly increasing the time to run the simulation; (ii) we demonstrate this approach using a case study of the implementation of EVs (electric trailers) in long haul logistics.

3 METHODOLOGY

We begin the modeling process by analyzing three separate data sets, provided by one of the UK's largest HGV operators (referred to hereafter as the *target operator*), each describes pickup and delivery operations. These data sets are:

- **Order and route data from 2016:** It describes pickup and delivery locations, payload volume and weight. No information regarding the type of the payload (i.e., whether it is ambient, cold or frozen), which vehicle being used, the distribution center from which the vehicle was dispatched, or energy consumption.
- **Controller Area Network (CAN bus) data from 2018:** It describes the location of each stop, the movement of each vehicle and energy consumption. No information on payload, or whether the vehicle is picking or delivering.
- **Order and route data from 2018:** It describes the pickup and delivery locations, the payload's volume and type, which vehicle being used and the distribution center from which the vehicle was dispatched. No information regarding the payload weight and energy consumption.

Issues such as changes in information systems, changes in data protection policy and changes in organizational structure prevented us from acquiring a single unified data set.

3.1 Developing Base ABMS of HGV Operations

Figure 1 describes in general the processes within our ABMS. We define three types of agents in our ABMS, namely: (i) the customer agent (5,535 agents), whose role is to generate pickup, delivery or both pickup and delivery orders to be placed with the distribution center agents; (ii) the distribution center (DC) agent (7 agents) whose role is to allocate the payload and route to the vehicles; and (iii) the vehicle agent (1,166 agents, we assume the tractor unit and the trailer as one entity and each is attached to one distribution center agent) who carry out the pickup and delivery operations.

We use AnyLogic® version 8.3 to develop our ABMS and it is implemented with 30 minute time intervals. The position of all agents is initiated based on real data and are projected to a GIS layer obtained from OpenStreetMap (OpenStreetMap. 2019) in which the road network data is obtained from Geofabrik GmbH (Geofabrik. 2019).

Each day in the simulation starts by randomly generating the number of orders to each DC agent using Poisson distributions with parameters in accordance with daily order statistics from the target operator's data ($\lambda_1 = 102.62$; $\lambda_2 = 20.63$; $\lambda_3 = 54.86$; $\lambda_4 = 2.49$; $\lambda_5 = 254.94$; $\lambda_6 = 39.10$; $\lambda_7 = 16.78$). Each of these orders is then randomly assigned to a pair of customer agents (using an empirical distribution), one customer serves as a pickup location and the other serves as delivery location. Based on empirical data, not all customer agent pairs can be selected by a DC agent. Later on we group pairs that contain the same location into a journey, so that a journey may consists of multiple pickups or multiple drops.

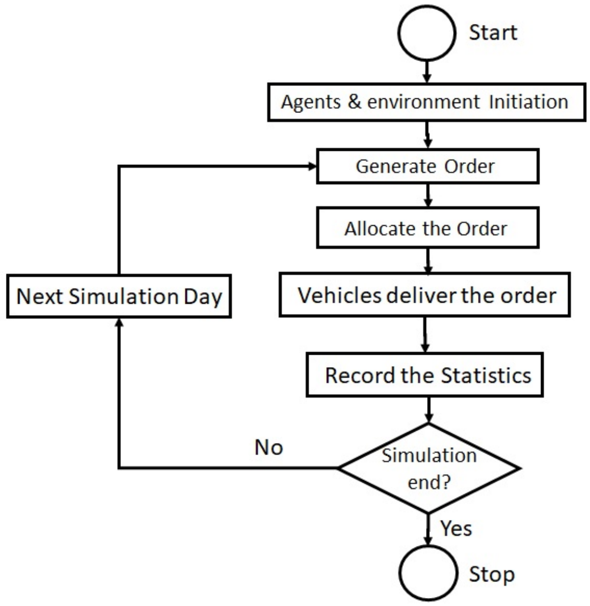

Figure 1: General description of the ABMS.

The next step is to determine the type of the payload in every order. Each order can be of ambient, cold or frozen payload type. The proportion of the type of orders received by each DC agent is heterogeneous as explained in Table 1.

Table 1: Proportion of the type of order received by DC agent.

DC	Ambient	Cold	Frozen
1	3%	68%	29%
2	13%	87%	0%
3	22%	72%	6%
4	0.1%	99.7%	0.2%
5	100%	0%	0%
6	3%	97%	0%
7	0%	100%	0%

The target operator never mixes the payload, hence the next step is to determine the number of pallets in each order by sampling a normal distribution with parameters ($\mu = 6.56$; $\sigma^2 = 15.54$) if the payload is ambient, ($\mu = 5.46$; $\sigma^2 = 6.33$) if the payload is cold, and ($\mu = 5.23$; $\sigma^2 = 19.23$) if the payload is frozen.

The next step is to group the orders into several vehicle journeys. In reality, this process is done using commercial software. However, we do not know how exactly this commercial software works due to business confidentiality. Hence our ABMS relies on heuristics to obtain feasible solutions. This is because we are only aiming at establishing a system that resembles the target retailer's operations and not to propose a more efficient routing algorithm. The heuristics in our ABMS is based on the Nearest Neighbor heuristics, as explained by for example by Balakrishnan (1993). Indeed, the target operator's order data includes delivery time windows. However, the amount of missing data is very high (more than 50%) and this data was not recorded in a consistent format. Therefore the delivery time window is neglected in this version of the model. And hence, the Nearest Neighbor heuristics is considered to be sufficient for this work.

Insight obtained from analyzing the target operator's order data shows that there are at least three types of vehicle journey:

- the vehicle collects payload from several pickup locations and then delivers it to one delivery location;
- the vehicle collects payload from one pickup location and then distributes it to several delivery locations; and
- the vehicle collects payload from one pickup location and delivers it to one delivery location.

Therefore the first step in constructing the vehicle journeys is to group orders that have the same pickup location or delivery locations. This is done by each DC agent.

For each group of orders a 'grand route' is constructed using the Nearest Neighbor Heuristics. A vehicle is dispatched to travel according this grand route until its capacity is full or all destinations have been visited. If one vehicle is inadequate to serve all destinations in one grand route, the next vehicle is dispatched. The vehicle journey allocation process is carried out until all groups of orders are served. Figure 2 describes this process. When a vehicle moves along an arc, its speed is assumed to be constant and randomly determined by sampling a normal distribution described in Table 2. Subsequently, the arrival time of the vehicle to the target node is calculated using the selected speed value. The energy consumed by the vehicle along a particular arc is calculated by considering the speed and weight of the payload it carries using the meta-model described in subsection 3.2. Figure 3 provides the screenshot of our running model.

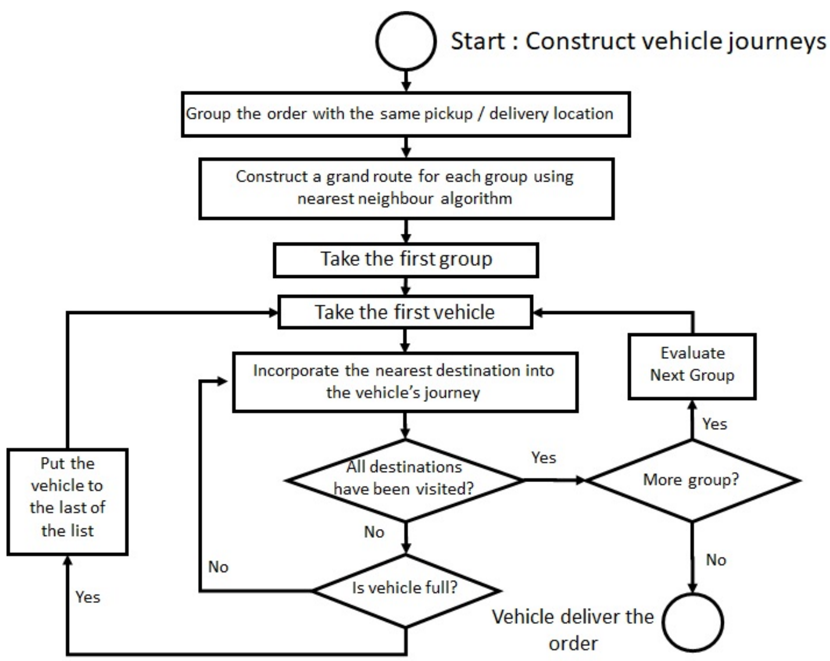

Figure 2: Process to allocate the payload to each vehicle.

3.2 Developing a Meta-model of Energy Consumption

This section discusses a process to develop an energy consumption model that will be incorporated into our ABMS. Energy consumption estimation is important in evaluating the benefits of electric trailers for the target operator. However, it may significantly increase the computational cost of the ABMS. Hence the criteria of our energy consumption model are:

- It must be relatively easy to integrate into our ABMS.
- the execution time must be relatively fast.

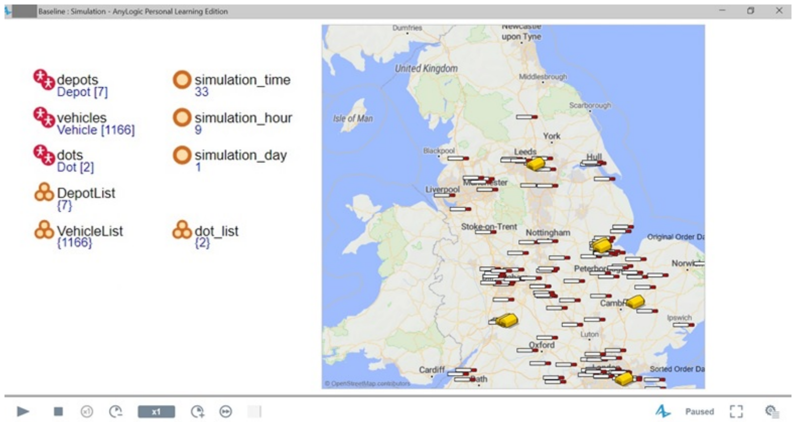

Figure 3: Screenshot of the running model.

- it can estimate the energy consumption based on several known factors (e.g. payload, distance, travel time) with sufficient accuracy.

We consider that an approach proposed by Vepsäläinen et al. (2019) can fulfill these criteria. The first phase of this approach is to develop a mathematical model of the power required to move the vehicle. The second phase is to run a Monte Carlo simulation with plausible range of parameters. And finally, to develop a statistical model from the Monte Carlo result.

For the mathematical modeling phase, we adopt a model proposed by Goeke and Schneider (2015) to calculate the power (P_M) required by the vehicle per time interval to overcome rolling resistance (F_r), aerodynamic resistance (F_a) and gravitational force (F_g). In (1) m, a and v denote the total vehicle mass, acceleration and velocity respectively.

$$P_M = (m * a + F_r + F_a + F_g) * v \tag{1}$$

The rolling resistance is formulated in (2), in which g is the gravitational constant (9.81 m/s^2), c_r is the coefficient of rolling friction and α is the gradient angle.

$$F_r = c_r * m * g * cos(\alpha) \tag{2}$$

(3) describes the aerodynamic resistance where c_d denotes the coefficient of aerodynamic drag, ρ denotes the air density and A is the frontal area of the vehicle.

$$F_a = \frac{1}{2} * c_d * \rho * A * v^2 \tag{3}$$

Finally the gravitational force is described in (4).

$$F_g = m * g * sin(\alpha) \tag{4}$$

There are two application cases considered, i.e., diesel engines and electric engines.

- **Diesel engine:** If the power is produced by diesel, P_M in (1) can be translated into fuel consumption per time interval (FR) (Demir et al. 2012) as described in (5). Following Goeke and Schneider (2015) we assume FR to be 0 when the vehicle is driving downhill. In (5), ξ represents the fuel to air mass ratio, κ represents the heating value of diesel fuel, and ψ is a constant to convert fuel rate from grams per second to liters per second, k is the friction factor of the engine, N is the engine speed, D is the engine displacement, η and η_{tf} are the efficiency of the diesel engine and the drive train respectively.

$$FR = max(\frac{\xi}{\kappa\psi}(kND + \frac{P_M}{\eta\eta_{tf}}), 0) \tag{5}$$

- **Electric engine:** If the power is produced by electric engine then we can calculate the power required from the battery (P_B) to achieve P_M per time interval using (6), in which, ϕ^d and φ^d are the efficiency parameters for the engine and battery energy discharge. ϕ^r and φ^r are the efficiency parameters for the engine and battery energy generation (recuperation). These parameters are derived by Goeke and Schneider (2015) from Guzzella and Amstutz (2005) and van Keulen et al. (2010).

$$P_B = \begin{cases} \phi^d * \varphi^d * P_M, & \text{if } P_M \geq 0\text{kW} \\ \phi^r * \varphi^r * P_M, & \text{if } P_M < 0\text{kW} \end{cases} \tag{6}$$

In the second phase, we carry out a Monte Carlo simulation to evaluate whether or not this mathematical model can describe the distribution of the real energy consumption, when it is parametrized with the real world data. The Monte Carlo simulation was done for diesel engine so that the result can be compared with the fuel consumption of the target operator's existing fleet. Table 2 shows the main parameters value used in the Monte Carlo simulation.

Table 2: Main parameters in the Monte Carlo simulation.

Main parameter	**Source**	**Value**
Vehicle Speed	Operator's CANbus data	N($\mu = 46.93, \sigma^2 = 12.5$) *km/h*
Mass (empty)	Demir et al. (2012)	6350 *kg*
Payload	Operator's 2018 order data	0.5 – 225 pallets (empirical distribution was used)
Weight per pallet	Operator's 2016 order data	400 *kg*
Gradient	Assumptions	U(-0.19, 0.19) *rad*
Acceleration	Assumptions	Tri(-2,0,2) *m/s*
c_r & c_d	Demir et al. (2012)	0.01 & 0.7
ρ	Demir et al. (2012)	1.2041 kg/m^3
A	Demir et al. (2012)	3.912 m^2
ξ	Demir et al. (2012)	1
κ	Demir et al. (2012)	44 kJ/g
ψ	Demir et al. (2012)	737 l/g
k	Demir et al. (2012)	0.2 *kJ per revolution per liter*
N	Demir et al. (2012)	33 *rps*
D	Demir et al. (2012)	5 *l*
$\eta \& \eta_{tf}$	Demir et al. (2012)	0.9 & 0.4
$\phi^d \& \phi^r$	Goeke and Schneider (2015)	1.184692 & 0.846055
$\varphi^d \& \varphi^r$	Goeke and Schneider (2015)	1.112434 & 0.928465

The simulation was done for 500 replications. For validation, we compare the distribution of the MPG produced from the Monte Carlo simulation with that of the target operator's CANbus data.

Figure 4 shows that the MPG distribution both produced by Monte Carlo Simulation and real data are quite symmetrical. The average and standard deviation values of the two distributions are also similar (i.e., $\mu = 9.96$, $\sigma = 1.431$ for the simulation output and $\mu = 9.1$, $\sigma = 1.098$ for the real data). The only contrasting feature of the two distributions is the kurtosis. Although it seems that the underlying mathematical model still requires some improvements, at this research stage we consider that it could describe the distribution of energy consumption in real data with sufficient accuracy.

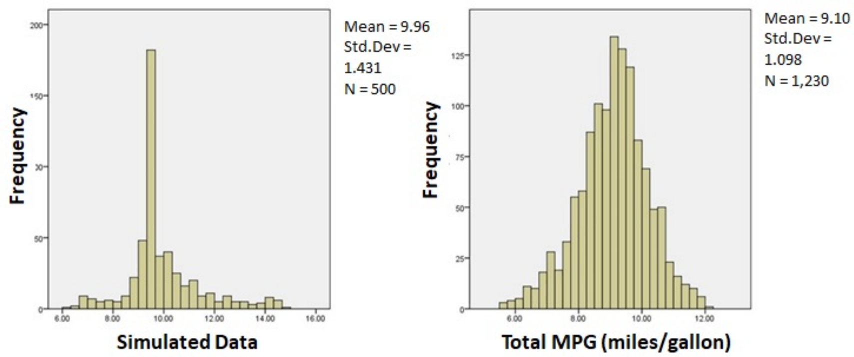

Figure 4: Comparison between the MPG produced by Monte Carlo simulation and the real data.

We then develop a linear model to describe the relationship between the mechanical power required and the main parameters listed in Table 2. Equation (7) describes P_M as a function of Total Mass (i.e., total of empty mass and payload) and the vehicle speed. Please note that even though the Monte Carlo simulation takes acceleration into account, we neglected this factor in (7). This is because in the ABMS we assume that the vehicles are always traveling at constant speed. The R^2 of (7) is 58.9%. In the ABMS we use (7) instead of (1) to calculate the mechanical power required.

$$P_M = 21.52 * TotalMass + 12849.91 * VehicleSpeed - 689572.20 \tag{7}$$

3.3 Incorporating the Meta-Model into ABMS

In this section we integrate electric trailers into our ABMS. We assume that the target operator still operates diesel tractor units but replace the trailers they are using with electric trailers designed by one of our industrial partners. The trailer is equipped with electric engine and can independently produce propulsion to support the tractor unit. The battery capacity of the electric trailer is 170 *kWh*.

This electric trailer is still under development and hence we assume that it has the same payload capacity and weight as the ordinary trailers. How the energy consumption will be distributed between the tractor unit and the trailer in reality is also unknown. This is because generally trailer axles are not powered. Therefore, we assume that energy consumption will be distributed evenly (50% taken from the tractor unit and 50% taken from the trailer) as long as the energy in the trailer's battery is more than 20 % of its total capacity. Please note that to maintain its lifetime, the power in a battery pack may not be fully utilized, the best practice is to ensure that remaining power never falls below 20% of its capacity.

Figure 5 illustrates a process to calculate the amount of energy taken from the battery pack and the amount of diesel fuel consumed by a vehicle agent.

3.4 Validation of the Base ABMS

For validation, we ran our ABMS for 60 simulation days and the experiment was replicated 5 times. In these experiments we assume that the target operator operates diesel tractor units and ordinary trailers. Table 3 shows the comparison between our simulation's outputs to the target operator's order data in 2018. Please note that at the beginning of section 3 we mentioned that the order data does not tell us about the amount of fuel consumed by the vehicle. Hence the real energy consumption value in Table 3 was obtained using the mathematical model explained in subsection 3.2.

The number of our experiment replications is quite small. This is because running an ABMS at national level is computationally expensive. With this small number of replications, the statistical power to carry out a hypothesis testing will be very low. However, descriptively we can observe that the operator agent in our ABMS carries out similar daily operations to the target operator. Therefore, it is reasonable to assume

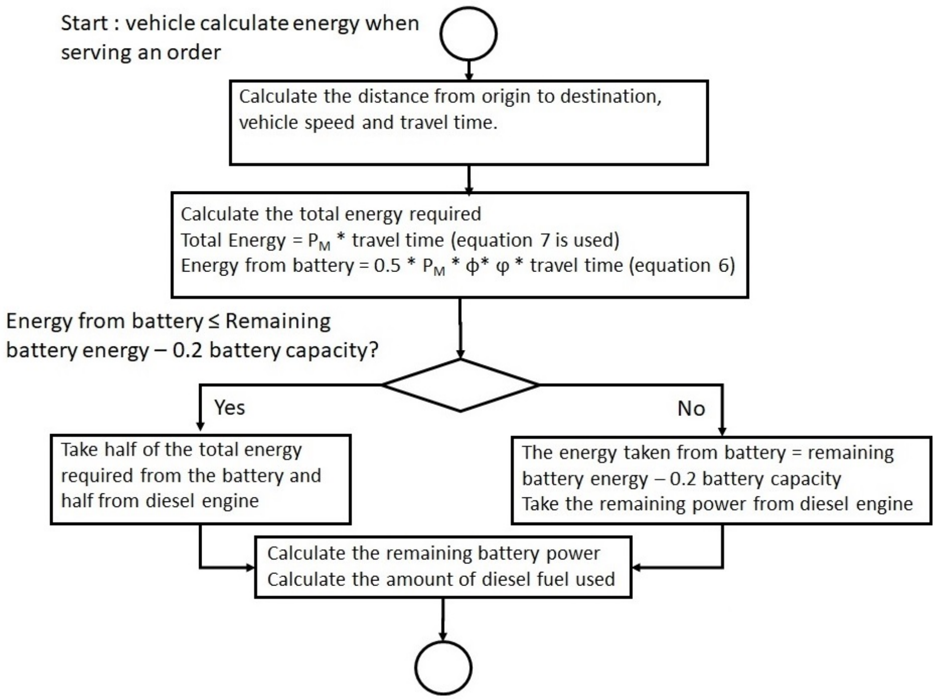

Figure 5: Process to calculate the amount of energy taken from the battery pack and the amount of diesel fuel consumed.

that an intervention adopted by the operator agent, such as adoption of electric trailer, will influence the target operator in a similar manner.

3.5 Experimentation with the New Trailer Concept

In this section we carry out experiments to evaluate the benefits of electric trailers for the target operator. In the first scenario we assume that the target operator only operates ordinary trailers. In the second scenario we replace all trailers with electric trailers. Each scenario was run for 60 simulation days. The simulation's random seed value was controlled, so that each vehicle travels exactly the journey in each scenario. Controlling the random seed is also beneficial in improving the reproducibility of our experiments (i.e., when the same random seed is used, the same program will produce the same outputs if it is given the same set of inputs).

The outputs from the two scenarios are then compared using the t-test for non independence of samples. The null hypothesis being tested is that the average MPG of the diesel fleet is equal to the average MPG

Table 3: Comparison between the base model outputs to the real data.

Output Variables	**Simulation Average**	**Simulation Std.Dev**	**Real Data Average**	**Real Data Std.Dev**
Ambient pallets per order	23.31	15.58	23.08	6.86
Cold pallets per order	5.36	8.13	5.62	7.36
Frozen pallets per order	12.4	7.9	8.41	9.75
Total Km travelled per route	462.22	2.28	392.73	0.63
Number of drops per route	3.54	2.42	3.51	4.82
Travel Time per route	7.7	5.67	7.17	6.35
Energy consumption (MPG)	7.33	4.25	8.47	2.05

of the electric trailer fleet. The last row of Table 4 shows the p-value from this hypothesis testing. The p-value indicates that the use of electric trailers can lead to a significant fuel savings for the target operator. However, Table 4 also shows that the variance in electric trailers scenario is very high. This is because when the journey is very long, the vehicle travels by mainly using the diesel engine and produce lower MPG value. Conversely, if the journey is very short, then the saving from electric engine is very high. Hence there is an indication that the uncertainty in energy consumption can be very high when implementing electric trailers.

In addition, this result must also be treated with caution. Firstly, we did not consider the efficiency of diesel (60%) and electric (90%) power trains (and their combination). Therefore, even though the vehicle uses an electric trailer, when the journey is very long and the vehicle must depend on the diesel engine, the amount of fuel consumed can be far greater than the results presented here. Secondly, we only consider the benefits of electric trailers in terms of saving in the diesel fuel consumption (assuming that the electricity is free). To completely evaluate the benefits of electric trailers we must also take into account the costs associated with the electricity.

Table 4: MPG comparison between the existing diesel fleet and electric trailer fleet.

Parameter	Existing Diesel Fleet	Electric Trailer Fleet
Mean	7.16	19.75
Variance	18.3	164,051
Observations	20,659	20,659
p-value (two tail)	7.98E-06	

4 CONCLUSIONS, LIMITATIONS AND FURTHER RESEARCH

4.1 Conclusions

In this study we have proposed an empirical ABMS of long haul logistics operations, and we have used it to evaluate the potential benefit of incorporating electric trailers.

Modeling vehicle energy consumption with sufficient accuracy is very important because long haul operations can be very energy intensive. However, this should not significantly increase the time needed to run the simulation. We overcome this challenge by adopting a meta-modeling approach. Our ABMS validation shows that descriptively this approach can produce outputs that mimic the target operator's daily operations. Subsequently, we introduce electric trailers into our ABMS. Our experiment shows that the use of electric trailers is very beneficial in reducing the amount of fuel consumed by the target operator.

Although this paper only presents the initial results from our study, it still has some merits and novelties. This study addresses the following shortcomings in the current research base:

- The applications of ABMS for long haul logistics operations at a national level, not to mention those that also consider an electric vehicle, are very limited in the literature.
- Most of the previous ABMS studies used a static average value (e.g., average miles per gallon, or average KWh per km) when calculating the energy consumed during the vehicle movement.
- Our approach in incorporating energy consumption model is also suitable for ABMS that aims at modeling other types of private or commercial vehicles, as well as electric and internal combustion engines.

4.2 Limitations and Further Research

There are still many limitations in the study presented in this paper. The first limitation is related to the meta-modeling of the vehicle energy consumption. We are currently neglecting the acceleration and braking factors. The CANbus data obtained from the target operator does include the count of acceleration and braking events that occurred along the vehicle journeys. However, it is still a challenge to identify how to accurately translate this information into the actual magnitude of acceleration and braking (in m/s^2) required for the model. In terms of changes in vehicle speed, we are currently investigating how to incorporate congestion models into our ABMS. Congestion can affect the number of acceleration and braking events that happen to the vehicle, and subsequently affects the amount of energy used in the operation.

We are also integrating more advanced innovations in the field of logistics in our ABMS. The first innovation is that of the Electronic Road System (ERS). This innovation enables the vehicle to travel by using grid-provided power along strategic routes (e.g. overhead catenary or an embedded rail in the carriageway). The vehicle can then switch to battery when it exits the electrified section. This innovation may significantly increase the electric miles of the vehicle. The second innovation, known as the "pony express" system, sees the vehicle travel from one charging point to another, dropping the trailer it is carrying to be charged at each charging point, and picking up a new pre-charged trailer for the next leg. This innovation requires us to efficiently locate the charging points, schedule the use of each charging point and synchronize the vehicle journeys. Both innovations may potentially reduce the uncertainty when implementing electric trailers.

To evaluate the benefits of these new innovations, we must analyze trade-offs between, for example, savings in diesel fuel consumption, time penalties because the vehicle having to travel from one charging point to another, and reduction in the amount of payload due to the battery size. Answering this question is very challenging because to produce robust answers we must have a model that is sufficiently accurate and can be efficiently used to explore a vast solution space. The approach proposed in this paper is one of our efforts to achieve this goal. Our other efforts are, firstly, we are also developing a specialized modeling platform that can handle a large scale ABMS efficiently, and secondly we are developing design of experiments that can efficiently produce robust solutions.

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