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Transportation Research Procedia 70 (2023) 338–346

Transportation Research Procedia

www.elsevier.com/locate/procedia

8th International Electric Vehicle Conference (EVC 2023)

Optimisation of Electric Vehicle Battery Size

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Abstract

Energy storage and battery technologies have taken centre stage in the race to meet the UK government target to ban new petrol and diesel cars by 2030. However, underlying key issues such as resource demand and negative public opinion must be solved before the high uptake of electric vehicles. The research conducted in this paper proposed viable solutions to these challenges through modelling of real driver data utilising an agent based modelling approach. Per month state of charge analysis confirmed that the current charging infrastructure in circulation will not accommodate the miniaturisation of electric vehicle battery size. Thus, an improved alternative charging infrastructure was proposed, which enabled the optimal battery size to be reduced by up to 40%. The users stop times were analysed to assign an optimal battery size based upon monthly driving behaviour concluding daily inner city drivers require a 30kWh battery and daily long distance drivers require a 40kWh battery. When decreasing the battery size by the proposed 40% there is a £2650.60 saving and a 6.4kg lithium demand decrease per battery when compared to the current average battery size.

Keywords: Electric Vehicles; Battery Optimisation; Agent-Based Modelling; Charging Infrastructure

1. Introduction

In June 2019, parliament issued law requiring the government to reduce the UK's net emissions of greenhouse gases by 100% in relation to levels in 1990 by 2050. Cars accounted for 55.6% of carbon emissions in transport in 2019 and need to be decarbonised accordingly (Department for Transport, 2021)). Energy storage, especially in the case of

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10.1016/j.trpro.2023.11.038

battery technology will be at the forefront of the solution as by 2030 sale of new petrol or diesel cars will be banned (HM Government, 2021)).

The key objective of this paper is to create a scalable agent-based model that determines the optimal battery size for real drivers, which can prove the current average battery size can be reduced whilst ensuring users maintain an appropriate battery size for their average usage scenarios. Allowing for a smooth transition to electrified alternatives once the current 2030 deadline arrives, whilst also being conscious of the scarcity of the elements needed to construct batteries required in the automotive sector.

This paper models real driver trips using the agent-based modelling software AnyLogic where the real data of travel patterns for a single driver is used as an input. Based on the travel behaviour and travel distance an optimal battery size for the driver is proposed. Different types and number of charging stations are included in the model with the goal of finding the link between charging infrastructure and battery range determining the optimal charging routine and battery size.

Section two opens with a brief literature review, which analyses the key fundamentals alongside existing work, which has been used to guide the analysis conducted within this paper. The final agent-based model is presented and divided into modules where the operation of each module is explained. Finally, the individual case studies that the agent-based model will be applied to for an individual driver in Glasgow are described. Section three examines the monthly state of charge for each case study, determining the optimal battery size for the user. The section concludes with a brief economic and material analysis is conducted to evaluate the selected battery sizes. Section four reinforces all the paper's key findings in the form of a short conclusion.

2. Theoretical Basis and Methodology

To accurately model a real driver's journey an understanding of electric vehicle energy consumption and electric vehicle charging is necessary.

The two most important factors that need to be accounted for when modelling electric vehicle energy consumption are the driving patterns and the ambient temperature that the vehicle operates (Di Martino et al., 2022; Miri et al. 2021; Sweeting et al., 2011). Driving patterns can be divided into subcategories: driving behaviour, traffic, and altitudes (Di Martino et al., 2022; Miri et al., 2021). Ambient temperature directly influences the electric vehicles auxiliary systems e.g., air conditioning and temperature regulation (Di Martino et al., 2022; Sweeting et al., 2011).

van Haaren (2011) investigates the potential of range anxiety when the full electrification of automotive transport takes place. By characterizing driver behaviour alongside values of energy consumption the number of driver trips that can be completed by an electrified alternative can be confirmed. The paper utilises data acquired by Straubel (2008), which records energy consumption at different speeds. The energy consumption data provided by Straubel (2008) is adjusted to factor in ambient temperature using findings presented by Al-Wreikat et al. (2022).

Al-Wreikat et al. (2022) analyses the overall effect that ambient temperature has on energy consumption for specific real-world journeys. Journeys are summarised based upon their distance, stop percentage, and average speed to calculate consumption, which is then modelled based upon the ambient temperature. Through data analysis it was found that the energy consumption at cold temperatures is much higher than at moderate temperatures with the largest difference when travelling at speeds less the 60km/h. The paper establishes that the large increase in energy consumption at low temperatures is due to the increased use in vehicle auxiliaries, which can lead to a 28% decrease in vehicle range when operating in winter months compared to summer months (Al-Wreikat et al., 2022).

By applying the ambient temperature effects to the original energy consumption dataset, the final agent-based model can accurately simulate a real driver's journey. This is used to find an optimal battery size by also incorporating external factors such as charging infrastructure.

Within literature the key architecture of the charging systems used for electric vehicles can be split into separate levels: slow, semi-fast and fast/rapid charging. Slow chargers and semi-fast (level 1) chargers are typically at home chargers with charging times varying from 30 minutes to 10 hours. Slow and semi-fast chargers (level 2) have low power levels with typical values of 1.1kW to 19.2kW. Fast/rapid chargers (level 3) are typically used in forecourts with a low charge time of 15 to 30 minutes but a high-power level of 20kW to 150kW (Veneri, 2016; Bayram and Tajer, 2017; Vahidinasab and Mohammad-Ivatloo, 2022).

The previous research in the field of electric vehicle optimisation by Pearre et al. (2011) compared over four hundred daily driving patterns of combustion engine vehicle owners to decide on the most suitable size of electric vehicle for each owner based upon total distance travelled. Concluding that an electric vehicle with a range of 100 or 150 miles would be suitable for up to 32% of drivers. However, this research only assumed a user would charge once a day overnight and determined optimal range rather than optimal battery size.

2.1. Agent-Based Model

Agent-based modelling was utilised to create the model as it is a flexible modelling type, which allows each key component of a real driver's journey to be defined by an individual module that can be tuned easily enabling an accurate simulation of a real driver. AnyLogic was chosen to develop the model as the software incorporates three main modelling types: agent-based, discrete events, and system dynamics. AnyLogic has specifically designed simulation libraries for transportation and vehicle modelling, which allows vehicles to be modelled on an interactive Geographic Information System (GIS) map enabling real driver data to be implemented (Borshchev, 2013).

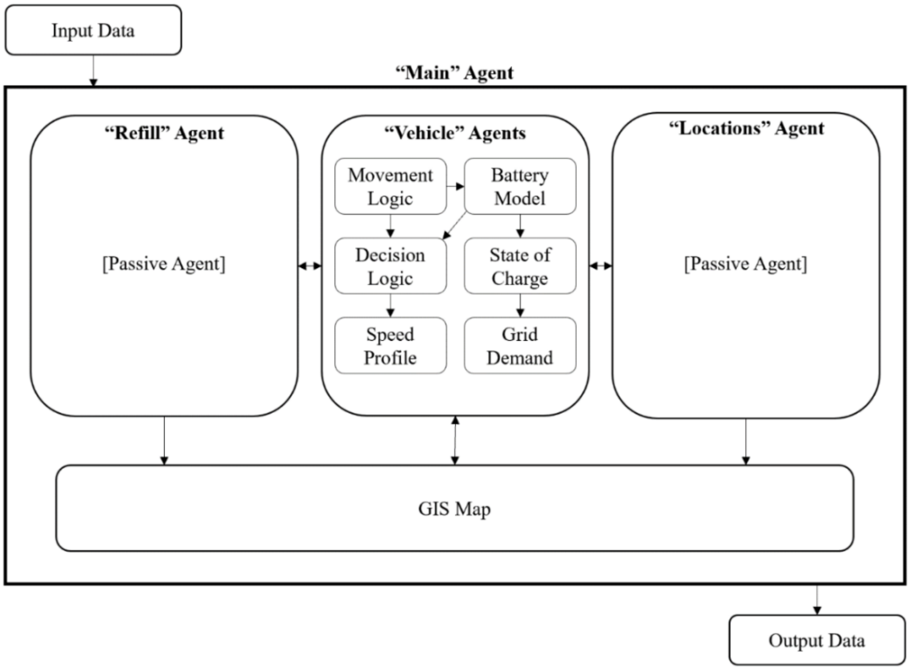

Fig. 1. System level diagram of the agent-based model.

The structure of the final agent-based model is illustrated in Figure 1. The top level entity of the model is the *Main* agent. Within the *Main* agent input data is assigned to the *Refill*, *Vehicle*, and *Locations* agents, which are embedded inside the *Main* agent. The *GIS* map is used to place these embedded agents and simulate the interaction of these agents together. The *Refill* and *Locations* agents are specifically controlled by the *Main* agent whereas the *Vehicle* agents operate individually only presenting meaningful data, which is outputted via the *Main* agent.

Refill and *Locations* are used to place multiple charging locations and real driver routes on the GIS map, respectively. Thus, they are defined as a population of agents. The *Vehicle* agents are utilised to simulate the real driver data for each month using a movement logic state chart with incorporated decision logic and a battery model. The *Vehicle* agents gather the speed profile, state of charge, and grid demand for each month, which formulates the output data.

2.2. Refill and Locations Agents

To accurately simulate a real user's daily driving behaviour the model must know the routes the user has taken alongside potential locations where the user can stop to refill their car. These routes and refill locations are stored by the population of agents *Locations* and *Refill*, respectively.

For the case studies investigated by this paper ZapMap and Open Street Map were used to acquire locations of real charging stations and petrol stations, which fill the population of *Refill* agents. Each individual refill location forms an entry in an excel file where the latitude and longitude of the location is defined. The *Refill* agent places each agent using the *setLatLon(latitude, longitude)* function by reading from the excel file containing the latitude and longitude of each charger or petrol station location.

The real driver data utilised in the case studies was acquired by the application TravelAi, which acted as an input to the *Locations* and *Vehicle* agents. Figure 2 best illustrates how TravelAi works.

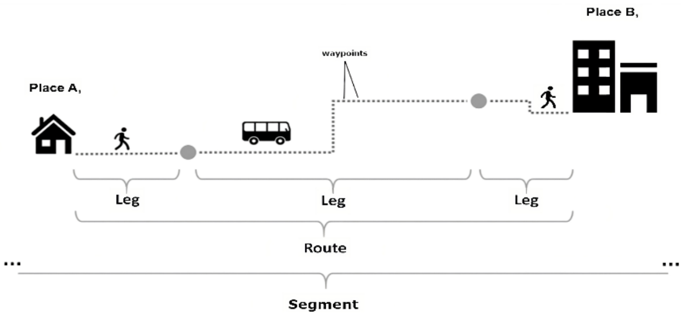

Fig. 2. Illustration of TravelAi data acquisition TravelAi (2022).

A user's journey from two places is defined by a route, which is constructed from a series of legs. Each leg is assigned to the form of transport used e.g., walking, car, or public transport. A leg has multiple waypoints, which give the user's exact path that was taken to reach their destination. The data utilised by the case studies only includes legs and waypoints that are travelled by a car. Each waypoint and leg are defined by the start time, start latitude, start longitude, end time, end latitude, and end longitude.

The start times, latitudes, and longitudes are used with the end times, latitudes, and longitudes to calculate the overall journey time and the distance covered, which allowed speed to be calculated for use in the *Vehicle* agent. The *Locations* agent places agents on the GIS map by using the setLatLon(latitude, longitude) function taking the latitudes and longitudes from an excel file containing all route definitions.

2.3. Main Agent

As described by Figure 1, the *Main* agent is the top-level entity of the model, which initialises each embedded agent via selections made by a user. When a user selects the desired modelling conditions events are triggered within the *Main* agent. These events allow for communication between the *Main* agent and the embedded agents. The agent *Refill* is not event dependent as the refill locations are not dependent on the real driver data thus, refill locations are placed on model start up. However, the agents *Locations* and *Vehicle* are event dependent as their placement and operation is dependent on the selected simulation month from the real driver data.

2.4. Vehicle Agent

Each month from the real driver data is simulated by an individual *Vehicle* agent. When the battery size and charging type is selected the *Main* agent will communicate this to the *Vehicle* agent, which defines the fundamental characteristics of the *Vehicle* agent for the selected month. These fundamental characteristics are the starting point for both the movement logic and battery model embedded within the agent.

Figure 3a illustrates the flow chart used to simulate the battery under test. The flow chart depicts the Battery's charging and discharging processes, regulated by *Charge_Flow* and *Discharge_Flow*. These rates rely on

Charge_Amount and *Discharge_Amount*, determined by the product of two variables indicating flow level and status (1/0). *Charge_Level* and *Vehicle_Consumption* control charge and discharge levels, while *Charge_On* and *Discharge_On* indicate charging or discharging. *Charge_Level* depends on the chosen charging type, initially set by the user, which uses the charger power levels described in Section 2. *Vehicle_Consumption* is determined by the average energy consumption associated with the velocity and ambient temperature at which the *Vehicle* agent is operating. This average energy consumption is derived from data provided by Straubel (2008), incorporating the influence of ambient temperature as established by Al-Wreikat et al. (2022), which was previously mentioned within Section 2. The derived energy consumption is illustrated in Figure 3b.

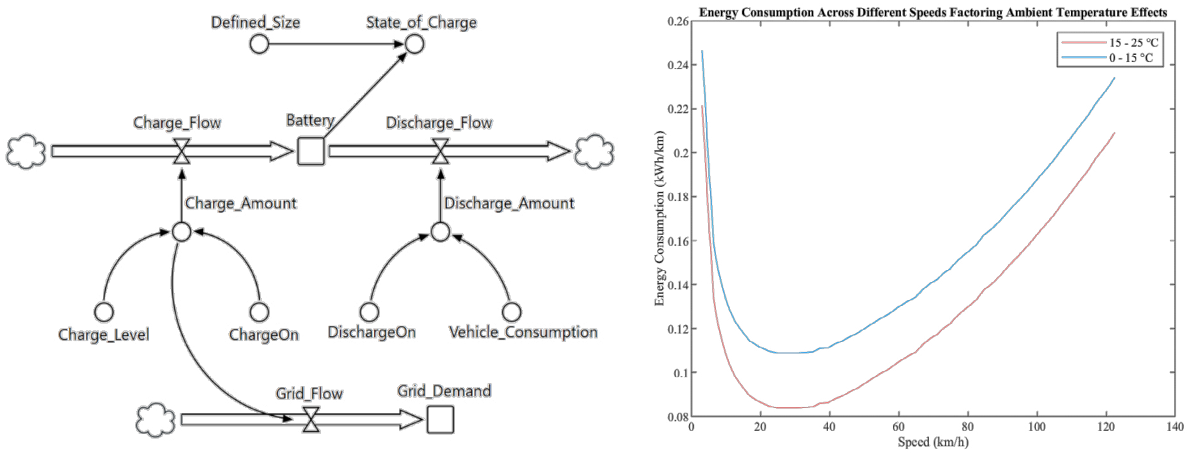

Fig. 3. (a) Battery flow diagram utilised in *Vehicle* agent. (b) Energy consumption incorporating ambient temperature (Straubel, 2008; Al-Wreikat et al., 2022).

2.5. Movement and Decision Logic

The simulation of real driver data and behaviour is achieved through the utilization of a state chart governing the movement and decision-making logic of the *Vehicle* agent. The state chart determines the initial starting point of the *Vehicle* agent, corresponding to the simulated month. Subsequently, during the journey, the state chart configures parameters such as speed, destination, and discharge rate for the *Vehicle* agent. Following the completion of a journey, the state chart evaluates whether to proceed with the next journey or not. If the *Vehicle* state of charge is $\leqslant$ 20% or if the next journey is infeasible based on the current battery level, the *Vehicle* agent initiates charging by traveling to a predefined *Refill* agent location. Upon reaching the desired battery level, as specified by the user, the *Vehicle* agent resumes the journey. At the end of each month, the model generates output data for subsequent analysis and returns to the initial definition menu, ready for the next case study.

2.6. Battery Size Optimisation Case Study

To assess the practical application of the agent-based model for battery size optimisation, four case studies were investigated using real driver data from a user in Glasgow across the months February to July (ambient temperatures detailed in Table 1). The four case studies are as follows: (1) 30kWh battery with rapid charging using current chargers in circulation within 500 metres, (2) 40kWh battery with rapid charging using current chargers in circulation within 500 metres, (3) 30kWh battery with rapid charging using an alternative charging infrastructure, and (4) 40kWh battery with rapid charging using an alternative charging infrastructure.

These studies were chosen as they investigate the feasibility of battery optimisation by reducing the current average battery size from 50kWh to 30kWh or 40kWh. Based upon current charging conditions and future charging conditions that can be expected once the 2030 deadline has arrived.

The alternative charging infrastructure consists of clustered charging points at commonly user visited locations and transitioned petrol stations into rapid charging forecourts. This infrastructure is proposed to find the potential benefit an optimised charging infrastructure can have on the minimisation of electric vehicle batteries.

Table 1. Average monthly temperatures for the UK Met Office (2023).

	February	March	April	May	June	July
Average Temperature (°C)	5.6	6.7	8.1	11.8	13.9	16.6

3. Results and Discussion

This section presents an analysis of the results obtained from the four conducted case studies, categorizing them according to their respective charging scenarios. The agent-based model employed in each case study generated per-minute data on the state of charge of the *Vehicle* agent. These state of charge values were evaluated to determine the appropriateness of the proposed battery size for the user including material and economic analysis, taking into consideration the predefined parameters outlined in the respective case study definitions.

3.1. Current Chargers in Circulation

This section investigates into whether the current charging infrastructure would allow for a user with a smaller battery size, whilst maintaining a positive state of charge ideally within the 20 – 80% bracket (Kostopoulos et al., 2020). Figure 4 details the per month state of charge for case study (1).

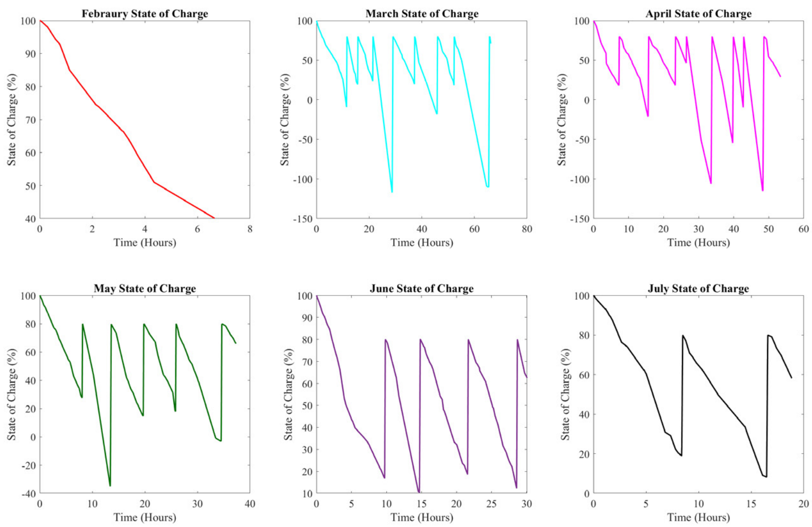

Fig. 4. Monthly state of charge for case study (1).

As seen in Figure 4 the existing charging infrastructure is suitable for short journeys and months with low distances traveled e.g., February, June, and July, where the user maintains a state of charge within the 20-80% range. In February, the vehicle doesn't require charging due to both the low average distance traveled and economical driving behavior. However, for further daily distances and higher average monthly distances, the current charging infrastructure cannot support a smaller optimized battery size, as observed in March, April, and May. Despite maintaining a state of charge within the 20-80% range, embarking on a journey of 80km or more leads to negative state of charge values, indicating the insufficiency of the current charging infrastructure for this battery size. In summary, the current charging infrastructure favours larger electric vehicle battery sizes and shorter journey durations. The results of case study (2) further expands upon this.

By increasing the battery size by 10kWh, the current charging infrastructure now becomes capable of accommodating the journeys during February, May, June, and July, ensuring the state of charge maintains the 20-80% range, as depicted in Figure 5. However, the infrastructure remains unsuitable for months characterized by further distances travelled, particularly in the case of March and April.

Despite April having a 2km lower total distance traveled compared to May, the negative state of charge observed in April can be attributed to individual journeys exceeding 80km. This is due to the sparse placement of existing charging stations, which results in insufficient charging opportunities for extended journeys. Overall, these findings underscore the need for an alternative charging infrastructure with a denser distribution and accessibility to effectively support electric vehicle usage during months with further distances travelled.

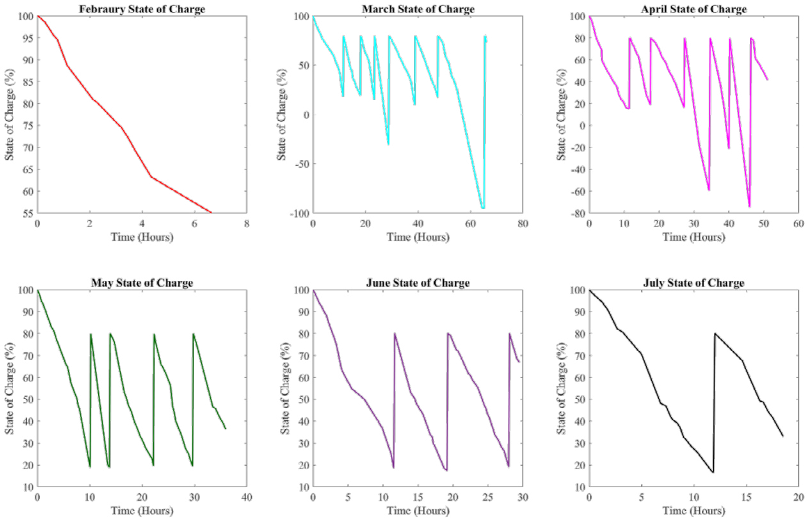

Fig. 5. Monthly state of charge for case study (2).

3.2. Alternative Charging Infrastructure

This section analyses the benefits of the proposed alternative charging infrastructure for a minimised battery size, whilst maintaining a positive state of charge ideally within the 20 – 80% bracket (Kostopoulos et al., 2020). Figure 6 details the per month state of charge for case study (3).

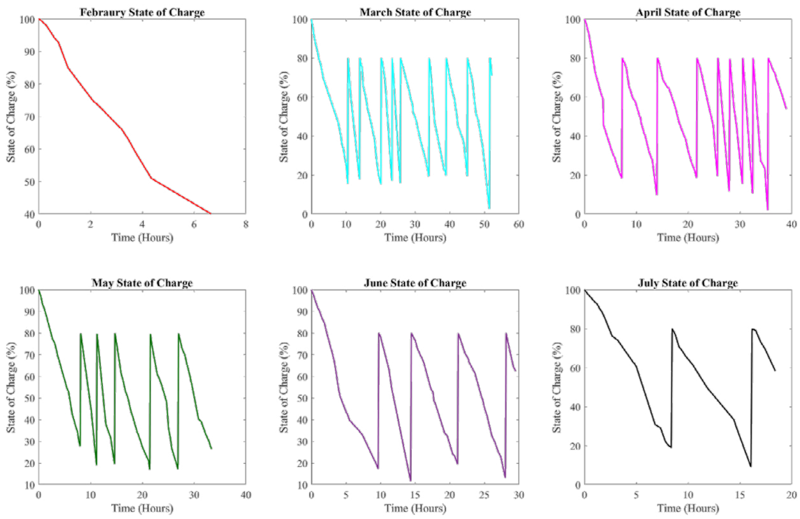

Fig. 6. Monthly state of charge for case study (3).

Figure 6 illustrates the clear benefit of the alternative infrastructure as the state of charge consistently maintains the desired level. However, due to the smaller battery size the user must charge more, which is clearly shown in the months of March, April, and May. The amount of time spent charging is between 1.6% - 3.2% of the total journey time, which is negligible as these 15 minute charge times can be completed whilst the user has stopped at one of their routinely visited locations, removing the need to travel to a charging location not near their chosen destination.

Case study (4) highlights the benefit of increasing the battery size by 10kWh on journey stop times. As seen in Figure 7 the number of stops has been approximately halved in comparison to case study (3). The amount of time spent charging is between 0.8% - 2.3%, which is a 0.8% decrease in added journey time compared to case study (3). Therefore, a 40kWh battery would be optimal for a user who has limited stops and a 30kWh battery would be optimal for a user with multiple stops. However, if a user with limited stops adjusted their driving behaviour N. Pearre et al. (2011) a 30kWh battery would become optimal.

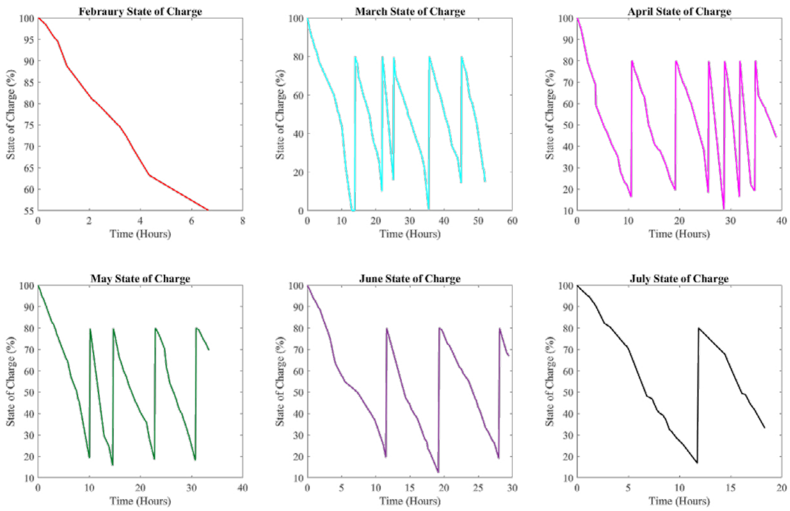

Fig. 7. Monthly state of charge for case study (4).

3.3. Economic and Material Benefits

This section highlights the economic and material benefits of reducing the average electric vehicle battery size by up to 40%. The reduction in size directly corresponds to a decrease in the average amount of lithium required for construction by up to 6.4kg, considering that approximately 320 grams of lithium is needed per available kWh of battery capacity (Tahil, 2010). Additionally, reducing the average battery size by 40% translates to potential savings for electric vehicle consumers. Based on an average cost of £132.53 per kWh for an electric vehicle battery pack (Nicholas and Lutsey, 2019), a reduction of 40% in battery size can lead to savings of up to £2650.60 when purchasing a new electric vehicle.

4. Conclusion

The research conducted by this paper has introduced an agent-based model that can take real driver data as an input to produce an optimised electric battery size based upon vehicle consumption and charging availability. By applying the model across four case studies for a single driver in Glasgow it was concluded that the average electric vehicle battery size can be decreased to 30kWh or 40kWh when supported by an improved charging infrastructure. This will benefit users through conveniently placed charging locations and a 40% reduction in battery cost alongside a lithium reduction of up to 6.4kg.

The agent-based model utilised within this paper has provided a valuable skeleton, which can be expanded further across multiple different applications factoring multiple unique sets of real driver data. Finally, the result of this paper demonstrates the importance of a high-level charging infrastructure when optimising battery size, which will aid government planners trying to meet the 2030 deadline.

Acknowledgments

This work was supported by DTE Network+, funded by EPSRC, grant reference EP/S032053/1.

References

Department for Transport, 2021. *Decarbonising Transport – A Better, Greener Britain. Transport Decarbonisation Plan.* https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1009448/decarbonising-transport-a-better-greener-britain.pdf

HM Government, 2021. *Net Zero Strategy: Build Back Greener.* https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/103 3990/net-zero-strategy-beis.pdf

A. Di Martino, S. M. Miraftabzadeh, and M. Longo, 2022. Strategies for the Modelisation of Electric Vehicle Energy Consumption: A Review, Energies, vol. 15, no. 21, p. 8115, doi: 10.3390/en15218115.

I. Miri, A. Fotouhi, and N. Ewin, 2021. Electric vehicle energy consumption modelling and estimation—A case study, International Journal of Energy Research, vol. 45, no. 1, pp. 501– 520, doi: 10.1002/er.5700.

W. J. Sweeting, A. Hutchinson, and S. D. Savage, 2011. Factors affecting electric vehicle energy consumption, International Journal of Sustainable Engineering, vol. 4, no. 3, pp. 192– 201, doi: 10.1080/19397038.2011.592956.

R. van Haaren, 2011. Assessment of Electric Cars – Range Requirements and Usage Patterns based on Driving Behavior recorded in the National Household Travel Survey of 2009.

JB. Straubel, 2008. Roadster Efficiency and Range. https://www.tesla.com/blog/roadster-efficiency-and-range

Y. Al-Wreikat, C. Serrano, and J. R. Sodré, 2022. Effects of ambient temperature and trip characteristics on the energy consumption of an electric vehicle, Energy, vol. 238, p. 122028, doi: 10.1016/j.energy.2021.122028.

O. Veneri, 2016. Technologies and Applications for Smart Charging of Electric and Plug-in Hybrid Vehicles. Springer.

I. S. Bayram and A. Tajer, 2017. Plug-in Electric Vehicle Grid Integration. Artech House.

V. Vahidinasab and B. Mohammadi-Ivatloo, 2022. Electric Vehicle Integration via Smart Charging: Technology, Standards, Implementation, and Applications. Springer Nature.

N. S. Pearre, W. Kempton, R. Guensler, and V. Elango, 2011. Electric vehicles: How much range is required for a day's driving?, Transportation Research Part C-emerging Technologies, vol. 19, no. 6, pp. 1171–1184, doi: 10.1016/j.trc.2010.12.010.

A. Borshchev, 2013. The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6. AnyLogic North America.

TravelAi, 2022. Data Export Specification, EV Serious Ltd., Croydon, UK.

MetOffice, 2023. Climate summaries. https://www.metoffice.gov.uk/research/climate/maps-and-data/summaries/index

E. D. Kostopoulos, G. D. Spyropoulos, and J. K. Kaldellis, 2020. Real-world study for the optimal charging of electric vehicles, Energy Reports, vol. 6, pp. 418–426, doi: 10.1016/j.egyr.2019.12.008.

W. Tahil, 2010. How Much Lithium does a LiIon EV battery really need? https://www.academia.edu/download/34381837/How_Much_Lithium_Per_Battery.pdf

M. Nicholas and N. Lutsey, 2019. Update on electric vehicle costs in the United States through 2030. https://theicct.org/sites/default/files/publications/EV_cost_2020_2030_20190401.pdf