EFFICIENT EV CHARGING INFRASTRUCTURE PLANNING USING DATA-DRIVEN OPTIMISATION

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Keywords: OPTIMISATION, SIMULATION, EV CHARGING INFRASTRUCTURE, TRANSPORT POLICY, NET ZERO EMISSION

Abstract

This paper presents a high-level overview of a data-driven methodology for optimising the implementation of policy commitments in the transportation sector, specifically focusing on electric vehicle (EV) charging infrastructure in Newcastle upon Tyne, United Kingdom. The study utilises a simulation model provided by the industrial partner, Arup Group Limited, and combines it with a genetic optimisation algorithm inspired by Long Short-Term Memory (LSTM) and fuzzy logic. Four future energy scenarios from National Grid are considered to predict EV quantities and the energy demand, reflecting varying levels of decarbonisation and societal change. The optimisation algorithm is applied to each scenario to determine the optimal charging point types, locations, quantities, total capital and operational expenditures, and operating hours of the charging points. This paper provides a high-level explanation of the methodology and results, without delving into the mathematical equations or detailed aspects of the simulation and optimisation processes. The proposed methodology demonstrates a promising approach to efficiently implement policy commitments in the transport sector, particularly in the context of EV charging infrastructure, enabling local authorities to effectively plan and manage the transition to zero-emission vehicles.

1 Introduction

Electric vehicles (EVs) have gained significant attention in recent years due to their potential to reduce greenhouse gas emissions and support the transition towards a sustainable transport system. Governments and policymakers worldwide are introducing policies and incentives to encourage EV adoption and the development of the necessary charges in the infrastructure. However, efficient implementation of these policies requires a well-planned and optimised EV charging infrastructure that caters to the diverse needs of EV users and minimises the overall costs.

Several studies have explored various aspects of EV charging infrastructure, such as charging point location optimisation [1], demand forecasting [2], and the impact on the power grid [3]. Some researchers have focused on the optimal placement of charging points using methods such as clustering algorithms [4], and geographic information systems [5].

In this paper, we present a data-driven methodology using simulation and multi-objective optimisation that incorporates Long Short-Term Memory (LSTM) networks [6] for efficient implementation of policy commitments in the transport sector. The advantages of using LSTM networks include their ability to learn long-term dependencies in time series data and effectively forecast EV charging demand. This study focuses on public charging point location optimisation, considering various charging point types such as slow, fast, rapid, and ultra-rapid chargers.

The goal of the optimisation is to consider and optimise the following factors needed to design and expand the EV charging infrastructure: charging point type, charging point location, charging point quantity, total capital and operational expenditures, and operating hours of charging points.

By integrating multiple data sources and using a comprehensive optimisation approach, we aim to provide valuable insights and practical solutions for policymakers and local authorities to efficiently implement EV charging infrastructure expansion and ensure a smooth transition towards electric mobility.

Related Work

In the ever-evolving landscape of EV adoption, the importance of developing efficient and effective EV charging infrastructure has been emphasised by numerous researchers. As a growing body of literature attests, the strategic planning and deployment of EV charging stations are crucial to ensuring a seamless transition to electric mobility and overcoming barriers such as range anxiety.

The paper [7] has proposed a location optimisation model that takes into account various costs associated with charging station deployments, such as construction, operation, and maintenance costs. The model also considers factors like land prices, charging demand, and user convenience. To solve the optimisation problem, the authors employ a genetic algorithm, which is an evolutionary optimisation technique inspired by the natural process of evolution. The genetic algorithm is used to find the optimal locations for EV charging stations that minimise the total cost.
Building on this foundation, the paper [8] has emphasised the importance of incorporating real-world data into optimisation models for EV charging infrastructure. The authors utilised GPS data from a fleet of electric vehicles to develop a demand-driven optimisation model, which accounted for factors such as driver behaviour and charging patterns. This study underscored the value of using empirical data to inform decision-making processes and improve the accuracy of optimisation outcomes.

The paper [8] focuses on developing an optimal charging strategy for EVs in power systems integrated with solar energy generation. The study aims to minimise the total operational cost of the power system while considering the uncertainties associated with solar power generation and EV charging demands. The authors propose a two-stage stochastic programming model to optimize the charging schedule of EVs, incorporating uncertainties in both solar power generation and EV charging demand.

Furthermore, the study in [10] focuses on developing an efficient charging planning strategy for EVs using deep reinforcement learning. The primary objective of this study is to minimise the charging costs for EV users while considering the limitations of the charging infrastructure and the varying electricity prices throughout the day. The authors propose a novel deep reinforcement learning approach to address the problem of optimal charging planning for EVs. They employ a deep Q-network to learn the optimal charging strategies, considering the state of charge of the EVs, the availability of charging stations, and the time-varying electricity prices.

In summary, the literature on optimisation and electric vehicle charging infrastructure highlights the significance of developing efficient and cost-effective solutions to support the widespread adoption of electric vehicles. By employing a range of optimisation techniques, from multi-objective models to advanced machine learning algorithms, researchers have made significant strides in addressing the challenges associated with EV charging infrastructure planning and deployment.

While the existing literature on optimisation and electric vehicle charging infrastructure presents valuable insights and approaches for planning and managing networks, there is a need for a comprehensive framework that integrates advanced techniques to effectively address the challenges associated with the rapid growth of EVs. We have proposed a novel data-driven optimisation framework that combines machine learning methods, such as LSTM and fuzzy logic, with multi-objective genetic algorithms to efficiently plan and deploy electric vehicle charging infrastructure. This framework not only considers multiple objectives, such as cost minimisation and charging network coverage but also accounts for real-world constraints and uncertainties to ensure its practical applicability.

2 Methodology

This section presents the designed framework for finding the best implementation of policy commitments in transport systems, as shown in Figure 1. At the core of this framework is a model that simulates the behaviour of the transport network when a policy commitment is implemented. This model can in principle take various forms, such as an agent-based model, a physics-based model implementation, a digital twin of the transportation network, or a machine learning model appropriately trained on a related dataset of the transport system.

These models should describe the system’s behaviour if a specific policy commitment is applied. Generally, these models are constructed based on a baseline model. The baseline model outlines the current situation in the network and should align with the datasets already available from the system. Additionally, these models need to incorporate the capability to reflect the effects of implementing new policy commitments.

The model is then employed in a loop to evaluate different policy commitment implementations and identify the best implementation using optimisation methods.

![Fig. 1 Framework for finding the best implementation of policy commitments in transport systems.](image)

2.1 National Grid’s Future Energy Scenarios

National Grid has developed four future energy scenarios to forecast the number of EVs [1]. These scenarios are based on the pace of decarbonisation and the extent of societal changes. The four scenarios are as follows:

1. **Steady Progression**: This pessimistic scenario envisions a slow pace of decarbonisation and a low level of societal change. It is characterised by the gradual adoption of EVs and the slow installation of charging points. The ban on new petrol/diesel vehicles is achieved in 2035 for cars and in 2040 for vans.

2. **System Transformation**: In this scenario, decarbonisation occurs at a moderate pace, accompanied by a medium level of societal change. Charging points for EVs are installed ahead of demand. The ban on new petrol/diesel vehicles is achieved in 2032.

3. **Consumer Transformation**: This scenario features a moderate pace of decarbonisation and a higher level of societal change. Decarbonisation begins earlier, and the ban on new petrol/diesel vehicles is achieved in 2030.
change. Drivers adopt EVs before the required charging infrastructure is in place. The ban on new petrol/diesel vehicles is achieved in 2030.

(4) Leading The Way: The most optimistic scenario envisions a rapid pace of decarbonisation and the highest level of societal change. The 2030 ban on new petrol/diesel vehicles is achieved.

These future energy scenarios provide a useful framework for planning and analysing potential EV adoption trends and their impact on the transport network and charging infrastructure. According to Figure 2, the peak years for the different scenarios are as follows: Consumer Transformation in 2046, Leading the Way in 2042, Steady Progression in 2050, and System Transformation in 2048. This information helps to understand the potential future demand for EVs in Newcastle upon Tyne and provides essential input for planning and analysis of the required charging infrastructure under different scenarios.

Fig. 2 Estimation of the number of EVs for Newcastle upon Tyne using the future energy scenarios of the National Grid. These estimations are also used in the scenarios developed by Arup.

2.2 Simulation

The simulation model used in this research is provided by the industrial partner of the project, Arup Group Limited. This comprehensive model is based on a destination modelling approach, which describes user behaviour and simulates the transport network in response to the implementation of various policy commitments related to EV charging infrastructure. From the destination model, the EV energy demand is calculated, and subsequently, the power demand is determined.

The simulation utilises estimated EV energy demand, along with EV quantity forecasts from the National Grid, to create the environment for the optimisation model. In the following section, the optimisation model, which is the main contribution of this paper, has been described at a high level without any detailed mathematical explanations or equations, focusing on the overall methodology and results.

2.3 Optimisation

Optimisation is the process of finding the best possible solution for a given problem, considering a set of constraints and objectives. In general, optimisation methods aim to minimise or maximise an objective function, which quantifies the quality of a solution. Optimisation techniques can be classified into deterministic and stochastic methods, with the latter employing random sampling to explore the search space. Some widely used optimisation methods include linear programming, integer programming, genetic algorithms, particle swarm optimisation, and simulated annealing, among others. The choice of an optimisation method depends on the specific characteristics of the problem at hand, such as the type and complexity of the objective function, the presence of constraints, and the size of the search space.

Genetic Algorithm with Fuzzy Logic and LSTM. This study incorporates a genetic optimisation solution inspired by the Long Short-Term Memory (LSTM) method and utilises fuzzy logic to enhance the optimisation process. LSTM is a type of recurrent neural network (RNN) architecture that is designed to handle sequence prediction problems by remembering long-term dependencies in the data [6]. Fuzzy logic, on the other hand, is an approach to computing that represents the uncertainty in data through the use of linguistic variables and fuzzy sets, allowing for approximate reasoning and decision making under uncertain conditions [11].

The overview of this optimisation approach is summarised in Figure 3. The integration of fuzzy logic and LSTM with the Genetic Algorithm (GA) demonstrates promising results in solving multi-objective problems.

The optimisation process leverages a simulation environment that models the EV demand, EV quantity, and EV locations. In the GA, EV charging points are treated as genes. Each gene encodes variables such as the location and type of the charging point. These genes are initially generated randomly.

The performance of the genes in the simulation environment is assessed based on the utilisation and costs of the charging points. A selection of high-performing genes is retained, while new genes are randomly generated in each iteration. This process continues until convergence is achieved, leading to an optimal solution.

By integrating fuzzy logic and LSTM networks into the GA, the optimisation method can efficiently handle the uncertainties and complexities of the transport network. This hybrid approach enables the identification of optimal policy measures for a well-balanced and efficient transition towards a more sustainable transport system, considering factors such as charging point type, location, quantity, total capital and operational expenditures, and operating hours of charging points.

3 Results

The optimisation results for the peak years in different scenarios are shown in Figure 3. The findings are summarised as follows:

3.1 Leading The Way

In the Leading The Way scenario, the peak year is 2042 with an estimated number of EVs equal to 134,606. A total of 4,753
charging points are needed, with an overall cost of £8,195,000. The average operating hours of charging points is 7.57 hours, and the average number of EV charging requests per charging point per day is 35.79.

3.2 Consumer Transformation

For the Consumer Transformation scenario, the peak year is 2046 with 145,345 EVs predicted. To accommodate this, 5,167 charging points are required, resulting in a total cost of £8,859,400. The average operating hours of charging points is 7.77 hours, and the average number of EV charging requests per charging point per day is 36.17.

3.3 System Transformation

The System Transformation scenario has a peak year of 2048 and an estimated 146,617 EVs. This scenario necessitates 5,386 charging points and incurs a total cost of £9,117,900. The average operating hours of charging points is 7.81 hours, and the average number of EV charging requests per charging point per day is 35.39.

3.4 Steady Progression

In the Steady Progression scenario, the peak year is 2050, with 160,403 EVs anticipated. This requires 5,817 charging points and a total cost of £9,880,200. The average operating hours of charging points is 7.95 hours, and the average number of EV charging requests per charging point per day is 35.36.

4 Discussion

The results indicate that the Leading The Way scenario, which is the most optimistic in terms of decarbonisation and societal change, has the lowest total cost and a moderate number of charging points. The Steady Progression scenario, on the other hand, has the highest total cost and requires the most charging points. The differences between the scenarios highlight the impact of decarbonisation speed and societal change on the required EV charging infrastructure.

It can also be observed that the average operating hours of charging points and the average number of EV charging requests per charging point per day remain relatively similar across all scenarios. This suggests that the optimisation solution is capable of balancing the charging demand and infrastructure needs regardless of the scenario being considered.

5 Conclusion

This paper has presented a data-driven methodology for optimising the implementation of policy commitments in the transportation sector, specifically focusing on electric vehicle (EV) charging infrastructure in Newcastle upon Tyne, United Kingdom. The study utilised a simulation model provided by the industrial partner, Arup, and combined it with a genetic optimisation algorithm inspired by Long Short-Term Memory (LSTM) and fuzzy logic.

Four future energy scenarios from National Grid were considered to predict EV quantities and energy demand. These scenarios reflect varying levels of decarbonisation and societal change. The optimisation algorithm was applied to each scenario to determine the optimal charging point types, locations, quantities, total capital and operational expenditures, and operating hours of the charging points.

The results show that the Leading The Way scenario, characterised by rapid decarbonisation and high societal change, has the lowest overall cost and a moderate number of required
charging points. In contrast, the Steady Progression scenario, with the slowest decarbonisation and low societal change, has the highest total cost and the most charging points needed. This highlights the importance of effective policy planning and commitment to decarbonisation in the transportation sector.

The proposed methodology demonstrates a promising approach to efficiently implement policy commitments in the transport sector, particularly in the context of EV charging infrastructure. By using data-driven simulations and optimisation techniques, local authorities can effectively plan and manage the transition to zero-emission vehicles, ensuring a more sustainable and environmentally friendly transportation system.

6 Acknowledgements

This work is supported by the EPSRC grant EP/V519571/1 and Arup Group Limited.

7 References