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Optimising electric vehicle charging stations on UK motorways using deep neural networks: A scenario-based case study of the M40

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***Abstract*—The UK's electric vehicle (EV) adoption is accelerating rapidly, with over 1.4 million EVs on the road and projections reaching 14 million by 2030. However, while approximately 75,000 public chargers have been installed to date, this remains far short of the govern-ment's 300,000 target by 2030. Planning adequate infrastructure involves more than fore-casting national demand—it requires estimating the number of chargers needed in specific locations, such as motorway corridors, while accounting for traffic volumes, grid capacity, and funding limitations. Most existing approaches rely on linear models that fail to capture the full complexity and interdependence of these factors.**

This study proposes a predictive framework using Deep Neural Networks (DNNs) to estimate the number of ultra-fast EV charging stations required under varying planning conditions and constraints. Unlike traditional methods, the DNN model learns nonlinear relationships across ten key input features, integrating both technical variables (e.g., traffic flow, substation capacity, energy consumption) and policy-relevant constraints (e.g., budgets, installation costs). A scenario-based case study was conducted on the M40 motorway to demonstrate the model's flexibility in real world contexts—covering Crowded, Energy Constrained, Budget-Constrained, and Balanced scenarios using actual traffic, charger, and substation data. The results show that this DNN-based approach offers a scalable, data informed planning tool that can support UK policymakers in making more resilient and adaptive infrastructure decisions.

Keywords*— *electric vehicles, charging infrastructure, deep neural networks, infra-structure forecasting, UK motorways

I. INTRODUCTION

The UK's transport sector remains one of the most significant contributors to greenhouse gas emissions, accounting for nearly 29% of the nation's CO_2 output in 2023 [1]. In response, the government has committed to banning the sale of new petrol and diesel vehicles by 2035 and achieving net-zero emissions by 2050 [1]. Projections estimate that the number of electric vehicles (EVs) on UK roads will reach around 14 million by 2030, up from just over 1 million in early 2025 [2]. Supporting this transition requires a robust public charging infrastructure, with an estimated 300,000 public chargers needed by 2030 [3]. However, current deployment falls significantly short, with only around 75,000 public chargers installed as of 2024 [4].

As of January 2025, there were approximately 73,334 public charging devices nationwide, including just 14,448 (20%) fast chargers—equating to roughly one charger per 14 EVs [5]. This gap is particularly acute along long-distance corridors, intercity routes, and high-traffic urban zones, where "charging deserts" remain common. Such shortages undermine user confidence, reduce accessibility, and slow wider EV adoption [6].

The planning process for EV infrastructure is increasingly recognised as complex and multifactorial. According to [3], effective deployment must reconcile "diverse and often competing factors" across national, regional, and local levels. The Taking Charge strategy similarly notes that planning requires aligning inputs from energy networks, transport forecasts, and investment frameworks [4]. Getting to the Point report adds that local authorities require tools that integrate traffic patterns, energy availability, budget constraints, and demand forecasts to plan effectively [5].

This complexity arises from two major dimensions:

- **Technical multi-factor complexity**: Infrastructure planning is shaped by multiple interdependent variables including total vehicle flow, EV penetration rates, peak demand windows, substation and grid capacity, energy availability, budget limitations, and charger installation costs. These variables interact in nonlinear ways, making simple ratio-based or linear models ineffective for predicting infrastructure needs [7].

- **Policy and governance-level uncertainty**: Strategic decisions must remain viable under shifting political priorities, varying funding scenarios, and long-term energy policies. Planning tools must therefore be flexible enough to adapt to different demand conditions and regional constraints [3] [4].

Due to this growing complexity in EV infrastructure planning—spanning both technical factors and policy-level constraints—there is a clear need for advanced, data-driven approaches that go beyond traditional linear planning tools. This study addresses that need by developing a Deep Neural Network (DNN) model to predict the optimal number of EV charging stations required under varying planning conditions. The model is designed to support policymakers, transport planners, and energy infrastructure authorities by offering a fast, scalable forecasting tool that adapts to different traffic volumes, energy availability, and budget levels. DNNs are particularly well-suited for this task because they can learn nonlinear relationships, generalise across high-dimensional inputs, and produce reliable forecasts without requiring repeated optimisation. By integrating diverse planning variables, the proposed model helps inform more realistic and flexible EV infrastructure strategies for future deployment.

II. LITERATURE REVIEW

A. Input Factors for EV Infrastructure Planning

Planning EV charging infrastructure involves multiple, interacting factors that influence charger deployment, usage, and investment decisions. Both academic research and UK policy documents consistently emphasise the need to account for a wide range of interdependent variables—technical, spatial, economic, and regulatory—that vary by region and scenario [8]. These factors do not operate in isolation but are closely linked, often requiring planners to consider trade-offs between system efficiency, public funding, and grid capacity [7] [8]. UK-specific reports further stress that planning must balance practical system constraints with national targets such as net-zero timelines and local infrastructure readiness [9].

Given the aim of this study—to develop a predictive model that estimates the number of chargers required under different planning scenarios—both academic literature and policy guidance were reviewed to identify the most influential and practically relevant input factors**.** These features were selected not only for their demonstrated importance in previous optimisation studies but also for their alignment with UK government strategies such as the Taking Charge report and National Grid energy capacity forecasts.

While the ten selected input features are primarily technical or economic in nature—relating to traffic flow, charger capacity, grid limitations, and infrastructure deployment—several of them are shaped or constrained by broader policy contexts. For example, factors such as budget constraints and regional energy limits are directly influenced by public funding decisions and energy planning regulations. Others, like EV adoption levels or installation costs, though technically observed, are indirectly affected by policy incentives, subsidies, or national targets.

This distinction is especially relevant when defining planning scenarios later in this study, as it allows the model to simulate not only technical variations but also real-world conditions influenced by policy or regulatory shifts. Table 1 summarises the ten input features, along with the academic and policy sources that validate their inclusion in the model.

TABLE 1 TEN INPUT FEATURES AND SUPPORTING ACADEMIC AND POLICY SOURCES

Factor	Brief Description / Relevance	Academic or Policy/Official Sources
Total Traffic Daily	Vehicle flow determines charging demand and congestion hotspots	[5] [11][12]
EV Traffic Daily	EV adoption rate affects charger utilisation and energy needs	[7][8][16]
Existing Charging Stations	Presence of chargers impacts siting strategy and future placement decisions	[16][21]
Peak Demand %	Temporal variation affects capacity planning	[14][15]
Installation Costs	High cost influences budget feasibility and charger type selection	[7][11][16][22]
Substation Capacity	Grid node load tolerance is a key constraint for fast charger deployment	[7][9][14]
Station Capacity	Determines how many vehicles can be served per unit time	[13][22]
Budget Constraint	Public funding availability limits the scale of implementation	[4][6][10][11]
Energy Consumption	Determines total power draw and grid impact for projected charging loads	[11][12][14]
Energy Limit	Regional or site-specific constraints that cap usable energy during peak periods	[7] [23]

B. Modelling Methods in EV Infrastructure Planning

Traditional infrastructure planning studies often relied on linear programming, rule-based heuristics, or simulation-based methods to optimise EV charger placement and sizing. These approaches, while intuitive and analytically tractable, typically assume fixed demand conditions or average-case scenarios. For example, early models using the p-median and set covering location models aimed to minimise travel distance or infrastructure cost under deterministic constraints [10] [11], However, such linear and location-only formulations struggle to address real-world variability in traffic flows, demand surges, and grid capacity fluctuations.

Recent research has highlighted the limitations of these linear assumptions, particularly in contexts involving multi-scenario constraints, regional demand variations, and nonlinear relationships between factors such as demand, cost, and capacity [7] [8]. For instance, [7] pointed out that traditional node-based models often oversimplify charging demand and fail to reflect interactions between traffic, grid, and location data. These shortcomings have driven the adoption of machine learning approaches for infrastructure planning, including regression models, decision trees, and clustering algorithms, which provide more flexible data-driven alternatives [9] [10] . However, even these approaches may fall short in capturing complex interdependencies across multiple variables—especially when input features are numerous and conditionally related.

In this context, Deep Neural Networks (DNNs) have gained traction due to their capacity to model nonlinear input-output relationships, adapt to diverse scenarios, and generalise across multiple planning conditions. DNNs consist of layered structures capable of learning high-dimensional patterns from data, enabling infrastructure predictions that respond to both technical constraints and policy-sensitive conditions without needing repeated re-optimisation [12]. For example, [8] applied DNNs to forecast energy consumption and infrastructure requirements under multiple scenarios and found improved accuracy compared to regression models and LSTMs. Similarly , [13] demonstrated that DNNs outperformed support vector regression in modelling EV charging demand when traffic patterns and energy limits were variable.

Beyond predictive accuracy, DNNs are especially well-suited to multi-constraint EV infrastructure planning because they allow planners to embed technical features (e.g., traffic volume, station capacity) and policy constraints (e.g., budget, substation capacity) directly into the modelling structure. This is essential for contexts like the UK, where infrastructure investment must adapt to regional traffic demands and evolving policy frameworks. While many reviewed studies focus on spatial placement, DNN-based models can also directly estimate optimal infrastructure quantity, which is the primary focus of this study.

Given these methodological advantages, and the proven relevance of DNNs in similar applications, this study employs a DNN with ReLU activation to predict the number of ultra-fast chargers needed along a UK motorway corridor under varying constraints.

III. RESEARCH QUESTION AND OBJECTIVE

This study aims to develop a predictive model using Deep Neural Networks (DNNs) to estimate the optimal number of ultra-fast electric vehicle (EV) charging stations required along the M40 motorway in the UK. The model integrates key technical and policy-sensitive input factors and simulates charger demand across multiple planning scenarios, including constraints related to traffic volume, energy availability, and budget limitations.

A. Research Question

How can a Deep Neural Network (DNN) model be applied to predict and optimise the number of ultra-fast EV charging stations required along the M40 motorway under varying traffic, energy, and budgetary constraints?

B. Research Objectives

- To design and implement a DNN-based model that estimates the optimal number of EV charging stations based on key features such as daily traffic, EV penetration rates, substation capacity, installation costs, and energy limits.
- To define and explore various planning scenarios that reflect diverse and interdependent real-world constraints—such as traffic density, energy limitations, and budgetary considerations—relevant to EV infrastructure deployment in the UK.
- To preprocess and normalise input data drawn from traffic statistics, EV growth projections, infrastructure records, and government energy reports.
- To train and validate the DNN using ReLU activation functions in hidden layers and linear activation in the output layer for regression-based predictions.
- To evaluate the model's outputs across different scenarios, focusing on trade-offs in the number of chargers, energy consumption, and infrastructure cost.
- To propose a scalable and adaptable planning tool that supports evidence-based decision-making for future EV infrastructure deployment in the UK.

IV. METHODOLOGY

This study applies a Deep Neural Network (DNN) approach to predict the number of ultra-fast EV charging stations needed along a major UK motorway. The methodology consists of five stages: (1) case study selection, (2) input factor identification, (3) data generation using a hybrid approach, (4) model development and training, and (5) scenario-based prediction and analysis.

A. Case Study and Model Structure

The selected case study is the M40 motorway, a strategic intercity corridor connecting London and Birmingham**.** This route carries heavy volumes of daily traffic, serving commuters, freight operators, and regional travellers. According to UK Department for Transport data, daily traffic on the M40 ranges between 65,000 and 130,000 vehicles, depending on the segment [4]. Despite national growth in EV infrastructure installed across the UK [5]—the M40 corridor remains under-equipped, particularly with regard to ultra-fast chargers. Several motorway service areas still suffer from limited capacity, risking bottlenecks as EV usage expands. National planning reviews have raised concerns about inconsistent charger distribution along strategic routes, with the [3] [6] both highlighting intercity corridors as critical pressure points.

To ensure that the model captures real-world spatial and infrastructure conditions, this study incorporates three M40-specific variables:

- Total daily traffic volume, gathered from DfT road segment traffic count data;
- Existing number of ultra-fast EV charging stations, extracted from the Zap-Map live platform and the UK National Chargepoint Registry

- Geographical coordinates of power substations located along or near the M40 corridor**,** which supply or can potentially support EV charging stations.

These M40-specific inputs were integrated with national-level estimates of other model features, such as EV penetration, energy demand forecasts, and installation costs. This allows the model to remain grounded in a realistic case study while supporting broader policy-oriented scenario analysis.

B. Input Feature Selection

The ten key input features used in this study were identified through a structured analysis of academic research and UK policy documents, as outlined in Section II.A of the Literature Review**.** This section reviewed the most influential variables affecting EV infrastructure planning—covering technical, cost-related, and energy-constrained considerations. The full list of features, along with their justification and supporting sources, is summarised in Table 1 of the Literature Review**.** This foundation ensures the model reflects both practical system constraints and strategic policy priorities**.**

C. Data Generation – A Hybrid Approach

To train the Deep Neural Network (DNN) model effectively and simulate realistic planning scenarios, a hybrid dataset was constructed using both real-world infrastructure data and calculated value ranges derived from UK policy documents and academic literature. This approach was adopted for two key reasons:

1. To reflect real-world variability in EV infrastructure planning, where many input features change across time or scenario conditions—such as budget constraints, energy limits, or traffic volume [2][4][14].

2. To meet the requirements of supervised learning in DNNs, which necessitate a range of input configurations to model complex, nonlinear patterns between influencing variables and predicted outputs [8][12].

The dataset was generated to simulate a one-year planning horizon (2023–2024)**.** For variables expected to fluctuate over this period—such as traffic volume**,** EV penetration, budget, and energy consumption**—**structured minimum and maximum values were defined. These values were informed by government reports and peer-reviewed studies [15][16]. Multiple input configurations were then generated per planning scenario to reflect plausible real-world combinations. This process did not involve formal random sampling; rather, it relied on calculated logic and scenario assumptions aligned with UK infrastructure policies. A subset of input features was held constant, as these reflect infrastructure elements that are fixed within the planning window. These include:

- The number of existing ultra-fast EV charging stations along the M40, derived from Zap-Map and the National Chargepoint Registry (Zap-Map, 2024);

- The station technology capacity (150–350 kW), which adheres to national standards (OZEV, 2023);

- The geographic locations of substations, sourced from the National Grid's infrastructure maps (National Grid, 2024).

This hybrid approach enables the DNN to train on a dataset that is both realistic and adaptable, grounded in actual system conditions and policy-aligned variability.

TABLE 2. INPUT FEATURES, DATA GENERATION STRATEGY, AND SOURCES USED IN THE 2023–2024 DNN TRAINING DATASET

Input Feature	**Type**	**Range or Fixed Value**	**Data Source (2023–2024)**
Total Traffic Daily	Ranged	65,000 – 130,000 vehicles/day	[4]
EV Traffic Daily (%)	Ranged	3.5% – 5.5%	[2][16]
Existing Charging Stations	Fixed	50 (ultra-fast)	[2][3]
Peak Demand (%)	Ranged	20% – 80%	[15][20]
Installation Cost (USD)	Ranged	25,000 – 150,000	[16]
Substation Capacity (MW)	Fixed	Location-dependent (e.g. 15–50 MW)	[20]
Station Capacity (kW)	Fixed	150 – 350	[24]
Budget Constraint (USD)	Ranged	150,000 – 4,000,000	[16]
Energy Consumption (MWh)	Ranged	0 – 50	[8]
Energy Limit (MWh)	Ranged	0 – 100	[23]

D. Model Training

A **Deep Neural Network (DNN)** architecture with three hidden layers was employed with 32, 16, and 8 neurons respectively as shown in Fig.1. Each hidden layer used the Rectified Linear Unit (ReLU) activation function, while the output layer applied a linear activation, suitable for continuous regression outputs—specifically, predicting the number of required ultra-fast chargers.

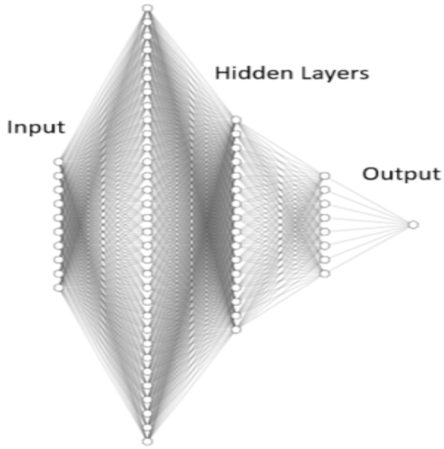

Fig. 1. Deep Neural Network (DNN) architecture.

The model was trained using **Mean Squared Error (MSE)** as the loss function and the RMSprop optimiser, in line with established best practices in DNN training [17]. The dataset, constructed through a hybrid approach combining real-world and synthesised values, was split into three parts:

- **70% for training** – to allow the model to learn feature-to-output mappings,
- **15% for validation** – to fine-tune model parameters and prevent overfitting,
- **15% for testing** – to assess final performance on unseen data [18].

This three-way split reflects standard DNN training workflows, ensuring robustness and generalisability of the model. ReLU was chosen over alternatives like Sigmoid or Tanh due to its computational efficiency and effectiveness in avoiding vanishing gradient problems in deep networks [19].

E. Scenario Logic and Forecasting

To simulate real-world planning conditions and constraint variability, four planning scenarios were developed: Crowded Motorway**,** Energy-Constrained**,** Budget-Constrained, and a Balanced Approach. These scenarios reflect common challenges in EV infrastructure deployment as highlighted by [4] [20].

Each scenario was represented by adjusting the values or ranges of selected input features to reflect plausible real-world conditions, such as peak demand, energy supply limitations, or funding restrictions. The DNN model was trained once using the full hybrid dataset (see Section IV.C), and predictions were made for each scenario by applying scenario-specific configurations to the model inputs. This allowed for comparison of infrastructure requirements under different planning contexts, without modifying the model architecture or retraining.

TABLE 3. PLANNING SCENARIOS AND INPUT FEATURE ADJUSTMENTS BASED ON REAL-WORLD CONSTRAINTS

Scenario	Adjusted Input Features	Adjustment Rationale
Crowded Motorway	Total Traffic, EV Share, Peak Demand	High congestion periods such as holidays or peak hours with elevated usage expectations
Energy-Constrained	Energy Limit, Energy Consumption, Substation Capacity	Grid availability limits charging expansion; lower energy throughput simulated
Budget-Constrained	Budget Constraint, Installation Cost	Reduced financial capacity for charger installation; focus on economic feasibility
Balanced Approach	All features set at moderate/average values	Represents a neutral scenario with no dominant constraint, allowing balanced deployment

V. Results and Discussion

The trained Deep Neural Network (DNN) model forecasted the optimal number of ultra-fast EV charging stations along the M40 under four planning scenarios: Crowded Motorway, Energy-Constrained, Budget-Constrained, and Balanced (see Section IV.E). Table 4 shows the predicted charger counts across five representative input sets (Table 5). The Crowded scenario yields the highest values (e.g., 108.63), reflecting high demand, while the Budget-Constrained scenario predicts fewer chargers (e.g., 54.36) due to funding limits. The Energy-Constrained scenario remains moderate, constrained by grid capacity, and the Balanced scenario offers intermediate outputs.These results demonstrate the model's flexibility to respond to input variations without retraining and show how planning outcomes shift across scenarios..

TABLE 4. PREDICTED NUMBER OF EV CHARGING STATIONS BY SCENARIO

Crowded Motorway	Energy-Constrained	Budget-Constrained	Balanced
108.63	88.88	83.94	98.76
77.84	63.69	60.15	70.76
98.77	80.81	76.32	89.79
70.35	57.56	54.36	63.95
93.77	76.72	72.46	85.25

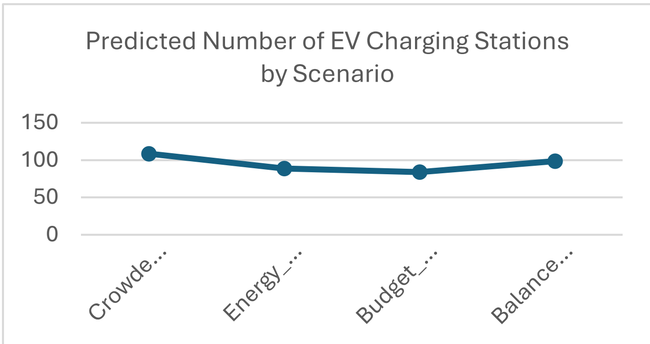

Fig. 2. Predicted charger demand across planning scenarios.

As the line chart shows from Fig.2, predicted charger demand peaks under congestion-heavy conditions and dips where energy or funding constraints are present. The Balanced case maintains moderate demand levels, providing a middle ground.Table 5 presents the charger-to-EV ratios forecasted by the model for each scenario. The Crowded Motorway case requires more chargers per EV (e.g., 1:35 to 1:50), while the Energy and Budget-Constrained scenarios result in higher ratios (e.g., up to 1:65), reflecting constrained deployment. The Balanced scenario provides intermediate accessibility.

TABLE 5. PREDICTED CHARGER-TO-EV RATIOS

Sample	Crowded	Energy-C.	Budget-C.	Balanced
1	1:50	1:61	1:64	1:55
2	1:41	1:50	1:53	1:45
3	1:43	1:53	1:56	1:48
4	1:35	1:43	1:45	1:38
5	1:50	1:62	1:65	1:55

Table 6 simulates a forecasted increase in EV traffic over a 5-year period, assuming an annual growth rate of 5%. If no additional infrastructure is added, the charger-to-EV ratio will degrade from 1:50 in 2025 to 1:72 by 2030, suggesting mounting pressure on the network. These findings underline the need for proactive and flexible planning aligned with EV adoption trends.

TABLE 6. PROJECTED CHARGER-TO-EV RATIOS (2025–2030)

Year	EV Traffic	Ratio
2025	5,400	1:50
2026	5,670	1:54
2027	5,954	1:58
2028	6,251	1:62
2029	6,564	1:67
2030	6,892	1:72

VI. CONCLUSION

This study presents a Deep Neural Network (DNN)-based framework to predict the optimal number of EV charging stations along the M40 motorway under four planning scenarios: Crowded, Energy-Constrained, Budget-Constrained, and Balanced. Using ten technical and policy-relevant inputs—such as traffic flow, EV adoption, substation capacity, and installation cost—the model supports scenario-based infrastructure planning beyond traditional fixed-assumption methods.

The approach offers a practical tool for evaluating how various constraints influence charger demand, providing baseline insights for motorway infrastructure in the UK. While focused on charger quantity, the method can be extended to spatial allocation, cost-benefit analysis, or adaptive demand forecasting. As the UK moves toward its 2035 ICE vehicle phase-out, such tools can support data-driven, resilient charging network planning.

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