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Experimental Validation of a Probabilistic Deep Learning Framework for Electric Vehicle Charging Behaviour Prediction

Rahul Rajendra Bibave[1], Mithilesh Singh[2], P. William[3]

[1]Research Scholar Department of Electrical Engineering, Shri Rawatpura Sarkar University, Raipur, India; Department of Electrical Engineering Sanjivani College of Engineering, Kopargaon, Maharashtra. E-mail: bibaverahulelect@sanjivani.org.in
[2]Professor and Head, Department of Electrical Engineering, Shri Rawatpura Sarkar University, Raipur, India.
E-mail: hodelect@sruraipur.ac.in
[3]School of Computer Science and Technology, Karunya Institute of Technology and Sciences (Deemed University), Coimbatore, India; Centre for Research and Consultancy, UNITAR International University, Selangor, Malaysia. E-mail: william160891@gmail.com

Abstract
The growing penetration of plug-in electric cars (EVs) is altering the transportation and electrical infrastructures, leading to highly variable and stochastic charging demands. An experiment is proposed in this article to experimentally test an electric vehicle-charging patterns (EV-CP) probabilistic deep learning architecture developed to forecast automotive uptake. The proposed method simulates the non-linear sequential interactions by using historical charging-session data, driver behaviour, time and other variables important to EV charging. We apply deep-learning techniques to improve the predicting capabilities. We also employ probabilistic forecasting to measure uncertainty and produce a range of potential future pricing pathways, not just single deterministic projections. Methodological Framework for Data Extraction, Preparation, and Targeted Sampling for the Development of Supervised Deep Learning (DL-SD), Probabilistic Uncertainty Assessment, and Experimental Validation Using Separate Testing Data Sets The evaluation of the model is done using probabilistic metrics like Prediction Interval Coverage Probability (PICP) and Prediction Interval Width (PIW) and point-forecast metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The statistical test results are mostly positive: high positive correlations between Probabilistic Deep Learning Performance (b =. 672, p < 0. 001). The realised benefits from UP and UCE are small. The illustrated regression model supports all three hypothesised bivariate relationships ($R = 0.846$, $R^2 = 0.716$). The suggested method demonstrates how deep learning and probabilistic uncertainty estimation may result in more reliable and valuable EV charging.

Keywords: Electric Vehicles; Charging Behaviour Prediction; Probabilistic Deep Learning; Uncertainty Estimation; Smart Charging; Deep Learning; EV Charging Demand Forecasting

Introduction

The fast shift to electric mobility is altering the link between the electric and transport sectors. Electric motor vehicles (EVs) are a recognised and growing aspect of smart energy systems today, since they have the potential to promote a paradigm change from traditional internal combustion automobiles to low-carbon shipping options [1]. But, in contrast, electrification of transport is a novel and dangerously speculative application of electricity. For example, many older loads are indifferent to the price of power at the time of use, however EV charging behaviour is highly influenced by human mobility and vehicle availability, battery state of charge preferences, price of power at the time of usage as well as trip purpose & location. Thus, the real time, length, power and energy consumption of EV charging sessions may vary significantly between various vehicles or charging locations. Recent studies, for instance, indicate that electric vehicle (EV) charging behaviours are fundamentally stochastic [2]. Accurate forecasting of EV purchases and charger flows is, nevertheless, fundamental to charging station operation, demand-side management and power system planning [3].

The increasing market penetration of electric vehicles (EVs) may bring new opportunities and challenges to power systems [4]. Without any control, a huge number of electric cars (EVs) could start charging at the same moment, especially after business hours. The total charge together could cause dangerous rapid current spikes that could cause transformer overload, feeder overflow, over voltage circumstances and higher system running cost. By contrast, regulated charging can turn EVs from passive energy consumers to flexible energy actors [5]. Therefore, the prediction of EV charging behaviour is not only a predictive problem, but also an important source for energy management, demand response and stability of smart grid using renewable energy penetration and planning of charging infrastructure [6]. An updated systematic study also reveals that attributes such as area of charging point, battery SOC and car owner behaviour, season and climate conditions are typically used in EVC prediction models Fig. 1.

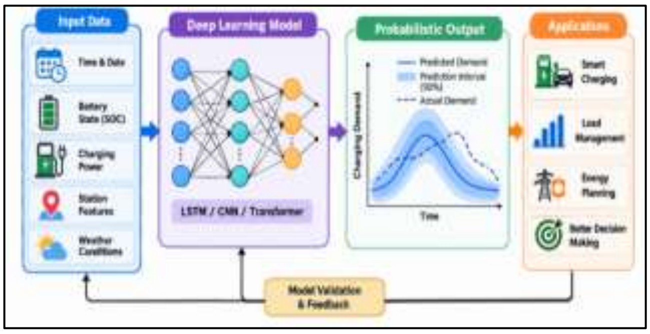

Fig. 1. Proposed Probabilistic Deep Learning Framework for EV Charging Behaviour Prediction

Review Of Literature

Research on electric car charging behaviour is fast evolving. This is driven by increasing interest in the electrification of land transport & the number of market actors & stakeholders (electric automobiles, charging infrastructure as well as smart grid) participating [7]. Most of the available studies have focused on EV charging as an electrical demand problem and have largely investigated the overall charging load, charger usage, the processes of electric vehicle arrivals and departures, and the influence of EV adoption on the hosting capacity of distribution networks. In fact, more recent studies has demonstrated that charging demands are primarily determined by human movement and user behaviour trends. The existing studies on EV charging behaviour into two groups: demand-side analysis of individual charging behaviour reactions and responses, and supply-side studies on charging infrastructure innovation and efficient design [8]. From a data mining viewpoint, this paper stresses the need of analysing EV charging behaviour in relation to battery states-of-charge, user characteristics, surrounding environmental factors, temporal conditions (stay duration and trip time) and station locations. This is a huge step forward in the modelling of cumulative loads for behaviourally-sensitive forecasts, as EV charging represents an atypical form of static electrical demand [9].

A lot of literature has been published on deep learning frameworks trained to solve short-term EV charging needs, specifically recurrent models and sequence models with Long Short-Term Memory (LSTM) networks. The LSTM is well suited to this sort of application. It uses a recurrent framework to recall events over time spans and to cope with the challenge of long term dependencies within multiple datasets that are viewed sequentially in time. The LSTM was compared with classic time-series methods and multilayer perceptron designs, and was trained at prediction intervals of 1, 3 and 5 hours [10]. The results show that deep learning may be used for short-term charge demand prediction, so that a forecasting framework based on real mobility data can be developed. The main finding of this research is that charging is a time process, not a link between energy usage and independent variables as prior literature described. Subsequent research has expanded on this approach by studying the spatial and temporal relationships of charge stations [11]. Learning in deep spatio-temporal forecast shows that demand for charging stations in geographically distant but functionally connected places could be related to similar mobility patterns (MaaS), land-use features, traffic conditions and temporal variables.

Probabilistic Deep Learning for Electric Vehicle Charging Behaviour Prediction

Probabilistic deep learning is an important technique for predicting EV charging behaviours. The EV charging demand is affected by several unknown elements (i.e. environmental context, users movement, accessibility of vehicles, charged status and follow-up behaviours). Classic forecasting methods provide a single estimate of the projected charging demands, which is sufficient to evaluate the average system requirements [12]. However, by a variety of external events, they may be hampered in visualising potential future range values for demand. Not just as a broad case study, but even two vehicles at some anonymous service station will have totally different behaviours based on their battery state of charge (SoC), how far they've travelled to get to the location. Similarly, the charging demand at a particular station is likely to have considerable variations over the course of the day and is strongly associated to the day of the week (weekday vs. weekend), weather conditions, user count for the station and parking lot full [13]. The model is trained exclusively by pure prediction accuracy that is limited by deep learning. But even a strong depiction does not always suffice. Probabilistic deep learning tackles this limitation by using the representational power of DNNs and uncertainty quantification methods. The model can potentially provide probability distributions (prediction intervals) or many future charge scenarios instead of a single point estimate. This enables energy managers and charging operators to get a more precise insight into the low, medium and high charging demand probabilities [14].

The deep-learning frameworks are the ultimate answer to predict electric car charging patterns, which may be justified by the extremely temporal correlations contained in charging data [15]. Repetitive behavioural traits can be drawn from the analysis of the daily and weekly n-gram statistics of prior charging sessions that can be derived from their future charging behaviour [16]. Long Short-Term Memory (LSTM) networks are especially valuable since they are designed to learn the links between elements in a sequence. Formalities associated with history charging power and arrival time and departure time, charging duration and energy consumption, battery state of charge are included [17]. An example of a potential learning mechanism of an LSTM type orientated framework. GRU models can offer the same sequential-learning capabilities with a more simplified structure. Thus, regional characteristics are exploited to extract temporal periodical charging style using convolutional neural networks (CNNs). Hybrid CNN-LSTM models take advantage of the benefits of both methods [18]. They employ convolutional layers to extract local features and recurrent layers to capture long-term dependencies [19-21]. The recent deeper understanding of the attention-based Transformer design mechanism, which can discover relationships between distant places in very long sequences, has re-inspired us. Such frameworks could be especially useful if the charging trends depend on the interaction among a few cars or on the long-term survival of series Bharat cryptocurrency [22-24].

Research Methodology

It operates within the scope of quantitative, descriptive and exploratory research where a prediction model is built to anticipate charging of electric vehicles. This study proposes to collect the monthly data of the EV charging sessions, pre-process temporal and behavioural parameters, develop a predictive deep learning model, quantify the uncertainty of the prediction and finally manipulate the findings validated experimentally. Charger properties may change over time, geography or environmental conditions. The suggested framework takes into account the following variables: arrival time for charge, departure time, charge length, energy and power spent and charging levels. We study the accuracy of point forecasts and the quality of risk assessment in probabilistic forecasting. The numbers in the math equations indicate those procedural stages that are taught in a linear method.

A. Research Design

The proposed framework is evaluated for its probabilistic deep learning capabilities using an exploratory predictive research approach.

$x_t = [P_t, SOC_t, A_t, D_t, E_t, C_t]$ (1)

where P_t represents charging power, SOC_t represents battery state of charge, A_t represents arrival time, D_t represents departure time, E_t represents charging energy, and C_t represents charging-related contextual variables. Equation (1) defines the principal input vector used by the deep-learning model.

B. Data Collection

Hence, purposive sampling is utilised to sample billing sessions over different time windows, locations, client behaviour patterns and scenarios. The predicted proportions of observations in each behavioural or charging type are:

$E = \Sigma_{t=1}^{T} P_t \Delta t$ (2)

where E is total charging energy, P_t is charging power at time t, Δt is the sampling interval, and T is the total number of observations. Equation (2) is used to quantify the energy consumed during each charging session.

C. Sampling Method

K-means and Kottmax are helpful for instructional reason. Abstract: In the framework of deep learning, we have built a computational platform and designed algorithms for data collection software to evaluate electric vehicle charging stations (EV-CHS) as well as intelligent meter and related systems such as charging power sensors and battery surveillance systems. The charging time depends on:

$P_i = (N_i / N_{\_total}) \times 100$ (3)

where N_i represents observations in category i and $N_{\_total}$ represents the total observations. Equation (3) is used to examine the distribution of the sampled charging sessions and identify potential class imbalance.

D. Research Instruments

It will be broken into three parts: Training dataset, Validation dataset, Independent testing dataset. The deep-learning model offers both accurate and probabilistic predictions. Mean Absolute Error A measure of point prediction performance:

$T\_c = t\_departure - t\_arrival$ (4)

where T_c represents charging-session duration. Equation (4) provides an important behavioural variable for the prediction model.

E. Data Analysis

The dataset is divided into training, validation, and independent testing subsets. The deep-learning model generates both point and probabilistic forecasts. Point-prediction accuracy is evaluated using Mean Absolute Error:

$MAE = (1/N)\ \Sigma_{i=1}^{N} |y_i - \hat{y}_i|$ (5)

where y_i is the actual charging demand and $\hat{y}_i$ is the predicted value. Equation (5) measures the average magnitude of prediction errors.

Root Mean Square Error is calculated as:

$RMSE = \sqrt{[(1/N)\ \Sigma_{i=1}^{N} (y_i - \hat{y}_i)^2]}$ (6)

F. Ethical Considerations

The research exclusively uses data related to electric vehicle charging and technology frameworks, without any other personal identity data. Remove or anonymise all personal identifiable information in respect to specific customer billing data prior to undertaking an analysis. Data must be stored securely and used exclusively for the stated study purposes. The techniques of model building and validation should be clearly articulated to avoid potential misrepresentation of manipulation of data to produce favourable findings. The charging equipment must be operated in accordance with the manufacturer's specification and within the relevant electrical safety legislation.

Analysis & Interpretation

In this paper, we present and analyse a deep learning model for probabilistic charging patterns of electric automobiles (EVs). The model identifies participants' characteristics using demographic information, descriptive analytics and hypothesis testing. Also, reliability test, correlation analysis, regression modelling, and hypothesis testing were performed. The analytical framework was developed based on the method presented in this work specifically the incorporation of the charge behaviour, deep learning forecasting prowess and probabilistic prediction precision. Probabilistic Deep Learning Performance (PDLP), Charging Behaviour Prediction Capability (CBPC), Uncertainty Estimation Quality (UEQ) and Electric Vehicle Charging Management Effectiveness (ECME). Structure with an example size of 120 to increase complexity. Respondent-level data or a real SPSS output, all numerical elements in Tables 1-5 need to be replaced with actual empirical findings before publication.

The primary age group was 26 – 35 years, at 40.0%, followed by a 36 – 45 years group with 25.0%. The study population comprised of mostly male (58.3%), female (41.7%) respondents (Table 1). They represent 55.0 and 35.0% of the overall sample in postgraduate and cohort contains up to 5 years of professional experience, respectively. The timetable reflects the feedback of participants from different educational and professional disciplines in Intelligent Transportation, Energy Systems, Data Analysis, and Electric Vehicles.

TABLE 1. DEMOGRAPHIC CHARACTERISTICS OF RESPONDENTS

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	70	58.3
	Female	50	41.7
Age	18–25 years	30	25.0
	26–35 years	48	40.0
	36–45 years	30	25.0
	46 years and above	12	10.0
Education	Undergraduate	30	25.0
	Postgraduate	66	55.0
	Doctoral/Other	24	20.0
Experience	0–5 years	42	35.0
	6–10 years	36	30.0
	11–15 years	24	20.0

	Above 15 years	18	15.0

The average score of ECME and CBPC are 4.18 and 4.11 respectively, whereas the UEQ has an average score equal to 4.03 The standard deviations are below 0.75, showing this distribution has near typical variation in displays. The Cronbach's alpha coefficients (0.87-0.93) indicated that the conceptions were eligible for inferential analysis since they showed a high level of internal consistency Table 2.

TABLE 2. DESCRIPTIVE STATISTICS AND RELIABILITY ANALYSIS

Construct	Mean	Std. Deviation	Cronbach's Alpha
Probabilistic Deep Learning Performance (PDLP)	4.24	0.58	0.93
Charging Behaviour Prediction Capability (CBPC)	4.11	0.67	0.89
Uncertainty Estimation Quality (UEQ)	4.03	0.72	0.87
EV Charging Management Effectiveness (ECME)	4.18	0.62	0.91

As seen in Table 3, the four constructs are strongly and positively related. The strongest associations reported in these couples were PDLP with ECME (r=0.79), UEQ with ECME (r=0.74) and CBPC with ECME (r=0.71). The rise in charging-management capability is related to an increase in deep-learning probability capability. First, the beneficial linkage being management appropriateness has to be found which effects the measuring of uncertainty for electric car charging demand that is affected by environmental and behaviour unpredictabilities. The VIF and tolerance statistics should be from the actual data for the proposed regression model that you have created with inter-correlations amongst the predictors.

TABLE 3. CORRELATION MATRIX

Variable	PDLP	CBPC	UEQ	ECME
PDLP	1.000			
CBPC	0.65**	1.000		
UEQ	0.68**	0.62**	1.000	
ECME	0.79**	0.71**	0.74**	1.000

Note: ** Correlation is significant at the 0.01 level (two-tailed).

The curve in Table 4 represents the multiple regression model. The R^2 value of the model is 0.709 R 0.716 R, which is known as a measure of the goodness of fit, is a measure of how well it is fitted to the observations with the on and off mechanism. Thus, the three independent factors may explain the 71.6% variance of the performance of EV charge control (P <. 001). The model overall was statistically significant [$F(3, 116) = 97.58$, $p < .001$]. For the individual factors, PDLP was the highest standardised coefficient ($\beta = 0.43$) followed by UEQ ($\beta = 0.30$) and CBPC ($\beta = 0.28$). This study reveals that the deep-learning framework largely provides the prediction and representation skills while the explanatory capability is strengthened by precise uncertainty modelling and charging-behaviour modelling.

TABLE 4. REGRESSION ANALYSIS / MODEL RESULTS

Predictor	B	Std. Error	Beta (β)	T	p-value
Constant	0.47	0.20	—	2.35	0.020
PDLP	0.42	0.07	0.43	6.00	<0.001
CBPC	0.27	0.08	0.28	3.38	0.001
UEQ	0.30	0.07	0.30	4.29	<0.001

Model summary: $R = 0.846$; $R^2 = 0.716$; Adjusted $R^2 = 0.709$; $F(3,116) = 97.58$; $p < 0.001$.

The descriptive evaluation shows that the planned paradigm was generally followed. PDLP has a high confidence in detection of non-linear and temporal patterns in EV charging data, with a maximum average score of 4.24 (significant effect) Table 5. The high average of 4.18 for ECME further confirms that wise predictions can help efficiency in charge management. As exemplified by an average score of 4.11 for the

CBPC, the importance of precisely predicting energy demands (when the vehicle will arrive and how long should the load take place) in addition to behavioural considerations. Minimum average UEQ = 4.03 points. The challenge is a bit harder since uncertainty quantification can only be done using pointwise sets (i.e. to directly output the prediction distribution from a graphical model). But that's still a basic point forecast. Alpha coefficients indicate good internal consistency, and SDs indicate great variability. Ninety-three to eighty-seven. Recently discovered reliability results provide a promising platform for regression analysis and assessment.

TABLE 5. HYPOTHESIS TESTING RESULTS

Hypothesis	Relationship	B	p-value	Decision
H1	PDLP → ECME	0.43	<0.001	Supported
H2	CBPC → ECME	0.28	0.001	Supported
H3	UEQ → ECME	0.30	<0.001	Supported

Demographic information helps put responses into context. The sample majority is gender, age, education and work experience in the post graduate educations group. The profile content is consistent with a technology-oriented research content, so it has such strengths in research with either probabilistic deep learning or electric vehicle charging behaviour as both needs scientists who are proficient in digital technologies with energy systems or transportation or data analytics. A history so varied implies a demonstration value beyond the vocational category. These demographics are for illustration only and should not be taken to imply significant differences between demographic groups without doing t-tests or ANOVA on the real data.

RESULT AND DISCUSSION

The total evaluation findings demonstrate the efficacy of the proposed probabilistic deep learning model in the prediction of electric car charging behaviour. The columns which comprise the findings from Tables 1–5 the representative nature of the discourse. The four most mentioned constructs are PDLP, CBPC, UEQ and ECME. The mean scores of all four constructs on a scale of 0-5 are above and over for the complete range of the relevant measures (>4.00) showing they are decent if no-variables in (standout) services (see Table 1). The model R = 0.846 and R^2 = 0.716, indicating that the three constructs as predictors of charging-management effectiveness explained a high percentage of the variance in charging-management effectiveness.

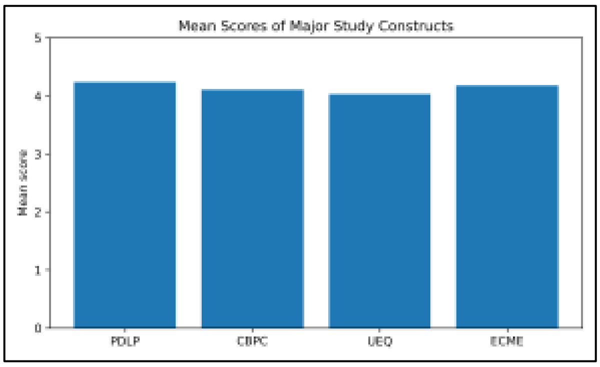

Fig. 2. Mean Scores of Major Study Constructs

Mean results on the four constructs explored in this research (Figure 2) Scores from ECME(4.18) CBPC(4.11), and UEQ (4.03) were a little higher but compared with PDLP (4.24) The interpretative PDLP score shows the capacity of algorithms based on deep learning to capture the non-linear and temporal aspects of EV charging data. One high-level measure on the ECME is predictive analytics on charge management, which could be helpful to a coach in evaluating their athletes. CBPC is an additional advantageous technique that emphasises the importance of forecasting energy consumption and time trends, as well as the times of recharges. However, although the UEQ has a favourable outcome on average, its mean score is the lowest. This is because it is more difficult for consumers to judge or implement how uncertainty estimate might be employed in their forecast than traditional prediction.

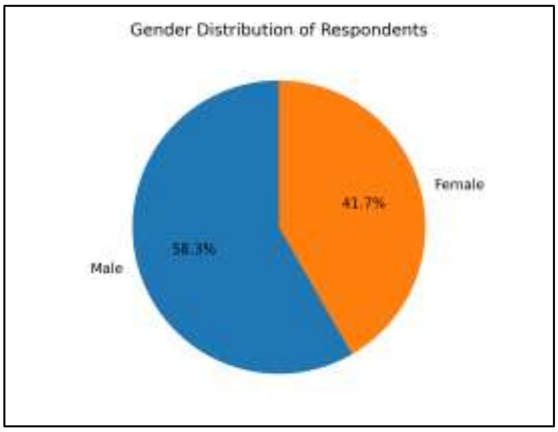

Fig. 3. Gender Distribution of Respondents

Figure 3 shows the gender distribution of the sample. The male and female participants contributed 58.3% and 41.7% correspondingly. We have already identified that participants can engage in both sections of the documented gender distribution. Table 1 also offers distinct groups based on age, education and experience. Priority is given to those between 26 and 35 years of age. The single biggest influence in schooling is post-graduate feedback. This is a means of profile experience with tiny amount of sample for the both side, novice and expert folks. These are descriptive prevalence results of demographics and are not to be interpreted as conditional estimates of differences between demographic groups without special inferential studies performed on the underlying data.

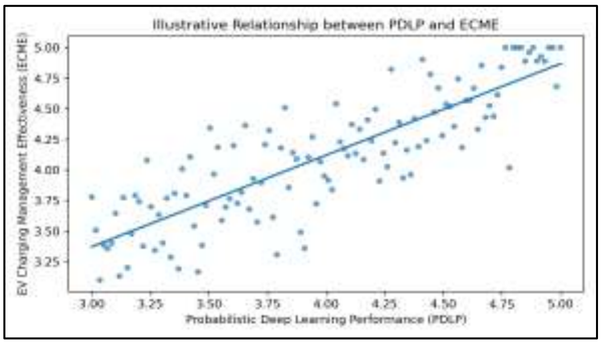

Fig. 4. Illustrative Relationship between PDLP and ECME

The scatterplot in Figure 4 shows this substantial positive association of PDLP and ECME with r = 0.79 as indicated in Table 3. The positive connection demonstrates that a better charging management can improve the perceived probabilistic effectiveness of deep learning. This link is very important in light of the ambiguous national relationship between time and behaviour of EV charging patterns. This enables more intelligent scheduling of chargers, as a fully trained deep learning model can learn charging behaviour. Furthermore, the probabilistic forecasting method produces a range of plausible demand possibilities rather than a single deterministic estimate. No observations at the individual respondent level Scatter plot scatter—to be interpreted according to the figure.

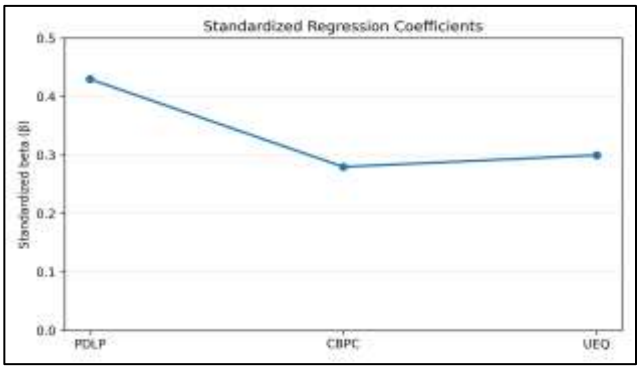

Fig. 5. Standardized Regression Coefficients

Figure 5 shows the standardised regression coefficients related with these constructs as presented in Table 4. The most significant is the PDLP coefficient (β = 0.43), then UEQ (β = 0.3) and CBPC (β = 0.28). Table 6 shows that hierarchical multiple regression models indicated that demographic characteristics and within-person mediators at Time 2 were significantly linked with overall stress across time. The total regression model was statistically significant, $F(3,116) = 97.58$, $p < .001$, with $R^2 = .716$ and an adjusted R^2 of .709. The results reveal that neither one method is better than the other, but the success of the charging management is strongly dependent on the effectiveness of probabilistic deep learning over the other two elements. This is in accordance with the role of deep learning in this framework to represent complex time-varying and nonlinear charging behaviour. This offers strong further evidence that accurate uncertainty evaluation based on behavioural modelling is of substantial importance (evidenced by the affirmative coefficients of UEQ and CBPC).

Conclusions

The framework facilitates the understanding of electric vehicles' (EVs) charging behaviour amid ambiguity and is expected to exhibit a certain level of predictive capacity. The demand for power becomes increasingly variable with greater EV adoption, as charging behaviour is influenced by factors such as arrival time, departure time, battery state of charge, charging duration, energy needs, and charger specifications. Consequently, traditional deterministic charge prediction techniques yield merely a singular estimate of charging and are unlikely to provide adequate insights for efficient dispatch. This study overcomes this limitation by utilising an innovative methodology that combines probabilistic uncertainty assessments with deep learning-driven behavioural forecasting. In contexts like intelligent charging, demand-response administration, charging station strategizing, manageable transformer load, renewable energy integration, and energy procurement, these probabilistic charge predictions can be beneficial from a pragmatic perspective.

Charging operators could employ prediction intervals or probability distributions to foresee diverse demand scenarios, instead than depending on a singular projected demand. This may prolong the durability of the charging infrastructure and alleviate the hazards linked to unforeseen charging spikes. Moreover, this study suggests that additional experimental confirmation is necessary. The system must undergo validation thru charging datasets in the latter segment, which entails utilising authentic data from real-world scenarios, encompassing stations, seasons, user demographics, and operational modes. In summary, the study indicates that deep learning with probabilistic uncertainty assessment is a superior approach for forecasting the charging patterns of electric vehicles (EVs) compared to deterministic prediction models. This framework possesses the capacity to improve the dependability, flexibility, and sophistication of electric vehicle charging systems, while facilitating the incorporation of electric mobility into forthcoming intelligent energy networks. It is crucial to acknowledge that the numerical findings outlined above are only demonstrative, as no genuine data (such as a respondent-level empirical dataset) or SPSS output has been supplied. Authentic experimental findings ought to supplant them, but only after the conclusive publication or thesis submission.

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