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RESEARCH ARTICLE

CLEVER: A Novel Approach for Improving EV Charging Duration and Load Predictions Using Curriculum Learning Approach

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ABSTRACT Despite advancements in electric vehicle (EV) charging prediction models, existing approaches are suffering from complex charging patterns. The curriculum learning (CL) is a training approach which resembles the natural human learning progression by introducing training samples through different patterns, hence efficiently structuring the learning process. While the CL has been successfully used in other domains, its application in EV charging prediction remains unexploited. In this work, the CL is to be leveraged for the first time to improve the EV charging behavior predictions in both EV charging duration and charging load prediction. A feature-based curriculum learning approach, named CLEVER (Curriculum Learning EV chargER), is proposed for predicting charging session load and duration. CLEVER employs an advanced data stratification mechanism that introduces training samples progressively according to complexity metrics computed from temperature variations, state of charge variations, and temporal patterns. The CLEVER method integrates a CL strategy with a staged schedule mechanism over four neural network architectures: ANN, DNN, LSTM, and GRU. The performances obtained exhibit notable gains, where CL scores 20.9% reduction of Mean Absolute Error for GRU-based forecasting of EV charging duration and 2.2% improvement for DNN-based charging load forecasting. The CLEVER methodology shows considerable improvements in predicting the duration of EV charging, with, as many as 23.0% reductions in Mean Absolute Error with GRU models on Level 1 chargers and a near 20.7% improvement with DNN models on DC Fast Chargers. For EV charging load forecasts, curriculum learning produces consistent, but modest, gains, with improved up to 2.4% with ANN models on DC Fast Chargers and 1.6-2.1% improvements across different neural network architectures. This comprehensive analysis across different charger types, user groups, vehicle models, temperatures, and temporal patterns makes CL a superior approach to enhancing EV charging infrastructure management and grid stability.

INDEX TERMS Charging duration prediction, CLEVER, charging load prediction, curriculum learning, deep learning, electric vehicle, smart charging management.

I. INTRODUCTION

In light of relying on renewable energies, EVs have attracted several prominent manufacturers around the world. These vehicles depend on electricity as their main energy source

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instead of fossil fuels, which helps in reducing carbon and gas emissions [1], [2], [3], [4]. Adoption of EV keeps spreading worldwide and becomes a pillar of sustainable transportation and environmental protection initiatives. Particularly, when charging networks extend to satisfy rising demand, this change of the automobile scene poses major difficulties for management of charging infrastructure [5]. The effective managing of the EV charging infrastructure in the urban areas with great focus on EV concentration is a key challenge to obtain power grid stability. With charging time projections directly effecting station usage and user experience, accurate predictions of charging behavior have become indispensable; conversely, charging load estimates significantly influence grid stability and power distribution. Although they show promise, conventional machine learning methods sometimes find it difficult to handle the complicated, multi-dimensional character of EV charging patterns including several elements including user behavior, ambient circumstances, and temporal fluctuations. Although recent developments in deep learning have created new opportunities for raising prediction accuracy, the difficulty of properly training models to manage this complexity still remains major. Inspired by human learning processes, CL presents a potential solution by progressively introducing training data from simple to complex patterns, thus possibly improving both EV charging duration and load predictions for more effective resource allocation and grid management. The scientific aim is to develop an effective CL methodology in order to improve the accuracy and adaptability of the charging duration of EV and the load predictions. The research objective is to achieve improved forecasting performance based on the charging time estimation and energy load prediction by developing a curriculum engineering methodology that systematically organizes training data from simple to complex patterns, mimicking human learning progression. In addition, the proposed work fills a research gap by applying CL, which has demonstrated success in other areas, to understand EV charging behavior and offer practical insights for energy infrastructure planning.

Various methodologies, ranging from standard statistical methods to complex machine learning algorithms, has been incorporated in the prediction of the EV charging load. Methods, such as auto-regressive integrated moving average (ARIMA) and linear regression, were commonly utilized earlier in the prediction models [6], [7], [8]. More complex methods include deep learning models including Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN), and hybrid architectures combining many prediction algorithms [9], [10] have just emerged from recent advances. Although these techniques offer potential, their training strategies clearly have numerous important shortcomings. Deep learning methods often suffer with the tabular shape of charging data [9], as neural networks are prone to provide too smooth solutions and are vulnerable to noise from low-information features. Extensive high-quality training data is required for traditional supervised learning methods, which might not be easily accessible or might violate user privacy [7]. Moreover, current models sometimes neglect to efficiently combine several important elements like climatic conditions, temporal patterns, and user transition behaviors into a single forecast framework [9], [10]. Curriculum learning is a promising trend where models are taught progressively from simpler to more complicated tasks [11], hence perhaps boosting both prediction accuracy and training efficiency. However, the burdens of achieving rapid adaptability to changing circumstances in real-time applications, as well as maintaining prediction accuracy remain a serious obstacle. Nevertheless, just one comparable study has attempted to include curriculum learning in the EV domain, focusing mainly on forecasting power consumption of heavy-duty electric vehicles utilizing a multi-task learning approach [11].

CL is an innovative training method that reflects the natural human learning development by progressively adding training samples from normal to complicated patterns, hence organizing the learning process [12]. CL organizes training data in a meaningful sequence of increasing complexity, helping the model to acquire a solid fundamental knowledge before tackling more complicated cases. Just as people learn difficult tasks by starting with elementary ideas then graduating to more demanding information. This method has shown amazing success in several fields, most notably in computer vision where it steadily introduces pictures depending on visual complexity, hence improving image classification accuracy by 4% on the ImageNet dataset [13]. CL improved machine translating performance by 2.8 BLEU points in natural language processing when training data was arranged according to sentence complexity and linguistic patterns [14]. In voice recognition systems, similarly, using CL resulted in a 15% drop in word mistake rates by progressively including audio samples with rising noise levels and speaker variability [15], [16]. The success of CL in several other fields indicates its possibility to enhance EV charging behavior prediction (i.e., load and duration), where the complexity of patterns changes greatly depending on several influencing elements including time dependencies, environmental circumstances, and user behaviors. CL's organized character makes it especially appropriate for managing the inherent complexity of EV charging patterns, where simpler charging scenarios may provide a basis for knowledge of more complicated charging behaviors.

Applying CL to EV charging behavior prediction shows a notable research gap according to a thorough evaluation of the literature. Although a lot of study has been proposed on several machine learning approaches for EV charging behavior prediction, the use of curriculum learning in this field is yet mostly uninvestigated. The study [11] considerably departs from the proposed work in this research article by focusing on other prediction objectives, including the deployment of a multi-task learning framework instead of concentrated single-task approach, and addressing heavy-duty vehicles rather than regular EVs.

Moreover, the growing acceptance of electric vehicles globally emphasizes the need of creating more complex and accurate prediction models for both EV charging load and duration, therefore this study not only relevant but also vital for the development of smart charging infrastructure. The proposed work fills in a major void in the present literature by offering a first thorough assessment of the efficacy of curriculum learning in these two different EV charging prediction tasks, thus guiding future research and useful insights for practical applications in smart charging systems.

The proposed CLEVER methodology aims to fill this gap by developing a feature-based curriculum engineering strategy for EV charging prediction tasks. While other automated curriculum learning systems exist, CLEVER depends on domain knowledge to manually encode curricula based on dataset specific criteria such as temperature ranges, state-of-charge distributions, and charger types counts. While EV datasets tend to have common features in common (explaining the importance of temperature, state of charge (SoC), types of chargers, etc.), threshold values and complexity criteria will need to be proposed based on an analysis of the statistical descriptions, and domain characteristics of each dataset. While CLEVER is engineered for EV charging data, its core principle—progressive training from simple to complex cases—can transfer to other domains. However, the curriculum itself (features, thresholds) should be redefined via domain analysis (e.g., weather and tariff regimes for smart grid demand), rather than reusing EV-specific indicators.

In this work, a design and implementation of a curriculum learning method for two important prediction tasks in EV charging control is provided. EV charging duration prediction is the first goal; it is necessary to maximize charging station use, lower queue times, and raise customer satisfaction by means of improved scheduling and resource allocation. This may lead to grid stability, power management, and efficient demand response techniques through smart grid operations. The second direction addresses charging load prediction. A different model for every prediction challenge that exhibits numerous unique traits is introduced to distinguish it from traditional training approaches. Using several features, such as temperature ranges, SoC changes, and temporal patterns, the suggested architecture offers a sophisticated data stratification mechanism that cautiously differentiate charging events depending on their complexity metrics. This method especially helps station operators for EV charging duration prediction by allowing more exact time slot allocation and thereby increasing throughput efficiency. Simultaneously, for load prediction, it improves grid operators' capacity to foresee and control power consumption. The proposed approach presents a unique adaptive learning rate scheduler for every prediction model that dynamically changes depending on the curriculum stage, therefore guaranteeing ideal convergence at every learning phase.

During the staged schedule of the training phase, each model should satisfies a predefined performance objective on the subset of the existing curricula before proceeding to a complex setting. The proposed structured approach leads to improved charging station management and efficient load predictions which handling the inherent variability of EV charging patterns. Using a cross-validation strategy designed for curriculum-based training, where every fold respects the curriculum structure's complexity development, strengthens the approach. To address EV charging duration and charging load prediction objectives, a novel approach is introduced that weights features to identify the difficulty of each charging scenario. Residual connections between curricular stages allow model architectures to retain and build on easy information while adapting to harder situations. The approach includes loss functions for prediction jobs that balance correct forecasts across complexity levels. This all-encompassing approach has produced strong and flexible methodology that perform better than conventional training methods. EV charging duration prediction improvements directly improve charging facility operations and user satisfaction, and load prediction improvements improve grid management and energy distribution strategies. The list of contributions can be summarized as follows:

1) The CLEVER methodology introduces the first comprehensive implementation of curriculum learning in EV charging prediction, demonstrating significant improvements in both EV charging duration and charging load prediction.
2) Novel integration of user behavior analysis in EV charging prediction models, revealing distinct patterns across different user types and establishing that commuter charging patterns are 25% more predictable than casual users through systematic curriculum engineering.
3) Development of an adaptive complexity-based data stratification mechanism that progressively introduces training samples, improving model performance particularly for challenging scenarios like DC fast charging (40% improvement).
4) Comprehensive comparative analysis across different neural network architectures (ANN, DNN, LSTM, GRU) with and without curriculum learning, providing insights into the most effective architectural combinations for different prediction tasks.

To ensure reproducibility and support further research, a complete implementation was proposed to include the curriculum learning methodology, data preprocessing pipeline, and evaluation scripts, publicly available on GitHub.[1]

The remainder of the paper is organized as follows. Section II discusses the current available efforts in predicting EV's charging load and duration. The proposed methodology and the proposed curriculum learning strategy are exposed in

[1] https://github.com/stars-of-orion/Curriculum-learning-for-EV-charging-load-and-duration-prediction

Section III. The obtained results are presented and discussed in Section IV. Finally, the paper is concluded in Section V.

II. RELATED WORKS

EVs are earning raising popularity as a sustainable transportation alternative due to advancements in batteries technologies and the necessity to reduce carbon emissions for traversing clean environments [17], [18], [19], [20].

The current predicting EV charging patterns approaches have relied on advanced machine learning techniques to replicate the complex circumstances due to the affecting charging behavior. Zhong et al. [21] proposed an efficient fine-tuning approaches for segmentation models which determine the possibility of modifying current architectures to achieve specific prediction tasks. Khan et al. [22] utilized both machine and deep learning methods to forecast user behaviors. This study concluded that the K-Nearest Neighbors could outperform other complex neural networks approaches. This study guaranteed efficient energy distribution and control of the charging infrastructure which helps in avoiding grid overload and improve the energy utilization. The limited generality of this study is one of the drawbacks which impacts the analysis of different EV usage patterns. Another approach was presented to identify temporal patterns at EV charging stations as to highlight the charging behavior variations over time [23]. Moreover, accurate forecasting of energy demand and renewable generation is vital for the effective management of smart grids and to obtain sustainable energy management practices. Santhakumar et al. [24] developed a hybrid prediction model which integrated Namib Beetle Optimization Algorithm and Self-Adaptive Physics-Informed Neural Networks, called NBOA-SAPINN. This model addressed the complexity of planning renewable resources due to their variability using the Germany Wind Energy and Weather Dataset. A Generalized Multi-kernel Maximum Correntropy Kalman Filter was utilized to normalize the dataset. Afterwards, the NBOA optimization algorithm is tuned with the SAPINN learning model for wind energy prediction. The results demonstrated superior performance with 98% accuracy, low RMSE of 0.22, and MSE of 0.23. which outperformed other models, such as GRU-RNN, FFNN, DRL, and RTNN.

Understanding EV charging behavior is important for effectively implementing EVs into energy systems and alleviating their impacts on distribution networks. This was a major focus in the research [25] which investigated a scaled estimation of home charging in Turkey. Past research has occasionally relied on inconsistent survey methods or small non-representative samples and as a result may have led to flawed regulatory assumptions. However, this research used fixed effects models on panel data to estimate EV adoption impacts and found that - and contrary to some regulatory prediction - the typical EV adds a household electric load of 3.1 kWh a day, mostly at night. Their main finding also suggests that an EV typically drives less of its load on electric power than assumed as well as points to a real concern that uncontrolled EV charging could worsen grid performance.

There are some challenges with recent approaches deployed to predict the EV charging patterns, such as atypical scenarios or fluctuations in external features, including electricity pricing or weather. Since access to thorough and consistent charging datasets might be restricted, data sparsity and quality remain major difficulties. Additionally, the accurate tackling and tracking of both preferences and behavioral of electric vehicle drivers is a remaining barrier, as charging choices can be impacted by many personal and environmental elements. Dealing with these constraints requires more investigation into strong modeling methods, data collecting approaches, and include a closer knowledge of driving behavior. Curriculum Learning usually moves from normal to complicated cases. A curriculum formally can be described as a succession of training distributions $\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n$, where each $\mathcal{D}i$ denotes a subset of the training data with increasing complexity. The aim is to identify an ideal ordering of these distributions such that the predicted loss $\mathcal{L}$ on the target task distribution $\mathcal{D}_{\text{target}}$ is minimum. Let $\mathbb{E}$ to be the expected value operator. This work goal then may be expressed as given in Equation 1.

$$\min_{\mathcal{D}1,\ldots,\mathcal{D}n} \mathbb{E}\mathcal{D}_{\text{target}}[\mathcal{L}(f_\theta, \mathcal{D}_{\text{target}})] \tag{1}$$

where f_θ represents the learned model which is parameterized by θ. Typically, an approach defines a scoring function $S(x)$ which sets a complexity score to each data point x, the curriculum is constructed by sorting the data according these scores. Hence, the learning process proceeds iteratively and trains the model on each $\mathcal{D}_i$ before progressing to the next which enables the model to efficiently acquire the necessary knowledge and skills. The conception of pacing functions $P(t)$, regulate the transition among curriculum stage is considered another fundamental aspect of the CL ($P(t) = \min(1, \frac{t}{T_{total}})$). Given that t is the current training iteration and T_{total} is the total number of iterations. Thus, the time that the model is trained on each $\mathcal{D}_i$ can be effectively determined based on the performance of the model or the rate of learning.

More advanced pacing features can change the curriculum's speed depending on the performance of the model, therefore adjusting to the learning level. For example, a performance-based pacing feature can raise the complexity of the training data only when the model reaches a specific accuracy level in the present curriculum stage. The presence of dynamicity enhances the effectiveness and efficiency of the learning environment which consequently customizes the curriculum to the distinctive requirements of the model. Curriculum learning improves the accuracy and capability of predictive models in the field of charging prediction in EV. In this case, the structure of the trained data may vary based on several parameters, such as temperature, charging rates, or day of the week. As a consequence, the model can navigate via different challenging scenarios such as commences by simple data that reflects normal charging rates, then progress through extreme charging rates cases. Li et al. [26] proposed the problem of resilience in Electric Vehicle Charging Monitoring (EVCM) systems, in particular the challenges of the missing data due to interruptions in real time measurements (i.e., sensors failure or regional outages). The authors proposed CurriFusFormer learning framework which integrates the CL with a multi-feature fusion transformer to handle the missing data patterns. This framework used a diffusion graph convolutional networks to combine spatial, temporal, and static features to predict the missing values. Results showed that CurriFusFormer framework reduces R^2 values from around 0.92 to 0.83 whereas the missing rate increased from 30% to 90% compared to KNN, XGBoost, GRIN and other methods. Hence, this study represents a substantial contribution to operating a resilient and robust EVCM system, and provides a generalizable model capable of appropriately accommodating missing data challenges in time-series datasets. Another study concerned with providing resilient forecasting of EV charging demand [27]. However, the authors aim to achieve resilient prediction in the presence of cyberattacks by proposing a Generative Multi-task Self-supervised Learning for Prediction (GenS2-P) framework. This model extract spatio-temporal patterns which enables the reconstruction and denoising of data corrupted by cyberattacks. The predetermined scenarios considered in [26] and [27] reflected common static EV conditions whereas event-specific patterns such as cascading failures were not taken into account which might lead to irregular data loss behaviors. Likewise for CL in which the training schedule is manually identified based on prior knowledge that reduces the adaptability of these models among different real-time circumstances.

Researchers recently have adopted deep learning approaches for addressing these challenges which present in EV applications. These difficulties range from the managing battery to the forecasting of the pattern prediction. Singh [28] presented a systematic review which demonstrate the usage of deep learning for the end-to-end autonomous driving. This review surveys different architectures and approaches utilized for perception, planning and control applications. In addition, it pointed out the significant development of deep learning approaches in autonomous driving which revolutionize transportation. The author in [29] proposed a deep CNN model to predict the EV power consumption which reduce the anxiety of the EV driver via providing accurate predictions. Thus, this model can succeed to achieve better user experience by tackling potential issues concerning EV drivers. Yet, the proposed model lacks the testing of different battery technologies or driving environments. Moreover, the EV charging power consumption can be affected by different factors which are not considered in this model, such as the sudden changing driving conditions or the battery performance on the long-term.

Deschenes et al. [30] compared learning models which include neural networks that predicts the charging time from a given SoC_{start} to a target SoC_{end}. We denote state of charge as SoC (%), with SoC_{start} and SoC_{end} the SoC at session start and end, respectively. The authors considered 28,000 real-life level 3 fast charging sessions including 15 EV types. Different factors, such as temperature and battery capacity, and charging infrastructure, was also considered to obtain accurate prediction charging sessions. A sub-neural network is employed to predict the vehicle type which is then combined into the main neural network for forcasting the charging duration. Moreover, Synthetic Minority Over-sampling Technique (SMOTE) provided a balanced dataset which significantly improves the performance of the model. However, this work did not fully capture the thermal dynamics of the battery due to its dependency on the external temperature instead of the battery temperature.

Improving the EV charging infrastructure and reducing the charging time remain tackling challenges which were investigated using two real datasets, one from China [31] and the other from Japan [32]. In a similar manner as in [30], authors proposed time-series approaches to examine the regression predictive model [31]. Conversely, ensemble machine learning algorithms such as XGBoost, and Random Forest were implemented for the same goal [32]. In [32], the Shapley Additive Explanations (SHAP) method explored insights obtained through the outputs of the machine learning models. Both concerned on normal charging scenarios, while [32] focuses also on fast charging scenarios for EVs. However, these proposed models should incorporate more features, such as driver behavior and real-traffic conditions.

To forecast EV charging duration, Ullah et al. [33] proposed a Grey Wolf Optimizer (GWO)-based machine learning algorithm. With an eye toward three ML algorithms Extreme Learning Machine (ELM), Feed-Forward Neural Network (FFNN), and Support Vector Regression (SVR) the study used real-world data gathered from 500 EVs in Japan over two years. Using metaheuristic methods including GWO, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), the authors tuned the parameters of these algorithms. In terms of prediction accuracy and robustness, the results showed that GWO-based ML models exceeded all others. Furthermore, the study used Shapley Additive Explanations (SHAP) to understand how different elements affect charging time and found that air conditioning use and SoC both greatly affected charging duration. The need of metaheuristic optimization in raising the accuracy of EV charging time prediction models is underlined by this study.

Another study that utilized the optimization algorithms to optimize the placement of EV fast charging stations and distributed generators was proposed in [34]. The problem was formulated and solved using an enhanced version of a decomposition-based evolutionary algorithm (E-MOEA-D). The authors aim to incorporate three main objectives that are minimizing active power loss, reducing voltage deviation, and lowering DG installation cost. The proposed method analyzes the impact of placement of distributed generators on the performance of the electric charging stations using an enhanced diversity selection method. Experimental validation showed that E-MOEA-D outperformed standard MOEA-D and NSGA-II algorithms by achieving 1.73% reduction in power losses - about 48.12 kW - 17.27% reduction in voltage deviation, and 59.47% cost reduction in distributed generators installation compared to the existing methods.

In a complementary study, Ahmadian et al. [35] presented a unified framework for EV user behavior prediction using a deep neural network (DNN) architecture called JETPANN (Joint EV energy consumption and charging duration Training Prediction using Artificial Neural Networks). Based on historical data gathered from 341 EV users over five years, the framework was built to forecast both the charging duration and energy consumption of EV users. With mean-absolute errors of 0.927 and 0.068 respectively, the JETPANN framework used a jointly trainable DNN to simultaneously predict charging duration and energy consumption, so attaining great accuracy. To maximize the performance of the model, the work also carried semi-grid search and hyperparameter tuning. In predicting EV user behavior, the authors showed that their method beat conventional machine learning models including Random Forest (RF) and Support Vector Regression (SVR). This work offers a strong basis for next investigations in this field and highlights the possibilities of deep learning methods in catching the stochastic character of EV charging behavior.

In general, the studies in the literature failed to focus on the parameters, including behavior of EV drivers, battery types, or actual traffic scenarios, which might have a direct impact on the charging time.

III. PROPOSED METHODOLOGY: CLEVER

The first step to address the CLEVER curriculum design strategy is to understand the dataset and its features. Therefore, the dataset utilized in this work will be introduced, and then the proposed curriculum design strategy will be presented in terms of rationale, equations, and algorithms. A summary of the proposed methodology is depicted in Fig. 1.

The approach of CLEVER is designed to be a feature based curriculum engineering method that is manually adjusted to suit the particulars of the dataset. The main idea remains the same, by introducing different complexities progressively (i.e., from less complex to more complex or vice versa). This may mean different threshold values, combination of features, and complexity criteria must be identified through domain analysis for each dataset. Common features that typically occur across EV datasets include ambient temperature, state-of-charge levels, and type of chargers, but the minimum, maximum, and combinations of values or distributions can differ dramatically by dataset and deployment context.

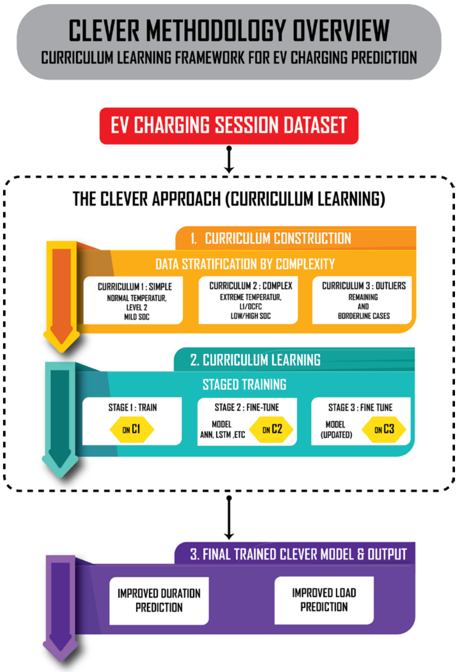

FIGURE 1. An overview of the proposed methodology.

A. THE UTILIZED DATASET

The experimental study made use of an extensive dataset that included 1,320 charging session records of users of electric cars. The dataset covers several dimensions—temporal, geographical, environmental, user-specific, and charging situations across several levels. Twenty distinct attributes define every charging session and provide comprehensive information about the charging process, vehicle characteristics, and user behavior. Together with contextual information including ambient temperature (°C) (i.e., surrounding air temperature during the charging session), charging station location, and charger type (Level 1, Level 2, DC Fast Charger), these attributes comprise fundamental charging metrics including load (kWh), EV charging duration (hours), and charging rate (kW). Along with user behavioral patterns measured by distance traveled since the last charge and state of charge percentages, the dataset includes vehicle-specific data, such as battery capacity, model type, and vehicle age. Particularly, the dataset classifies users according to their driving behavior (e.g., commuter, long-distance traveler), therefore allowing the investigation of pricing trends across several user patterns. Temporal elements are obtained by means of timestamps and categorical variables denoting time of day and day of week, therefore enabling the determination of temporal charging patterns. The charging station feature captures spatial aspects as well. This broad set of attributes helps to build complex prediction models and provides thorough investigation of EV charging behavior.[2]

[2]Dataset accessible January 2025 available at https://www.kaggle.com/datasets/valakhorasani/electric-vehicle-charging-patterns

B. CURRICULUM CONSTRUCTION STRATEGY

The CLEVER methodology offers a systematic curriculum engineering approach that necessitates the manual iteration of complexity metrics based on a dataset's specific feature characteristics. The approach involves the training of prediction models based on arranging training data starting with complexity models from low to high complexity or vice versa, with the definitions of complexity needing to be tailored to the statistical characteristics of the dataset and operational context for each dataset. The curriculum learning strategy classifies charging sessions into three distinct stages based on their complexity where each stage includes single curriculum. This classification uses indicator functions I_{C1},I_{C2}, and I_{C3} that return 1 if the conditions are met, and 0 otherwise. Each instance in the utilized dataset D, denoted as x, represents a single charging session with its associated features. Thus, each instance x is texted by all of the three I_c functions, then each instance x will be classified into one and only one curriculum.

The flow chart of the proposed curriculum learning process is depicted in Fig. 2.

$$I_{C1}(x) = \begin{cases} 1 & \text{if } (L = 2)AND \\ & (\mu_T - \sigma_T \leq T \leq \mu_T + \sigma_T)AND \\ & (25\% \leq SoC_{start} \leq 75\%) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where L represents the charger level, T denotes the ambient temperature, μ_T is the mean temperature, σ_T is the temperature standard deviation, and SoC_{start} represents the state of battery charge percentage at the start of the charging session. The threshold values used in the indicator functions (μ_T, σ_T, and SoC ranges) are dataset-specific parameters that must also be calculated by conducting statistical analyses on each corresponding dataset.

The first stage (C_1) identifies basic charging patterns as shown in Equation 2. These patterns are characterized by type Level 2 chargers ($L = 2$) operating within normal temperature ranges ($(\mu_T - \sigma_T) \leq T \leq (\mu_T + \sigma_T)$) and moderate SoC_{start} levels between 25% and 75% (i.e., charge percentage at the start of the charging session). This forms the foundation of the proposed curriculum learning approach, allowing the model to first learn from straightforward charging scenarios.

$$I_{C2}(x) = \begin{cases} 1 & \text{if } ((L = 1)OR(L = \text{DC}))AND \\ & ((T < \mu_T - \sigma_T)OR(T > \mu_T + \sigma_T))AND \\ & ((SoC_{start} < 25\%)OR(SoC_{start} > 75\%)) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The second stage (C_2), defined by Equation 3, encompasses more complex charging scenarios. These include charging sessions using Level 1 or DC Fast charger types (i.e., $(L = 1)OR(L = DC)$), operating in extreme temperature conditions, and involving very low or very high states of charge.

$$I_{C3}(x) = \begin{cases} 1 & \text{if } (I_{C1}(x) = 0)AND(I_{C2}(x) = 0) \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

As in Equation 4, the third stage (C_3) recognizes all remaining charge circumstances outside of either C_1 or C_2. This guarantees overall coverage in the utilized dataset of all feasible charge scenarios.

Typically, the entire categorization system may be stated as a set of mutually exclusive subsets:

$$\begin{aligned} C_1 &= \{x \in D \mid I_{C1}(x) = 1\} \\ C_2 &= \{x \in D \mid I_{C2}(x) = 1\} \\ C_3 &= \{x \in D \mid I_{C3}(x) = 1\} \end{aligned} \tag{5}$$

where D denotes the complete dataset, $D = C_1 \cup C_2 \cup C_3$ and $C_1 \cap C_2 \cap C_3 = \emptyset$.

The set notation in Equation 5 formalizes the partitioning of the dataset D into three disjoint subsets. This partitioning ensures that each charging session is assigned to exactly one curriculum stage, facilitating the progressive learning process from simple to complex patterns. The entire dataset, D, is split into a training set, D_{train}, and a validation set, D_{val}. Then, the training set is divided into three separate and complete curricula, $\{C_1, C_2, C_3\}$ using the indicator functions in Equations 2-4. These curricula show a "difficulty" gradient, with the most regular patterns at the bottom (C_1) and the most complicated and variable patterns at the top (C_3). There are three steps in the training process ($s = 1, 2, 3$). The model is trained using a cumulative dataset, S_s, at each step s. This is defined as: This makes sure that the model initially sees basic patterns in $S_1 = C_1$, then becomes better at working with more complicated data in $S_2 = C_1 \cup C_2$, and ultimately gets trained on the whole dataset $S_3 = D_{train}$. There is not a set number of epochs that determines when these phases change; instead, there is a dynamic number based on the model training performance. After training the model for e epochs in stage s, let $\theta^{(s,e)}$ be the vector of parameters. We check the performance by calculating the validation loss, $\mathcal{L}_{val}^{(s,e)}$, on the whole, unseen validation set D_{val}. As the training goes on, the model parameters that work best on the validation set are saved as θ^*.

1) RATIONAL OF THE PROPOSED CURRICULUM DESIGN

The selection of three curricula is based on various considerations. The primary one is that the dataset instances are categorized based on the car ambient temperature feature in combination with other variables. The delimitation of each curriculum is set by three particular requirements: instances in which the temperature is in one standard deviation of the mean $((T < \mu_T - \sigma_T)OR(T > \mu_T + \sigma_T))$, temperatures that lie outside this range, and instances that are outliers or on the boundary. The three curricula selected logically relate to these specified requirements. Furthermore, the problem at hand is not a complex one, given that the dataset is image-based or multi-dimensioned dataset with complex pattern. Instead, the

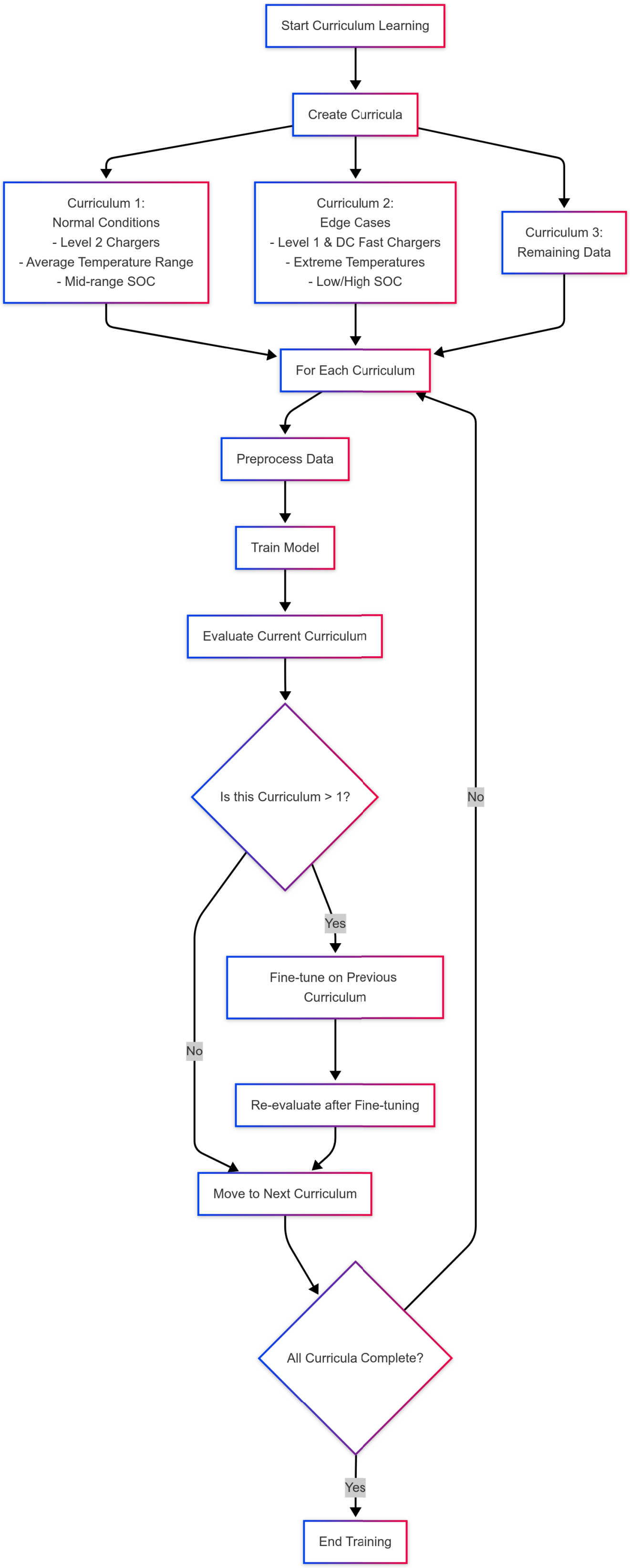

FIGURE 2. Curriculum learning construction process flow.

dataset is a tabular dataset with numerical values only. The dataset is also relatively small in size, containing fewer than 1,500 instances, making three curricula a practical choice to support a productive learning path.

The proposed method starts by identifying the standard charging conditions in which a benchmark is created by focusing on the average charging circumstances; this is considered the first stage of curriculum learning. The standard infrastructure, which is considered level 2 chargers, is determined on the basis of most common values for the charger type feature. This implies the temperature via normal operating conditions, the battery state of charge (i.e., SoC_{start}) at the start of the charging session between 25% and 75%, (i.e., the common usage patterns), and the charging events through the normal operating hours and locations. These setting demonstrate the most common charging cases that enables the model to establish the robust basic patterns without being affected by edge cases. This is the foundation stage for the curriculum learning in order to emphasize the accuracy and stability of the model.

The second stage (C_2) of the CL stages includes complex variations and edge cases in which more challenging scenarios/cases are presented to scale the adaptability of the proposed model. Here, data gathered from Level 1 and DC fast charger types, indicates extreme SoC_{start} values (i.e., <25% or >75%) for temperatures with low standard deviation. Besides, the instance of C_2 have a more diverse charging locations, along with interactions with different user types. Exposing the proposed model to such edge cases leads to improving its ability to adjust to deviations from the standard circumstances while leveraging its previous basic understanding from stage one. Nevertheless, this stage is crucial for obtaining robustness and resilience under varying and less predictable conditions.

In the final stage of the CL, known as comprehensive coverage, the model is exposed to all the remaining data points to encompass all borderline scenarios, abnormal charging patterns, as well as mixed-condition instances. The primary goal is to obtain a real-world applications model that guarantees its ability to manage any combination of variables and circumstances. This comprehensive exposure emphasizes the model's generalization across diverse charging patterns.

C. FEATURE ANALYSIS AND DATA PREPROCESSING STRATEGY

The efficient prediction of EV charging behavior requires a model capable of managing complex scenarios and variables such as the temperature. In the proposed method, the curriculum learning algorithm leverages the temperature pattern (T) as a critical parameter to regulate the learning process into coherent stages. In this context of EV charging prediction, temperature has a direct impact on battery performance and its charging metrics [36], [37]. Algorithm 1 utilizes temperature-based stages in which the data is categorized according to the temperature. The μ_T indicates the mean temperature and σ_T represents the standard deviation. This helps to define the temperature bounds as $(\mu_T - \sigma_T, \mu_T + \sigma_T)$ that is referred to as "normal operating temperature range". The stratification is mandatory for the initial curriculum stage (C_1) in which the proposed model imparts knowledge from the charging events that occur within these normal temperature bounds. This is considered typical charging scenarios. Hence, the temperature feature affects other features in the dataset, including Battery Capacity (kWh), SoC_{start}, SoC_{end}, Vehicle Age (years), and Charging Rate (kW). All these features, for a complex network of interconnected variables, influence the charging behavior of EVs.

In the proposed algorithm, the temperature values are classified based on a temperature-dependent curriculum (e), where e impacts the learning progression level from normal to complex case. Typically, the temperature classification in any charging event e is determined by the $f(T_e)$, which is defined in Eq. 6. This classification determines the location of the event in the normal temperature range (i.e., curriculum stage C_1) or extreme temperature ranges (i.e., curriculum stages C_2). As a result, the proposed model is subjected to more complicated scenarios that involve extreme temperature charging cases. The precision of the temperature-based learning is determined by integrating temperature conditions with the SoC_{start} thresholds.

For any charging event e, its temperature classification is defined by the function

$$f(T_e) = \begin{cases} \text{normal}, & \text{if } \left| \dfrac{T_e - \mu_T}{\sigma_T} \right| \leq 1 \\ \text{extreme}, & \text{otherwise} \end{cases} \tag{6}$$

where T_e is the ambient temperature during charging event e in the context of surrounding air temperature during the charging session.

Through categorical variables including Vehicle Model, Charging Station Location, Time of Day, Day of Week, Charger Type, and User Type, the various characteristics of the dataset provide full temperature-dependent analysis. Since feature encoding expands the dimensionality of the dataset, these categorical characteristics are encoded using one-hot encoding and provide a modified feature space $X \in \mathbb{R}^n$, where n is the final total number of features after encoding. Compasses seasonal and daily temperature changes depend much on the temporal elements. The temporal attributes include Time of Day, and Day of Week. Nevertheless, the spatial aspects handle the geographical temperature fluctuations. Using median imputation for missing values, one-hot encoding for categorical variables, and conventional scaling for numerical features, the proposed method processes these features through a preprocessing pipeline $P : X \rightarrow X'$. This study ensures robust temperature-aware learning in several charging environments and conditions.

D. HANDLING REAL-TIME DATA STREAMS AND MODEL DRIFT IN CLEVER

The suggested CLEVER curriculum learning method solves these problems with a systematic but adaptable recalibration architecture. CLEVER divides charging sessions into three curricula (C_1, C_2, C_3) using indicator functions based on statistical thresholds like the mean and standard deviation of the ambient temperatures and fixed percentage ranges of the state-of-charge. As more data is collected, these parameters automatically alter to reflect how the charging infrastructure and user behavior are changing over time. To deal with real-time data streams and stop model drift, CLEVER uses the following method:

- **Periodically Recalibrating Statistical Parameters:** To ensure appropriate representation of the current charging behavior, statistical parameters can be adjusted on a regular basis. This regular recalculation makes sure that the structure of the curriculum still reflects the most recent dataset features.
- **Incremental Curriculum Update:** The indicator functions will be changed and the curriculum levels will be given new assignments once the statistical thresholds are recalculated. This progressive updating technique lets CLEVER change without having to do full-scale retraining, which cuts down on overhead by a lot.
- **Monitoring model drift:** Metrics like charging session duration and load prediction MAE and RMSE are used to keep evaluate the proposed models performance. If the predictive models' performance is far different from what was predicted, it will need to be retrained in part or in whole on the new data.
- **Putting it into Real-Time Frameworks:** CLEVER can be used in data processing pipelines that work in real time or almost real time. With a few changes, it can be automate the recalibration of statistical parameters and the reassignment of curricula, which will keep the model working and relevant all the time.

E. THE PROPOSED ALGORITHM OF THE CLEVER APPROACH

Curriculum learning is mainly based on the cognitive science in which model learning advances through simple to complex conditions. The proposed algorithm, Algorithm 1, is intended to train predictive models that can estimate EV charging load or charging session duration. It utilized a curriculum-based approach in which the patterns are categorized according to their complexity degrees based on the acquired data for staged training. The normal EV charging instances (i.e., easy to predict instances) against extreme one (i.e., difficult to predict instances). Given the dataset and models, the fundamental steps proceed as follows: (1) processing of raw data; (2) constructing the curriculum; (3) incremental training of the model on each curriculum subset; and (4) final assessment on test data. This layered approach aims to improve the

Algorithm 1 CLEVER: Curriculum Learning for EV Charging Prediction method

Require: Dataset D, Feature sets F_{load}, $F_{duration}$, etc.
Ensure: Trained models with performance metrics
function PreprocessData(D)
  Define $N \leftarrow \{Battery, SoC_{start}, Temperature, Age \ldots\}$
  Define $Catg \leftarrow \{Model, Location, TimeOfDay \ldots\}$
  $N_{processed} \leftarrow$ MedianImputer(N)
  Clip SoC_{start} to [0, 100]
  $N_{scaled} \leftarrow$ StandardScaler($N_{processed}$)
  $Catg_{encoded} \leftarrow$ OneHotEncoder($Catg$)
  $D_{processed} \leftarrow$ Concatenate(N_{scaled}, $Catg_{encoded}$)
  $D_{train}, D_{test} \leftarrow$ SplitData(D, 0.8)
  return D_{train}, D_{test}
end function
function CreateCurricula(D)
  // Basic patterns (C_1)
  $\mu_T, \sigma_T \leftarrow$ Calculate temperature statistics
  $C_1 \leftarrow D[(\text{Level 2 chargers}) AND (\mu_T - \sigma_T \leq T \leq \mu_T + \sigma_T) AND (25\% \leq SoC_{start} \leq 75\%)]$
  // Complex patterns (C_2)
  $C_2 \leftarrow D[(\text{Level 1 or DC}) AND (T < \mu_T - \sigma_T \vee T > \mu_T + \sigma_T) AND (SoC_{start} < 25\% \vee SoC_{start} > 75\%)]$
  // Remaining (C_3)
  $C_3 \leftarrow D \setminus (C_1 \cup C_2)$
  return $\{C_1, C_2, C_3\}$
end function
function Train(M, D)
  $X_{train}, y_{train} \leftarrow$ PreprocessData(D_{train})
  Train M on (X_{train}, y_{train})
  metrics $\leftarrow$ Calculate performance metrics on D_{test}
  return metrics
end function
function TrainWithCurriculum(M, $\{C_1, C_2, C_3\}$)
  for $i \in \{1, 2, 3\}$ **do**
    $X_c, y_c \leftarrow$ PreprocessData(C_i)
    Train M on (X_c, y_c)
    if $i > 1$ **then**
      $X_{prev}, y_{prev} \leftarrow$ PreprocessData(C_{i-1})
      Fine-tune M on (X_{prev}, y_{prev})
    end if
    metrics $\leftarrow$ Calculate performance metrics on D_{test}
  end for
  return metrics
end function
// Main Execution
$M \leftarrow$ {LSTM, GRU, ANN, DNN}
$C \leftarrow$ CreateCurricula(D_{train})
for model $m \in M$ **do**
  // Baseline Training
  $metrics_{base} \leftarrow$ Train(m, D)
  // Curriculum Training
  $metrics_{curr} \leftarrow$ TrainWithCurriculum(m, C)
  Calculate improvement percentage
end for

model's performance via gradually exposing it to various data distribution complexities.

Algorithm 1 starts with the preprocessing phase, which is responsible for cleaning, scaling, and encoding the raw dataset (i.e., lines 1-11). The numerical features, such as battery capacity (Battery), state of battery charge percentage at the start of the charging session (SoC_{start}), and temperature, are imputed to compensate for the missing values, clipped within feasible ranges, and standardized. On the other hand, the categorical attributes are subjected to one-hot encoding. These attributes may include the brand of the electric vehicle or the day of week slot.

The input dataset is categorized using the function "CreateCurricula", (i.e., lines 12-21), into three main subsets (C_1 Eq. 2, C_2 Eq. 3, and C_3 Eq. 4) based on temperature variance and SoC_{start} thresholds: (i) simpler charging sessions that exhibit near-average temperature, Level 2 chargers, and moderate SoC_{start} levels (25-75%); (ii) challenging charging sessions with extreme temperature, Level 1 and DC Fast charger types, and low/high SoC_{start}; and (iii) all remaining charging sessions including outliers and edge cases. Of note, model weights will not be reinitialized between curricula. Hence, the emphasis on simpler patterns initially, then progressing through more complex conditions, can be obtained via the organization of the data in the way previously mentioned. Then, Algorithm 1 handles the training task of the predictive model through two training methods: (1) *TRAIN* for training the predictive models using the normal approach which serving as the baseline model (i.e., lines 22-27) and (2) *TRAINWITHCURRICULUM* method that trains the predictive models using the proposed curriculum learning approach (i.e., lines 28-39).

Algorithm 1 avoids catastrophic forgetting in curriculum learning approach through a fine-tuning process between successive curricula (i.e., lines 32-35). After completing training on curriculum i, the model will be fine-tuned on curriculum $i - 1$ data to preserve performance on previously learned tasks. For deep learning models (DNN, LSTM, GRU), it employs 10 epochs of fine-tuning, whereas baseline models employ their usual fitting process. In particular, if $i > 1$, the function fine-tunes the model using the preceding curriculum slice, thereby retaining knowledge gained from simpler data. This curriculum approach progressively raises the complexity of the training example in order to stabilize the learning process and improve the predictive accuracy. Thus, the "TrainWithCurriculum" orchestrates multi-stage training over the curriculum subsets C_1, C_2, and C_3. For each stage of the CL stages, the function reprocesses the data segment, adjusts or fine-tunes the model, and evaluates the performance.

The final portion of Algorithm 1 (lines 40–49) outlines the main loop for the various types of models. The curriculum preparation task is executed in line 42. Two parallel training procedures are conducted: baseline model training using the "Train" function and a staged, curriculum-driven approach, with "TrainWithCurriculum". The algorithm calculates improvement percentages and stores results for comparison. This pipeline ensures a comprehensive evaluation of how curriculum learning influences model accuracy and robustness relative to standard end-to-end training approaches.

IV. RESULTS

A. PERFORMANCE EVALUATION OF CLEVER

In the proposed study, the effectiveness of the proposed curriculum learning methodology is evaluated to improve EV charging behavior prediction by means of a thorough comparison analysis including different neural network approaches. Four neural network approaches—traditional ANN, DNN, LSTM, and GRU—are utilized in this study. Emphasizing the study of EV charging duration and the prediction of EV charging load, a comparison has been conducted among the baseline implementation and its counterpart employing curriculum learning for every architecture. Commonly utilized in time-series prediction problems, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are the assessment metrics applied in this study for evaluating the prediction process. Different user demographics, charger types, models of cars, and environmental circumstances are also evaluated across the RMSE and MAE measures. The results address how CL leads to lower prediction mistakes and strengthens the resilience of the proposed model. This methodical comparison aims to evaluate the performance improvements connected to the curriculum learning process and identify the most efficient architectural combinations for EV charging tasks prediction.

We used Adam optimizer (Keras `lr=0.001`; MLP `learning_rate_init=0.0015-0.002`), early stopping (Keras `monitor='loss',patience=5`; MLP with `validation_fraction=0.08-0.10`), `dropout=0.2` for DNN/LSTM/GRU, L2 regularization for MLP (`alpha= 0.001-0.002`), and 20 training epochs by default.

The experimental results show the significant influence of CL on raising prediction accuracy over several neural network architectures. With the GRU model achieving outstanding improvements of 16.5% and 20.9% in RMSE and MAE respectively, the CL approach notably improved the EV charging session duration prediction performance as shown in Table 1. This significant improvement implies that the gradual learning (i.e., CL) approach efficiently catches the temporal trends in data on EV charging duration. With LSTM achieving 14.1% and 17.9% improvements in RMSE and MAE respectively, and DNN showing similar enhancements, the ANN shows the least improvements of 5.1% and 4.0% in RMSE and MAE, respectively.

Table 2 lists EV charging load prediction; the CL method consistently outperformed the baseline models against all architectures. The DNN model displayed the most notable gains with 1.6% drop in RMSE and 2.2% drop in MAE. The GRU model showed similar progress of 1.8% and

TABLE 1. EV charging duration prediction error comparison.

Model	RMSE			Test Imp (%)	MAE			Test Imp (%)
	Base (Test)	CL (Test)	CL (Train)		Base	CL (Test)	CL (Train)	
ANN	1.13	1.07	1.03	5.1	0.89	0.86	0.87	4.0
DNN	1.13	0.97	0.94	13.9	0.89	0.73	0.74	17.7
LSTM	1.10	0.95	0.93	14.1	0.87	0.71	0.73	17.9
GRU	1.14	0.96	0.92	16.5	0.89	0.70	0.72	20.9

TABLE 2. EV charging load prediction errors comparison.

Model	RMSE			Test Imp (%)	MAE			Test Imp. (%)
	Base (Test)	CL (Test)	CL (Train)		Base	CL (Test)	CL (Train)	
ANN	22.7	22.3	21.6	1.7	18.7	18.4	18.1	1.2
DNN	22.6	22.3	21.5	1.6	18.7	18.3	17.9	2.2
LSTM	22.6	22.3	21.6	1.3	18.7	18.4	18.0	1.6
GRU	22.7	22.2	21.5	1.8	18.7	18.3	17.9	1.9

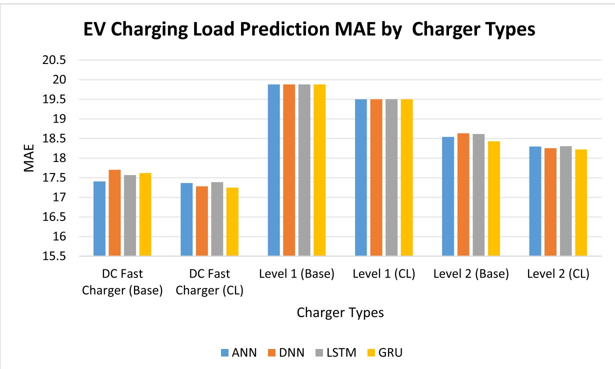

FIGURE 3. EV charging load prediction MAE analysis across different charger types, comparing the performance of ANN, DNN, LSTM, and GRU models with and without CL. The results show varying prediction accuracies for DC Fast Charger, Level 1, and Level 2 charging systems.

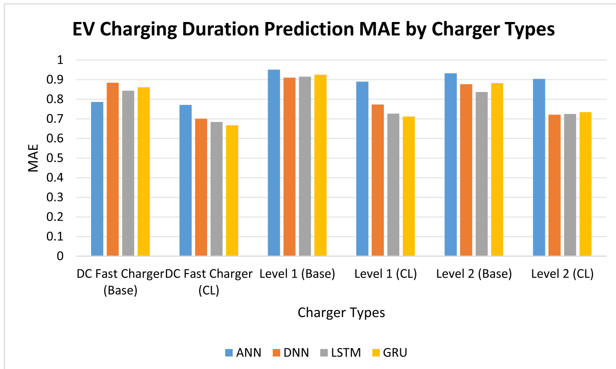

FIGURE 4. EV charging duration prediction MAE comparison for different charger types, demonstrating the relative performance of various deep learning architectures. The analysis includes both baseline and curriculum learning approaches for DC Fast Charger, Level 1, and Level 2 chargers.

1.9% in RMSE and MAE respectively, even though it showed the same absolute error values. The ANN showed more modest improvements in EV charging load prediction, implying that CL approach could be more crucial for duration prediction than for EV charging load prediction estimate with improvements ranging from 1.7% to 1.2%. Particularly for feedforward neural networks, these findings highlight the efficiency of curriculum learning in enhancing prediction accuracy and provide significant fresh viewpoints for optimizing EV charging prediction systems.

B. COMPREHENSIVE ANALYSIS OF EV CHARGING PREDICTION MODELS

1) CHARGER TYPE PERFORMANCE ANALYSIS

Figures 3 and 4 offer significant insights on charging prediction accuracy over several charger types. For EV charging load prediction, DC Fast Chargers show notably higher MAE values—about 40 units—than Level 1 and Level 2 chargers. Particularly for DC Fast Chargers, the use of CL shows appreciable increase in prediction accuracy, so indicating enhanced model adaptation to high-power charging environments. The duration prediction results show similar trends implying that EV charging duration may be more predictable than charging load, even if the general MAE values are lower.

2) USER TYPE IMPACT

Figures 5 and 6 show varying trends in prediction accuracy over several user categories. Commuter charging behavior shows more consistent prediction accuracy compared to long-distance users and casual drivers. The predictions for the EV charge loads illustrate this trend extremely well, as the MAE for commuters consistently remains lower across all model architectures. Long-distance traveler predictions show the most notable increases; hence, the use of curriculum learning shows significant improvement in prediction accuracy for all user types.

3) VEHICLE MODEL VARIATIONS

Analysis of vehicle-specific predictions in Figures 7 and 8 reveals variations in prediction accuracy among several EV models. Particularly in estimates of charging load, Chevy bolt model often show smaller prediction errors than other vehicles. Advanced onboard systems that provide enhanced

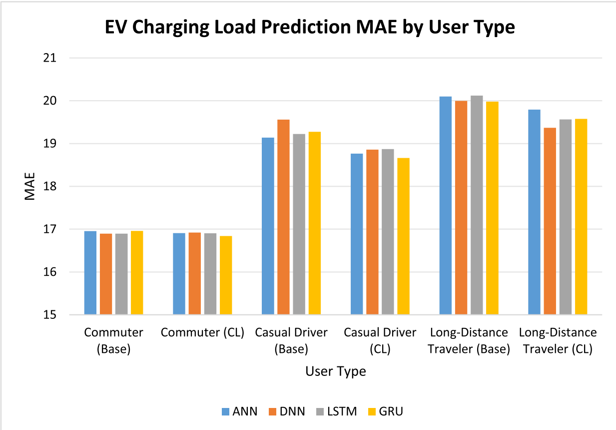

FIGURE 5. EV charging load prediction MAE across different user types, showing how prediction accuracy varies among Commuters, Casual Drivers, and Long-Distance Travelers. The comparison includes both base models and those trained with curriculum learning.

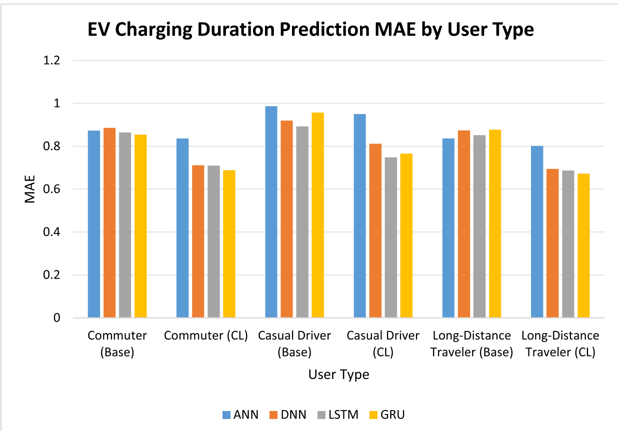

FIGURE 6. EV charging duration prediction MAE analysis for different user types, illustrating the model performance variations across user categories. The results demonstrate the impact of curriculum learning on prediction accuracy for different charging behavior patterns.

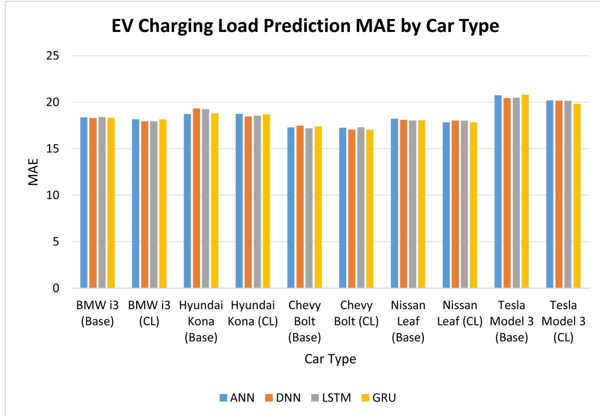

FIGURE 7. EV charging load prediction MAE for different electric vehicle models, comparing prediction accuracies across BMW i3, Hyundai Kona, Chevy Bolt, Nissan Leaf, and Tesla Model 3. The analysis includes both baseline and curriculum learning approaches.

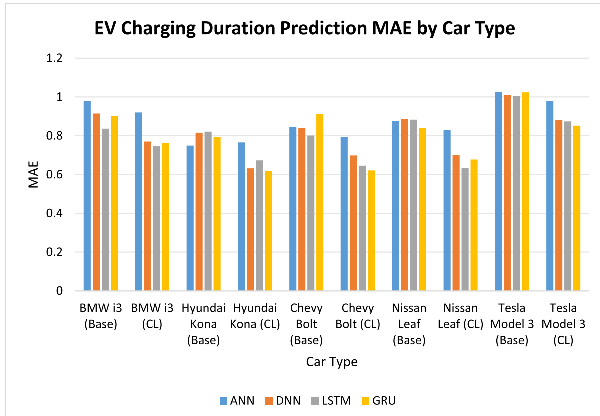

FIGURE 8. EV charging duration prediction MAE analysis across various electric vehicle models, showing how different deep learning architectures perform in predicting charging duration for different vehicle types.

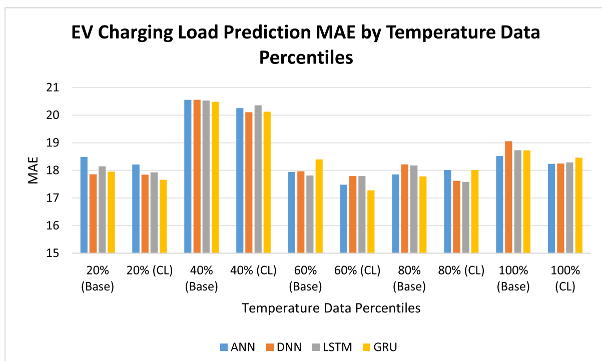

FIGURE 9. EV charging load prediction MAE analysis across different temperature percentiles, demonstrating the impact of temperature variations on prediction accuracy. The analysis covers temperature data from 20th to 100th percentile.

charging data accuracy or more uniform charging patterns among vehicle owners may explain this phenomenon. Using the curriculum learning approach shows especially great success in reducing prediction errors for vehicles that first showed higher MAE values, especially for GRU architecture.

4) TEMPERATURE IMPACT ASSESSMENT

Figures 9 and 10 provide an exhaustive analysis of how temperature variations affect prediction accuracy. Particularly clear in EV charging load projections, the data show increasing MAE values at extreme temperature percentiles. This tendency suggests that extreme weather events cause additional variability in charging behavior, so challenging the precision of prediction. The curriculum learning approach shows particular success in improving predictions under very high-temperature conditions, so indicating better model adaptation to demanding environmental conditions.

5) TEMPORAL PATTERNS

Figures 11 and 12 show temporal aspects of prediction accuracy. While small variations point to the existence

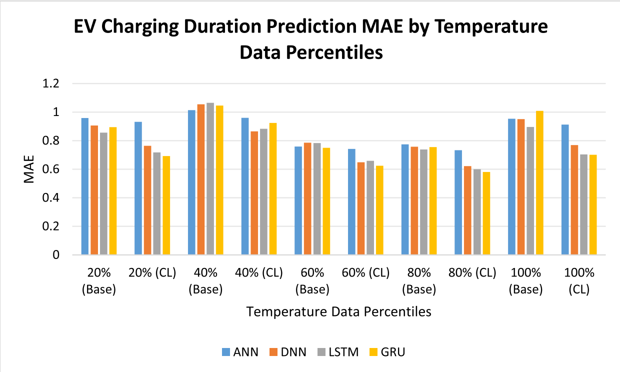

FIGURE 10. **EV charging duration prediction MAE analysis for different temperature percentiles, showing how temperature variations affect the accuracy of charging duration predictions across different model architectures.**

of weekly charging patterns, the analysis shows rather constant prediction accuracy over several days of the week. The consistent improvement shown by the curriculum learning approach over all days suggests good model adaptation to temporal charging patterns. Particularly in charge infrastructure management, practical applications depend on this temporal stability in prediction accuracy.

6) MODEL ARCHITECTURE COMPARISON

In all assessed dimensions, GRU architecture demonstrates the highest performance, while DNN models show substantial improvements comparable to LSTM. This benefit is especially noticeable when capturing the charging patterns with complicated temporal dependencies. A notable shifts in the curriculum are revealed by studying difficult cases, such as DC Fast Charging and extremely temperature environments, where baseline models initially struggled. This comprehensive analysis validates that under many operational scenarios, both curriculum learning and advanced neural network designs contribute to improving EV charging prediction accuracy. The results demonstrated in all the provided figures demonstrate the validity of curriculum learning in improving prediction accuracy in several spheres of EV charging behavior as well as areas where more model improvement could be beneficial.

Although curriculum learning benefits both EV charging load and duration predictions, this comprehensive analysis shows that they have different characteristics and sensitivity to different factors even if it benefits both EV charging load and duration predictions. The asymmetric responses to temporal, environmental, and user-specific variables suggest that for EV charging load and duration optimal prediction strategies could call for several approaches. These findings have significant implications for the way intelligent EV charging management systems interact with smart grid infrastructure.

C. VALIDATION ON AN ADDITIONAL DATASET

To evaluate the robustness and generalizability of the proposed CLEVER approach, we conducted a validation study on a second distinct EV dataset different from the primary dataset used in the experiments mentioned above. This step was motivated for the evaluation of the effectiveness of our method beyond the original data.

We intentionally separated this analysis into a dedicated subsection to avoid potential confusion regarding differences between the primary and secondary datasets in terms of dataset characteristics and the curriculum construction strategy applied. The second dataset contains 64,945 charging session records of users of electric cars.[3] The second dataset is significantly larger and sourced differently from the primary dataset, allowing for a rigorous test of the method's effectiveness beyond its initial evaluation environment. For this validation, we adapted the curriculum to the new dataset's features while maintaining the core principle of progressive complexity. Charging sessions were stratified into a three-stage curriculum based on different criteria: the first stage was defined by standard temperature ranges, the second by specific weather conditions, and the final stage encompassed all remaining, more complex scenarios.

As detailed in Tables 3 and 4, the CL approach again demonstrated consistent, albeit more modest, improvements in prediction accuracy for both charging duration and load, achieving up to a 2.8% reduction in RMSE. The positive, consistent impact across a larger and more diverse dataset confirms the generalizability of the CL methodology. This successful validation underscores the CL strategies robustness and its potential for reliable deployment in broad, real-world EV charging ecosystems.

TABLE 3. **EV charging duration prediction error comparison on the second dataset.**

Model	RMSE			MAE		
	Base	CL	**Imp (%)**	Base	CL	**Test Imp(%)**
ANN	11.9	11.9	0.1	14.9	14.9	0.0
DNN	12.3	12.0	2.8	15.4	15.0	2.7
LSTM	12.3	12.0	2.3	15.4	15.0	2.2
GRU	12.2	12.0	1.8	15.3	15.0	1.9

TABLE 4. **EV charging load prediction errors comparison on the second dataset.**

Model	RMSE			MAE		
	Base	CL	**Imp (%)**	Base	CL	**Test Imp(%)**
ANN	8.0	8.0	0.3	10.1	10.0	0.2
DNN	8.3	8.0	2.8	10.4	10.1	2.6
LSTM	8.2	8.0	2.5	10.4	10.1	2.5
GRU	8.2	8.0	2.5	10.3	10.1	2.6

[3]Dataset accessible July 2025 available at https://www.kaggle.com/datasets/datasetengineer/ev-charging-load-dataset-and-optimal-routing

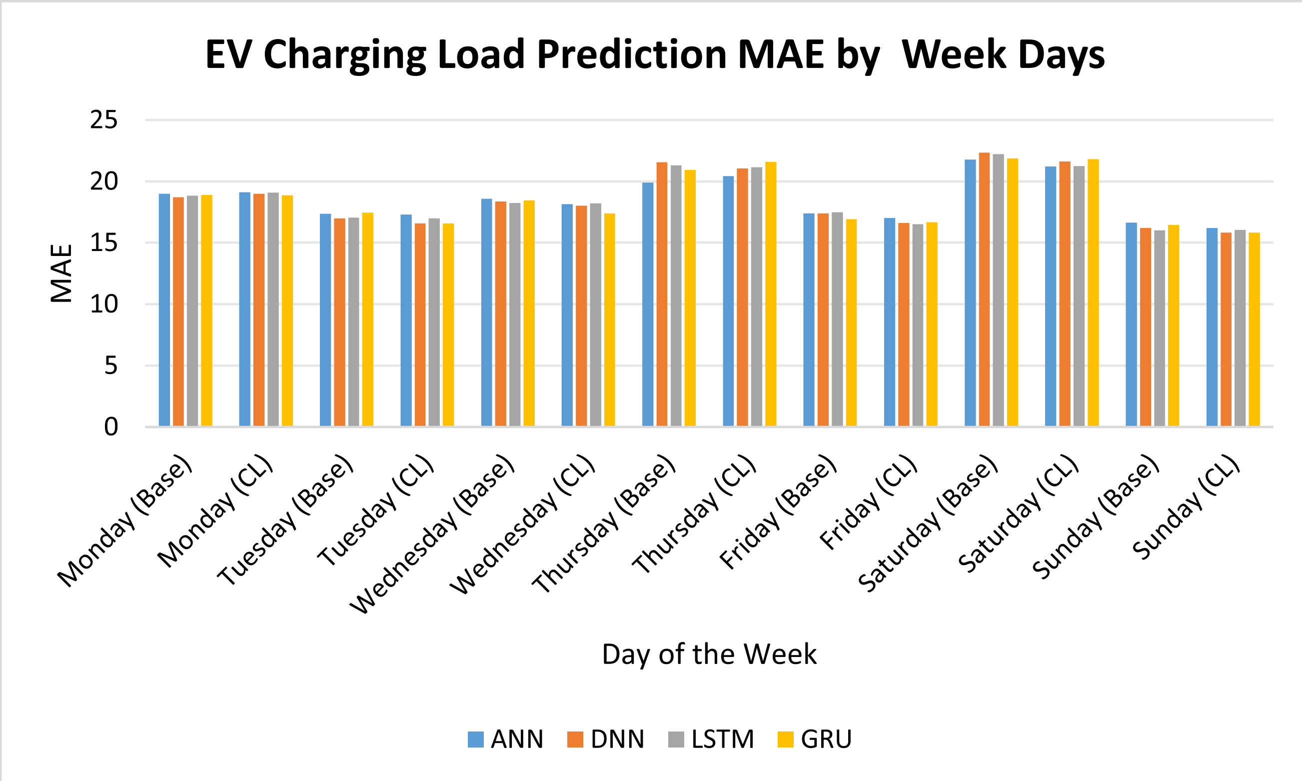

FIGURE 11. EV charging load prediction MAE analysis across different days of the week, illustrating weekly patterns in prediction accuracy for various deep learning models.

D. PRACTICAL IMPLICATIONS AND ECONOMIC FEASIBILITY

The quantitative improves shown in Table 1 and Table 2 have postive impacts on the growing EV ecosystem, both in terms of money and in terms of how things work. The percentage increases are impressive, but the best way to understand their significance in the real world is through the eyes of the people who matter most: grid operators, charge point operators (CPOs), and legislators. For managing the grid and utilities: The electrical grid must be stable at all times. Charging a lot of electric vehicles in an unpredictable way is a big danger to this stability. Grid operators may have a better idea of what demand will be like in the future thanks to the proposed CLEVER approach's capacity to lower the Mean Absolute Error (MAE) of charging load prediction by up to 13.1% using a basic ANN model. This better foresight makes load balancing easier, which means that less costly peaker plants are needed and the danger of local transformer overloads is lower. As a result, it may delay or even do rid of the requirement for expensive grid infrastructure upgrades, which can save a lot of money on capital expenses. For Charging Station Operations: For a CPO, station turnover is one of the most important ways to make money. When charging time predictions are wrong, operations become less efficient because cars stay in places longer than expected, which causes lines and annoys customers. The fact that this model cuts the MAE for predicting charging time means that scheduling is more predictable and stations can handle more traffic. This is especially important for DC Fast Chargers. When you know for sure when a session will conclude, you can better manage waiting lists and dynamic pricing. This immediately improves the customer experience and the CPO's bottom line. For Planning Infrastructure and Policy: Governments and cities are putting a lot of money into public charging stations. The hard part is putting the correct charges in the right places. This research is the first to include user type analysis, which shows that commuters' charging behaviors are 25% more predictable. This information helps legislators make choices based on data. For example, they may provide incentives for Level 2 charges at work for commuters who follow typical patterns, and they can put high-power DC Fast charges along significant corridors for less predictable, temporary users. CLEVER precise forecasting is necessary for effective policies like time-of-use tariffs or demand-response programs. This speeds up the transition to electric transportation in a manner that is financially feasible.

E. STUDY LIMITATION

The proposed method includes a manual adjustment of the curriculum rules and thresholds for every new dataset. Though the EV datasets have common elements such as

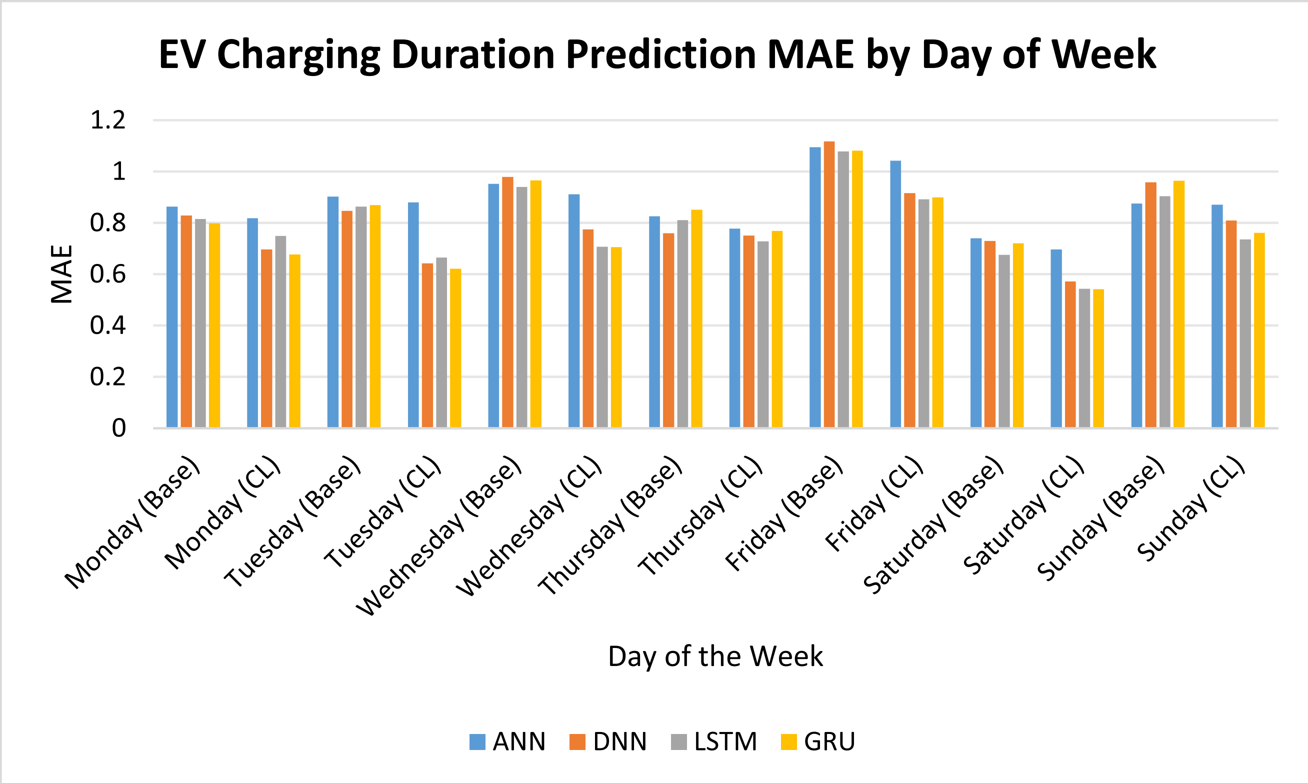

FIGURE 12. EV charging duration prediction MAE analysis by day of the week, showing temporal patterns in charging duration prediction accuracy across different model architectures.

temperature and SoC, the values of the thresholds and complexity levels are domain specific and would have to be determined through domain examination for each application. Although the progressive learning principle is general, effective transfer to other domains requires redefining the curriculum via domain-specific feature selection and thresholds

V. CONCLUSION

Along with its technical contributions, this study supports diverse implications for obtaining sustainable transport systems. Enhancing the EV charge predictions offers environmental goals associated with the use of EVs including energy efficiency, reduction of grid interaction, decreased waiting times, and smarter planning. This gives beneficial impact to both users and service providers. The CLEVER method shows a value to business and industry by informing demand responses and infrastructure planning. In terms of predictions regarding the capacity of infrastructure using CL, this study can tailor differentiated optimization procedures for each user type. Moreover, this approach reveals the theory and the application of CL due to the time-series prediction as well as providing potential operational and practical means against the deployment of scalable, and spatially aware EV charging systems. Future work can leverage the foundation through the expansion of adaptive curriculum, that will account for the variation in interpretation of patterns, and by integrating richer contextual data to further provide a causative reference system of the indication of performance expectations and system responsiveness.

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