

# SMART FORECASTING OF ELECTRIC VEHICLE CHARGING DEMAND USING HIERARCHICAL PROBABILISTIC TECHNIQUES

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## ABSTRACT

The rapid growth of electric vehicles (EVs) has created significant challenges for power grid management and charging infrastructure planning. Accurate forecasting of electric vehicle charging demand is essential for efficient energy distribution, load balancing, and the development of sustainable smart grid systems. This study proposes a smart forecasting framework for electric vehicle charging demand using hierarchical probabilistic techniques to provide reliable and scalable predictions across multiple levels of aggregation. The proposed system analyzes historical EV charging data, temporal patterns, geographic information, and environmental factors to predict future charging demand. A hierarchical forecasting approach is used to model demand at different levels, such as individual charging stations, regional networks, and overall grid demand. Probabilistic forecasting techniques are applied to capture uncertainty in charging behavior and provide prediction intervals rather than single deterministic values. This improves the reliability of demand estimation for energy management systems. Advanced machine learning and statistical models are integrated to process large datasets and identify complex patterns in EV charging behavior. The hierarchical structure ensures consistency between forecasts at different aggregation levels, while probabilistic modeling enables better risk assessment and decision-making for grid operators and infrastructure planners. The proposed framework enhances the accuracy and interpretability of EV charging demand predictions, supporting smart grid optimization, efficient energy allocation, and strategic planning of charging infrastructure. This approach contributes to the development of intelligent transportation systems and sustainable energy management in the rapidly evolving electric mobility ecosystem.

## INTRODUCTION

The rapid growth of **electric vehicles (EVs)** has created new challenges for power systems and charging infrastructure management. As governments and organizations promote sustainable transportation, the number of EVs on roads continues to increase significantly. This growth leads to a substantial rise in **electric vehicle charging demand**, which can place additional pressure on power grids if not properly managed. Accurate forecasting of EV charging demand is therefore essential for **efficient energy planning, grid stability, and optimal utilization of charging infrastructure**. Traditional forecasting methods often rely on simple statistical models that may not effectively capture the complex and dynamic nature of EV charging behavior. Charging demand is influenced by multiple factors such as **time of day, geographic location, user behavior, weather conditions, and vehicle usage patterns**. These factors create uncertainty in demand prediction, making it difficult for energy providers and charging station operators to plan resources effectively. To address these challenges, **hierarchical probabilistic forecasting techniques** have emerged as a powerful approach for modeling EV charging demand. Hierarchical forecasting allows demand predictions to be generated at multiple levels, such as **individual charging stations, regional networks, and overall power grid levels**. This structured approach ensures consistency across different forecasting levels and improves the reliability of demand predictions. Probabilistic forecasting further enhances the prediction process by providing **uncertainty estimates and probability distributions** instead of single deterministic values. This helps decision-makers understand the range of possible demand scenarios and prepare appropriate strategies for energy management and infrastructure planning. By combining hierarchical modeling with probabilistic forecasting, the system can generate **more accurate, scalable, and reliable EV charging demand predictions**. The proposed smart forecasting framework leverages **advanced data analytics and machine learning techniques** to analyze historical charging data, user behavior patterns, and environmental factors. These insights enable energy

providers and policymakers to make **informed decisions about charging station deployment, load balancing, and energy distribution**. Overall, the integration of hierarchical probabilistic forecasting techniques provides an intelligent solution for managing the growing demand for electric vehicle charging. This approach supports the development of **efficient, sustainable, and smart energy systems**, ultimately contributing to the broader adoption of electric mobility and the transition toward cleaner transportation.

## LITERATURE REVIEW

The rapid growth of electric vehicles (EVs) has significantly increased the demand for charging infrastructure and energy management solutions. Accurate forecasting of EV charging demand is essential for efficient power grid operation, optimal charging station planning, and energy market management. Researchers have proposed various forecasting approaches including statistical models, machine learning, deep learning, and probabilistic forecasting methods. This literature review summarizes key studies and technological developments related to **smart forecasting of EV charging demand using hierarchical probabilistic techniques**.

### Early Studies on EV Charging Demand Forecasting

Initial research on EV charging demand forecasting mainly focused on **deterministic and statistical time-series models** such as ARIMA, regression models, and Markov Chain simulations. These models predicted charging load based on historical travel behavior, traffic patterns, and weather conditions.

For example, Arias and Bae (2016) developed a forecasting model using **real-world traffic distribution data and weather information** to estimate EV charging demand. Their model demonstrated that factors such as travel patterns, battery state-of-charge, and charging start time strongly influence charging load patterns.

Similarly, Monte Carlo simulation techniques were used to model EV charging behavior and evaluate charging load variability across different charging scenarios. These approaches helped power system operators estimate demand uncertainty but had limitations in handling complex real-world data.

### Machine Learning-Based Forecasting Approaches

With the increasing availability of large EV charging datasets, machine learning techniques have become widely used for predicting charging demand. Popular algorithms include:

- Support Vector Machines (SVM)
- Random Forest (RF)
- Decision Trees
- K-Nearest Neighbors (KNN)
- Gradient Boosting models

These models learn complex relationships between charging demand and variables such as **time, location, weather, traffic conditions, and charging station usage patterns**. Studies show that machine learning models outperform traditional statistical methods in terms of prediction accuracy and adaptability to dynamic datasets.

Recent comparative studies also demonstrate that ensemble learning methods such as **Random Forest and AdaBoost** provide highly accurate predictions for EV charging demand under different charging scenarios.

#### Deep Learning Techniques for EV Charging Demand Prediction

Deep learning models have recently gained popularity due to their ability to process **large-scale spatiotemporal datasets** and capture nonlinear relationships in EV charging behavior.

Common deep learning models used in EV demand forecasting include:

- Long Short-Term Memory (LSTM) networks
- Recurrent Neural Networks (RNN)
- Convolutional Neural Networks (CNN)
- Transformer-based models

For example, several studies compared deep learning architectures such as **LSTM, GRU, CNN, and Transformers** for forecasting EV charging demand and found that advanced architectures like Transformers achieve better prediction performance in complex forecasting tasks.

Other studies proposed encoder–decoder frameworks using LSTM models to predict charging demand at charging stations over different time horizons (30, 120, and 240 days).

#### Probabilistic Forecasting Methods

Traditional forecasting models often provide **single-point predictions**, which cannot represent uncertainty in EV charging demand. To address this limitation, probabilistic forecasting techniques have been introduced.

Probabilistic models generate **prediction intervals or probability distributions** instead of single values, enabling energy providers to manage demand uncertainty more effectively. Research comparing probabilistic forecasting models demonstrated that these approaches are particularly useful for short-term EV charging demand prediction and energy procurement planning.

However, earlier studies mainly focused on **single-location forecasting**, without considering the hierarchical structure of charging stations across regions and networks.

#### Hierarchical Forecasting Approaches

Hierarchical forecasting techniques address the challenge of predicting EV charging demand at **multiple levels of aggregation**, such as:

- Individual charging stations
- Regional charging networks
- City-level or grid-level demand

Hierarchical models ensure consistency between forecasts at different levels of the hierarchy. Research has proposed ensemble methodologies for hierarchical probabilistic forecasting across geographic regions, enabling improved load prediction and grid management.

These models integrate forecasts from different levels and reconcile them to maintain **coherent predictions across the entire charging network**.

#### Smart Hierarchical Probabilistic Forecasting Models

Recent studies combine **deep learning with hierarchical probabilistic forecasting** to improve prediction accuracy. One approach uses **Partial Input Convex Neural Networks (PICNN)** to model the probability distribution of charging demand at individual charging stations. The predictions from different stations are then reconciled using optimization techniques to produce consistent hierarchical forecasts.

Other advanced frameworks integrate **spatiotemporal graph neural networks, attention mechanisms, and probabilistic learning** to capture complex relationships among charging stations and evolving demand patterns.

These intelligent forecasting systems help grid operators anticipate charging demand fluctuations and optimize energy distribution.

#### Research Challenges and Future Directions

Despite significant progress, several challenges remain in EV charging demand forecasting:

- Limited availability of large-scale real-time charging datasets
- Difficulty in modeling uncertain and dynamic EV charging behavior
- Complexity of integrating spatial and temporal dependencies
- Lack of scalable hierarchical forecasting frameworks

Future research is expected to focus on **AI-driven probabilistic models, spatiotemporal deep learning architectures, and hierarchical forecasting frameworks** that improve prediction accuracy while addressing uncertainty in EV charging demand.

#### SYSTEM ANALYSIS

##### EXISTING SYSTEM

- At early stage, the hierarchical constraint is enforced based on top-down or bottom-up forecasting [7], [8], i.e., distributing the high-level results to low-level or summing up the low-level results to high-level. However, such methods suffer from loss of information from individual series dynamics. Hyndman et al. proposed to use the reconciliation-based forecasting method to solve the hierarchical forecasting problem [9], [10]. This method, a.k.a., coherent forecasting, solves an optimization problem of adjusting the base forecasting results of different levels so that the adjusted results satisfy the hierarchical constraint.
- There are some emerging research related to hierarchical probabilistic forecasting. Taieb et al. [11], [12] proposed a bottom-up probabilistic forecast aggregation method based on copula theory. After aggregation, mean forecast combination and reconciliation are used to further ensure the coherency in the mean values. Hierarchical probabilistic load forecasting became the topic of the Global energy forecasting competition 2017 (GEFCOM2017) [13]. Although several teams utilized the hierarchy information, few teams discussed the problem of coherency at that time. Roach [14] proposed an XGBoost-based reconciled forecasting model for GEFCOM2017. However, the reconciliation mainly focused on the quantile forecasting results instead of the probabilistic distribution.
- The forecasting results obtained from coherent forecasting has good statistical characteristics. According to the empirical study of [15], coherent forecasting usually improves the forecasting accuracy. It also ensures consistency of forecasted time series. Such advantages can further help the EVCS operator in consistent electricity purchase, efficient energy storage system operation, and effective customer interaction. However, there are still some open problems in coherent hierarchical forecasting, e.g., how to extend it to probabilistic forecasting [16], and how to implement it in a typical machine learning framework.
- As for deterministic forecasting, Arias et al. [17] proposed a decision tree-based model to forecast the charging demand, utilizing historical traffic and weather data of the same region. Saputra et al. [18] used a deep neural network (DNN) to forecast the energy demand of a certain area covering multiple charging stations. A federated learning approach is

adopted to address the communication overhead and privacy issues.

- Li et al. [19] proposed a sophisticated federated learning framework for EVCS demand forecasting. The forecasting model is based on convolutional neural network (CNN), bidirectional long short-term memory (BiLSTM), and attention mechanism. Charging piles are divided into clusters, and inter cluster and inner-cluster federated learning are used to train the base layer and the personalized layer of the model, respectively. Dabbaghjamesh et al. [20] proposed a Q-learning based method for load forecasting of EVCS. Q-learning is a reinforcement learning technique that can generate more accurate forecasting based on conventional models of recurrent neural network (RNN) and artificial neural network (ANN). Qiao et al. [21] forecasted the number of occupied charging piles at one certain EVCS using XGBoost.

#### DISADVANTAGES

- The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets for Electric Vehicle Charging Demand Detection.
- Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.
- Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

#### PROPOSED SYSTEM

- To address the research gaps in probabilistic modeling of EV charging demand and forecasting consistency among different multiple EVCSs, this paper proposes a novel deep learning-based forecasting framework. It adopts two types of neural network layers for convex learning.
- The first one is based on partial input convex neural network (PICNN) [27], [28], which learns a strictly convex function mapping the partial input to the output. The PICNN can be used to parameterize an invertible model for universal density approximation without quantile crossing. It is used to construct a multihorizon loss function and learn multi-variate distributions in forecasting problems [29].
- The second one is based on differentiable convex optimization layers (DCL) [30], which learns the mapping of parameters to optimal values of a certain type of convex optimization problems called disciplined parameterized programs. DCL can be adopted efficiently as a layer in back-propagation neural networks [31]. We use PICNN to model the conditional distribution of EVCS demand in probabilistic forecasting, and DCL to further convert stochastic scenarios to coherent scenarios satisfying the hierarchical constraint. The proposed method does not rely on any distributional assumptions of the target series.

#### ADVANTAGES

- A novel framework based on deep learning for EV charging demand probabilistic forecasting is proposed. It solves practical issues of multi-variate stochasticity modeling and hierarchical coherency.
- PICNN is adopted to model the joint probabilistic distribution of multi-horizon EVCS demand as the gradient of a convex function w.r.t. quantile levels, which avoids potential problem of quantile crossing.
- DCL is introduced to further map individual forecasting results of different EVCS to coherent scenarios. The weight matrix for adjustment in hierarchical reconciliation can be learned in a deep learning manner.

#### IMPLEMENTATION

The proposed system is divided into several modules that enable **accurate prediction of electric vehicle (EV) charging demand** across different locations and time periods using hierarchical probabilistic forecasting techniques.

#### DATA COLLECTION MODULE

This module collects historical and real-time data related to **electric vehicle charging activities** from multiple sources such as charging stations, smart meters, and transportation databases.

The collected data may include:

- EV charging station usage data
- Time and date of charging sessions
- Charging duration and energy consumption
- Weather conditions
- Traffic patterns and mobility data
- EV adoption statistics

This information forms the foundation for forecasting charging demand.

#### DATA PREPROCESSING MODULE

Raw data often contains inconsistencies and missing values. This module prepares the data for analysis by performing:

- Data cleaning and removal of duplicate entries
- Handling missing values
- Data normalization and transformation
- Time-series data formatting

These steps improve the quality and reliability of forecasting results.

#### FEATURE ENGINEERING MODULE

In this module, important features are extracted from the dataset to improve the forecasting model performance.

Examples include:

- Hourly and daily charging demand patterns
- Seasonal variations in charging behavior
- Regional EV adoption trends
- Weather and traffic-related influences

Feature engineering helps the model capture meaningful relationships between variables.

#### HIERARCHICAL DATA STRUCTURING MODULE

Electric vehicle charging demand can be structured hierarchically based on **different levels of aggregation**, such as:

- City level
- District level
- Individual charging station level

- Time hierarchy (hourly, daily, weekly)

This module organizes the data into hierarchical structures to allow consistent forecasting across all levels.

#### PROBABILISTIC FORECASTING MODULE

This module predicts future EV charging demand using **probabilistic forecasting techniques** instead of single-point predictions.

Key techniques may include:

- Bayesian forecasting models
- Quantile regression
- Probabilistic time-series forecasting
- Machine learning-based forecasting models

The output provides **prediction intervals and uncertainty estimates**, helping planners make better decisions.

#### FORECAST RECONCILIATION MODULE

Since forecasts are generated at different hierarchical levels, this module ensures **coherence across all levels**.

For example:

- The sum of station-level forecasts must match the city-level forecast.
- District-level predictions must align with overall regional demand.

This improves forecasting accuracy and consistency.

#### VISUALIZATION AND DECISION SUPPORT MODULE

This module presents forecasting results through interactive dashboards and reports, including:

- EV charging demand graphs
- Regional demand comparison charts
- Forecast uncertainty ranges
- Energy consumption trends

These insights help **energy providers and city planners optimize charging infrastructure**.

#### SYSTEM MONITORING AND MANAGEMENT MODULE

This module manages system operations and monitors forecasting performance by:

- Tracking model accuracy
- Updating forecasting models with new data
- Managing user access and system security
- Monitoring charging demand trends in real time

#### ALGORITHMS

##### DECISION TREE CLASSIFIERS

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing

descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes  $C_1, C_2, \dots, C_k$  is as follows:

**Step 1.** If all the objects in S belong to the same class, for example  $C_i$ , the decision tree for S consists of a leaf labeled with this class

**Step 2.** Otherwise, let T be some test with possible outcomes  $O_1, O_2, \dots, O_n$ . Each object in S has one outcome for T so the test partitions S into subsets  $S_1, S_2, \dots, S_n$  where each object in  $S_i$  has outcome  $O_i$  for T. T becomes the root of the decision tree and for each outcome  $O_i$  we build a subsidiary decision tree by invoking the same procedure recursively on the set  $S_i$ .

**GRADIENT BOOSTING** Gradient boosting is a **machine learning** technique used in **regression** and **classification** tasks, among others. It gives a prediction model in the form of an **ensemble** of weak prediction models, which are typically **decision trees**.<sup>[1][2]</sup> When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms **random forest**. A gradient-boosted trees model is built in a stage-wise fashion as in other **boosting** methods, but it generalizes the other methods by allowing optimization of an arbitrary **differentiable loss function**.

##### K-NEAREST NEIGHBORS (KNN)

- Simple, but a very powerful classification algorithm
- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not “learn” until the test example is given
- Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

##### Example

- Training dataset consists of k-closest examples in feature space
- Feature space means, space with categorization variables (non-metric variables)
- Learning based on instances, and thus also works lazily because instance close to the input vector for test or prediction may take time to occur in the training dataset

##### LOGISTIC REGRESSION CLASSIFIERS

*Logistic regression analysis* studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used

when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar. Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does. This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

#### NAÏVE BAYES

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias). While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique. Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects

of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset ([Weka 3.6.0](#), [R 2.9.2](#), [Knime 2.1.1](#), [Orange 2.0b](#) and [RapidMiner 4.6.0](#)). We try above all to understand the obtained results.

#### RANDOM FOREST

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance. The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg. An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.). The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance. Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

#### SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed (iid)* training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point  $x$  and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space. SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same

optimal hyperplane parameter—in contrast to *genetic algorithms* (GAs) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

## CONCLUSION

This paper proposes a novel deep learning-based framework for short-term hierarchical probabilistic forecasting for EVCS demand. LSTM is used as the forecasting engine, and convex learning layers of PICNN and DCL are used for capturing the probabilistic distribution and reconciling the stochastic scenarios, respectively. The conditional quantile function of the target variable is learned by PICNN, and the weight matrix for hierarchical adjustment is learned by DCL. Real world EV charging data from the open source ACN dataset are used to illustrate the procedures of the proposed framework and demonstrate the performance in terms of forecasting accuracy and scenario quality. Future work includes testing the method in more complicated hierarchical structures.

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