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Data-Driven Modeling of Electric Vehicle Charging Sessions Based on Machine Learning Techniques

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Abstract: The increased demand for electricity is inevitable due to transport sector electrification. A major part of this demand is from electric vehicle (EV) charging on a large scale, which is now a growing concern for the grid power distribution system. The lack of insight into grid energy demand by EVs makes it difficult to manage these consumptions on a large scale. For any grid load management application to be effective in minimizing the impact of uncontrolled charging, there is a need to gain insight into EV energy demand. To address this issue, this study presents data-driven modeling of EV charging sessions based on machine learning (ML) techniques. The purpose of using ML as an approach is to provide insight for estimating future energy demand and minimizing the impact of EV charging on the grid. To achieve the aim of this study, firstly, we investigated the impact of large-scale charging of EVs on the grid. Based on this, we formulated an objective function, expressed as a sum of utility functions when EVs charge on the grid with constraints imposed on voltage levels and charging power. Secondly, we employed a graphical modeling approach to study the temporal distribution of EV energy consumption based on real-world datasets from EV charging sessions. Thirdly, using ML regression models, we predicted EV energy consumption using four different models of fine tree, linear regression, linear SVM (support vector machine), and neural network. We used 5-fold cross-validation to protect against overfitting and evaluated the performances of these models using regression analysis metrics. The results from our predictions showed better accuracy when compared with the results from the work of other authors.

Keywords: data-driven model; energy consumption; electric vehicle charging; grid impact; load modeling; machine learning

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1. Introduction

Minimizing the impact of large-scale charging of EVs on the grid is now a critical research area, due to the growing threat to grid stability. Recent advances in the electrification of the transport sector have brought about research interest in the smart charging of EVs on the grid. Current research centers around minimizing the impacts of high energy consumption through grid load balancing [1–4], dynamic pricing integration for EV charging [5–7], scheduling, and queueing algorithms [8–10]. Similarly, in EV load forecasting and predictive charging [11–13], intelligent communications between EVs and grid infrastructure [14–16], grid load stabilization [17], and in EVs providing ancillary services through integrated system design for monitoring, evaluation, and control [18,19]. However, the above-mentioned methods employed in the control of EV charging to curtail grid overload cannot be fully realized without analyzing EVs' charging behavior and their load profiles based on real-world datasets. This insight is necessary to maintain grid stability. Quantitative analysis of EV charging sessions, which provides actionable insights, implies that grid voltage fluctuations, unbalanced load, and the violation of transformer capacity will be curtailed [1,3,12].

Electric vehicles will play a significant role in the energy transition of the future. This includes the potential for deployment as distributed energy resources offering ancillary services for grid support [1,17–19]. By this means, EVs contribute to the United Nations Sustainable Development Goals (SDGs) 7 (affordable and clean energy), SDG 11 (sustainable cities and communities), and 13 (climate action) [20,21]. But large-scale, uncontrolled charging of EVs on the grid is a disturbing challenge for the power system [22–24] and upends the SDG targets. Here are some of the major reasons that can be traced to this challenge. Firstly, there are new peaks generated on the grid, which contribute to greenhouse gas (GHG) emissions due to large-scale charging of EVs [25,26]. Secondly, EVs charging on the grid are mainly uncontrolled, which places constraints on the distribution network, in addition to the constraints imposed by EV supply equipment and existing baseloads [27]. Thirdly, the lack of coherent industry standards for the load management of EVs charging on a large scale at residential, industrial, and commercial dwellings [28]. The fourth research gap that this study aims to address is the lack of real-world data-driven analysis of EV charging sessions, which is needed to model authentic charging operations. This will provide insight into EV grid load profiles and how EV charging sessions impact the grid operations. Having a real-world, data-driven EV charging session analysis will enhance the visibility and insight needed to manage grid power supply and minimize large-scale, uncontrolled charging of EVs. The fifth aspect relates to the need for topology-aware charging control, which is informed by data-driven models of EV charging sessions. Addressing these challenges has the potential to enhance the sustainable pathways for the electrification of the transportation sector, which currently relies on the grid power distribution system.

The remaining part of this study is structured as follows: Section 2 presents related research work, and outlines the research gaps and motivations, as well as the contributions made by this study. Section 3 presents the methods and tools employed for this study, Section 4 presents simulation, model predictions of EV energy consumptions, and results, and Section 5 discusses the results obtained and how they compare to the work of other authors. Finally, conclusions are drawn in Section 6 followed by future work recommendations.

2. Related Work

Utility managers and energy providers require insights into the large-scale penetration of EVs charging on the grid, which continues to present a potential threat to the safe operation and stability of power systems. In recognition of this concern, a study was conducted [29] using a statistical model and machine learning to predict EV load. This study was based on the aggregation of time-series datasets from EV charging stations at the University of California Los Angeles and the City of Santa Monica, for day-ahead predictions of EV load. According to the authors [29], the use of an unsupervised clustering algorithm and multilayer perceptron indicated good results. In another study [30], the impact of large-scale charging of EVs on the California distribution network was conducted. In this study [30], the authors investigated the behavior of EV charging patterns and how their charging operations impact the City of Los Angeles power distribution system. The study in [30] was sponsored by the Smart Grid Regional Demonstration Project of the Los Angeles Department of Water and Power (LADWP). The aim was to investigate, analyze, and evaluate how EV charging impacts the California grid. About twelve months of time-series datasets on EV charging sessions were gathered, analyzed, and used in the study [30].

The demonstration project at the LADWP comprises 64 EVs and power supply equipment (EVSE) including level 1, 2, and 3.

Data-driven models based on EV charging operations were proposed [31] for the analysis of EV charging sessions and impact assessment of EV penetration on the Saskatchewan power distribution system in Canada. In this study [31], Bur distribution, uniform distribution, and inverse distribution were notable statistical methods used for modeling the parameters of residential EV charging session. Models of aggregated EV charging were further developed in a simulation environment using the Monte Carlo method. In [32], an agent-based trip chain model (ABTCM) with a nested logit (NL) model was introduced to analyze and predict EV charging energy demand. Part of the objective here was to address the grid power imbalance problem that will arise due to increased charging of EVs. Using 13,114 selected trip chains from privately owned battery EVs (BEVs) in Beijing, China, this study [32] mostly evaluated the charging behaviors of EVs, considering EV state of charge (SoC), EV starting and ending trip records, and the charging strategies employed vis-à-vis slow or fast chargers. Using real-world datasets with over 35,000 residential charging sessions in Norway, the authors [33] analyzed residential charging behavior of EVs and how it impacts the grid. A range of methods were provided to predict EVs' battery capacity, charging power, and their SoC at plug-in, to determine the flexibility of shifting EV charging to off-peak periods.

Using clustering methods [34], the classification of EV charging session types was conducted to establish the typology of EV users and their behavior. One of the objectives in [34] was to improve EV user charging behavior in simulation models. However, the energy demand from large-scale charging by EVs was not the focus in the study [34] where EV charging session analysis was investigated. A data-driven smart charging approach was developed [35] using datasets from 1001 EVs. The model integrated machine learning regression with an XGBoost (extreme gradient boosting) library for training the datasets and predicting EV charging profiles. In a separate study [36], EV charging profiles were modeled based on real-world charging datasets. In [36], GPS travel data were gathered, and a Bayesian inference was used to generate EV travel patterns. However, EV energy demand calculations were inferred by translating EV travel patterns using a probabilistic charging model. In [37], a spatial–temporal distribution method for predicting the load profiles of EVs was conducted with the help of an improved random forest model. The aim in [37] was to achieve an optimal power dispatch from the grid, considering the accurate predictions of EV charging demand. Probabilistic modeling to estimate the load profile of plug-in EV (PEV) charging on the grid was conducted in [38], to ascertain the power demand required to charge large-scale EVs on the grid. In [38], the mobility behavior of PEVs was a factor considered and analyzed using United States national household travel survey datasets.

Based on real-world load datasets from EV charging operations, a short-term load forecasting of EVs was conducted to improve power system reliability [39]. One of the objectives in [39] was to determine ways to control EV charging behavior. For this reason, the study [39] employed a Monte Carlo method in conjunction with an EV driving distance probability function. A study in [40] used a predictive cost model of a hybrid search and rescue algorithm, which combines an adaptive Neuro-fuzzy interface system to minimize the cost of EV charging. Part of the objectives in [40] involved modeling complex dynamic energy emissions associated with large-scale charging of EVs. In [41], a data-driven method was employed to analyze EV charging impact on the grid and to simulate EV load models. The investigation was conducted using an aggregation of EV load profiles. In [42], the load profiles of EV charging sessions in a residential sector were investigated using real-world datasets. This data-driven model [42] was based on a kernel density estimation method of ML techniques used to estimate EV charging duration based on the parking duration of EVs. This was performed in such a way that the difference in the EV SoC at the time of parking and when the EVs depart from the parking was estimated to deduce if charging took place. In [43], a data-driven, charging load forecasting method for EVs was conducted based on travel data parameters. One of the objectives in [43] was to visualize the temporal and spatial distribution patterns of EVs on the grid based on their charging behavior and how this interaction impacts grid operations.

Data-driven models combined with ML have proven to be useful in studying the behavior of EV charging on the grid. This approach was implemented in [44]. It employed ML algorithms and historical datasets of EV charging and weather information to predict EV energy consumption and charging duration. The ML tools used included random forest, SVM, XGBoost, and deep neural networks. However, the best result obtained in the study [44] was based on an ensemble learning technique, which involved training multiple ML learning models. According to the authors [44], ensembled learning has the likelihood of compensating for inaccuracy generated by sub-optimal ML models used in this process. Similarly, the study conducted in [45] used ML to control EV charging and integration to the grid in order to minimize energy consumption. ML models used included decision tree, random forest, SVM, k-nearest neighbors, LSTM, and deep neural networks. According to the authors [45], the best prediction accuracy for peak shaving was based on the LSTM. Similarly, an ensembled stacking generalization was used in the study [46] to increase the accuracy of predicting grid energy consumption by EVs with an R^2 value of 0.9993 and an SMAPE value closer to zero percent (0.02%), indicating a higher forecast accuracy. The ML regression models in [46] included decision trees, random forests, and k-nearest neighbors. The study [46] investigated the California Institute of Technology infrastructure called the adaptive charging network (ACN), which has more than 30,000 EV charging session datasets that can be used for research and development.

2.1. Research Gaps and Motivations

From the literature studied as outlined in the related work section above, the analysis and modeling of EV charging sessions is very significant in providing insight and measurable metrics on the load management of EVs on the grid. The summary of the related research conducted in Section 2 is presented in Table 1 below. The data-driven methods for modeling EV charging sessions as outlined can be categorized to include probabilistic estimation of EV load demand and energy consumption based on EV travel history and GPS data [36,38,43]; analysis of EV charging demand based on a trip chain model and driver behavior [32,34,36,43]; state of charge estimation based on arrival and departure time from charging stations [34]; the typology of EV users [42]; and machine learning techniques combined with an ensembled method [44–46]. In summarizing the related work based on the literature referenced herein, the analysis of EVs' load profiles based on their charging behavior and the load models does not provide sufficient use of real-world datasets to show how large-scale charging of EVs is directly correlated with the impacts it has on the grid operations. There is a need to provide real-world analysis and evidence on the relationship between electric power system stability and the load implications of large-scale, uncontrolled charging of EVs on the grid. In this study, we provide insights using ML techniques to visualize and characterize EV charging on the grid. We go further to predict the grid energy consumption by EVs on a large scale using four different ML regression models based on real-world EV charging sessions. The charging session analysis is consequential to modeling the actual load profiles of EV charging and predicting EV energy consumption from the grid. To overcome the inherent problem of overfitting in the ML approaches studied in [44–46], we implemented a cross-validation scheme that protects against overfitting in the ML applications that we proposed. These include fine tree regression, linear regression, support vector machine (SVM), and neural networks.

Table 1. Overview of related research work.

Ref.	Data Source	Problem	Objective	Method
[29]	EVSE	Minimize EV Stochastic Charging	Online Prediction of EV Load Charging Control Scheduling	Machine Learning Unsupervised Clustering
[30]	EVSE	EV Impact on the Grid	Offset EV Load Impact	Investigate EV Charging 24 h EV Load Study
[31]	EVSE	Grid Impact of EVs	Predict EV Charging Load Estimate Load Impact of EVs	Monte Carlo/Burr Distri. Predict EV Load Model
[32]	EVSE	Grid Power Imbalance	Analysis of EV Charging Predict EV Charging	Trip Chain Model Nested Logit Model
[33]	EVSE	EV Charging Impact	Model EV Charging Behavior Energy Studies and Load Shifting	Analysis and Prediction R Statistical Computing
[34]	EVSE	EV Charging Behavior	Develop EV User Typology Define Charging Sessions	Two-Step Clustering
[35]	EVSE	Optimize EVSE	Predict EV Charging Profile	XGBoost Model Regression Model
[36]	GPS Travel Data	Model EV Charging	Generate EV Charging Profile Probabilistic Charging Model	EV Travel Pattern Bayesian Inference
[37]	EVSE	Improve Prediction Accura -cy of EV Charging	Predict EV Charging Demand	Improved Random F. Harmony Search
[38]	U.S. NHTS	EV Charging Uncertainty Distribution Planning	Estimate EV Power Demand	Multivariate Modeling Copula Theory
[39]	EVSE	Power System Reliability	Sort-Term Load Forecasting Control EV Charging	Monte Carlo Driving Distance Chance
[40]		Transient Charging Load Minimum Cost Optimization	Minimize EV Charging Cost Better Charging Coordination	ANFIS Model Hybrid Search and Rescue
[41]	ISO	EV Impact on Power System	Simulate EV Charging Impact Quantify EV Flexibility	Aggregate EV Load Model
[42]	Idaho NL	EV Charging Impact	EV Load Profile Generation Construct Charging Decision	Kernel Density Estimate
[43]	GPS Travel Data	EV Load Demand Planning	Analyze EV Travel Pattern Predict EV Charging Load	Monte Carlo EV Travel Data
[44]	Historical Charging Data and Weather Data	Increased EV Energy Demand EV Charging Scheduling	Predict EV Charging Session and Energy Consumption	Machine Learning with Ensembled Method
[45]	Residential Load Data	Managing EV Charging	Optimize EV Charging Minimize Power Losses	Machine Learning
[46]	GPS Travel Data	EV Load Demand Planning	Analyze EV Travel Pattern Predict EV Charging Load	Monte Carlo EV Travel Data

2.2. Contributions from This Study

Some of the contributions of this study are outlined as follows:

1. In order to reproduce the impact of uncontrolled charging of EVs on the grid, this study developed load models of EV charging sessions and analysis. This helps to show

the implications of high energy consumption vis-à-vis the power system stability. With this understanding of EV charging patterns on the grid, it informs energy planning and management of grid power supply for charging EVs.

2. By developing quantitative analysis and load models of EV charging sessions based on real-world datasets of EV energy consumption, this study provides a real-world charging scenario that is useful for load flow analysis, and for the impact assessment of large-scale charging of EVs on power distribution systems.
3. Grid asset enhancements: Through actionable insights that provide efficient load management pathways, grid operational activities are improved as EVs continue to penetrate the grid. This is made possible with this study as it provides insights into the charging patterns of large-scale EVs, which helps to inform energy planning, grid load management, and power supply strategies.
4. Researchers, energy managers, EV aggregators, and the industry can apply similar machine learning models from this study to make predictions on the future energy demand of EVs. This is made possible due to the generalization properties of machine learning algorithms.
5. Sustainable goals: this study contributes to the global decarbonization efforts through the advancement of research and development in the electrification of the transportation sector, contributing to the advancement of the United Nations Sustainable Development Goals no 7 (affordable and clean energy) [1], SDG 11 (sustainable cities and communities) [1,20,21,29,30], and SDG 13 (climate action) [20,21].

3. Methods and Tools

In this section, we examine the problem and the constraints imposed by uncontrolled, large-scale charging of EVs. The analysis of EV energy consumption profiles and the characteristics of EV charging sessions will be performed using real-time datasets from EV charging operations. A scenario of large-scale estimates of EV load demand due to uncontrolled charging on the grid will be examined and visualized. This is to understand how the characteristics of EV high power demand, as an example, and its stochastic load profiles impact the grid stability. To minimize the impact of EV uncontrolled charging on the grid, and the high energy consumption by EVs, machine learning techniques will be used to train large-scale datasets, predict, and evaluate the stochastic load profiles of EV uncontrolled charging on the grid. Figure 1 shows a graphical framework depicting the system model and workflow for the data-driven approach developed for this study.

3.1. Problem Definition

The problem of large-scale charging of EVs on the grid vis-à-vis the stochastic energy consumption arising from uncontrolled charging is a disturbing challenge for the safe operation of the grid distribution system. Using a "what if scenario", we imagine a power distribution system overloaded as a result of large-scale, uncontrolled charging of EVs, as shown in Figure 2 below. The potential impact of this overload will include transmission line and transformer congestion, under voltage, which may result in frequency issues below the nominal range, generation of harmonics, and other power quality issues that may lead to blackouts or partial grid collapse. These issues are typical characteristics of large-scale, uncontrolled charging of EVs on the grid. To illustrate this, the IEEE bus test systems have been used to analyze the impact of EV charging on the grid. As an example, the IEEE 19-bus and 33-bus test systems [13,19,47] were used to depict a radial distribution test system with EV charging under investigation. In this study, we adopted a modified IEEE 33 system to illustrate a grid model. Using a single-line diagram (SLD) in Figure 2, we present the basic load structure of a grid distribution system model with EVs as high energy consumption loads and solar photovoltaic (SPV) as distributed energy resources (DERs). In this study, the EVSE described here is assumed to be implemented with a unidirectional power flow, without vehicle-to-grid (V2G) application. EVSE is level 2 with a power output between 3.3 kW and 19.2 kW, and level 3 with DC fast chargers with rated power outputs between 50 kW and 350 kW. We assumed conductive charging, rather than inductive charging, was employed in residential, industrial, and commercial sectors of the grid. Other limitations considered in this study include the following:

- EV travel history, traffic data, user behaviors, and weather predictions are not considered as parameters affecting EV charging in the formulation of this study;
- That the transformer node is a fixed source of grid power supply to charge EVs;
- We considered the constraints on EVSE power supply and grid voltage levels.

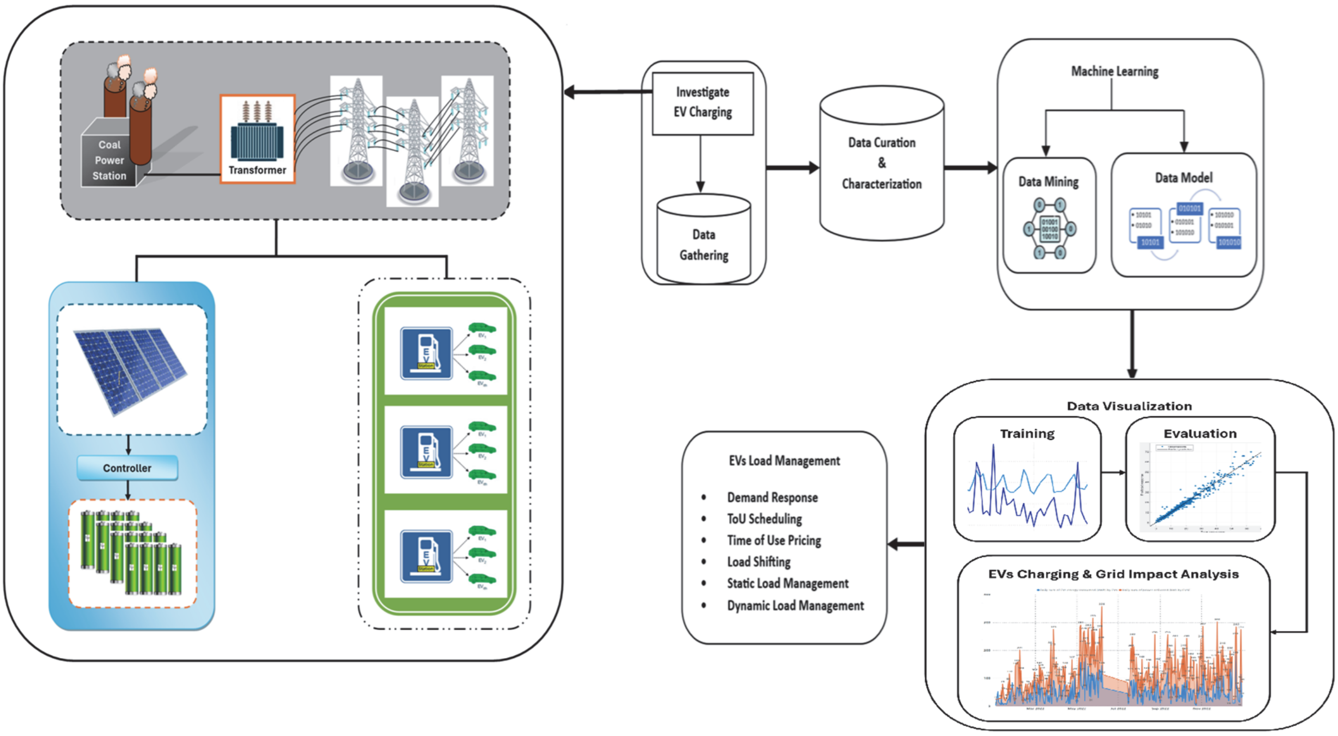


Figure 1. Graphical framework of system model and study workflow.

3.2. *Problem Formulation*

Based on the large-scale, uncontrolled charging scenario shown in the problem definition of Section 3.1, part of this study objective is to minimize EV high energy consumption from the grid, by providing valuable insights using a data-driven technique based on ML to model EV charging sessions. To achieve this objective, the IEEE 33-bus network with buses **b2**, **b8**, **b13**, **b19**, **b30,** and **b32** is selected to balance load demand across the distribution system. This optimization approach allows buses **b2** and **b19** with high load demand to maintain the supply and demand balance on the grid, while **b2**, **b8**, **b13**, and **b19** being closer to generation sources helps to minimize transmission losses, improve power delivery, and maintain voltage stability even with additional loads.

3.2.1. Objective Function

The objective function of this study is to minimize the aggregate energy consumption cost from large-scale, uncontrolled charging of EVs on the grid over a period of time (*t*). The objective function is formulated as Figure 1 and Table 2 explains the notations.

$$min\ E_a = min\ \sum_{i=1}^{N}\sum_{t=1}^{T} Ex_i(t)\cdot\$_i(t)\cdot\Delta n_i(t) \tag{1}$$

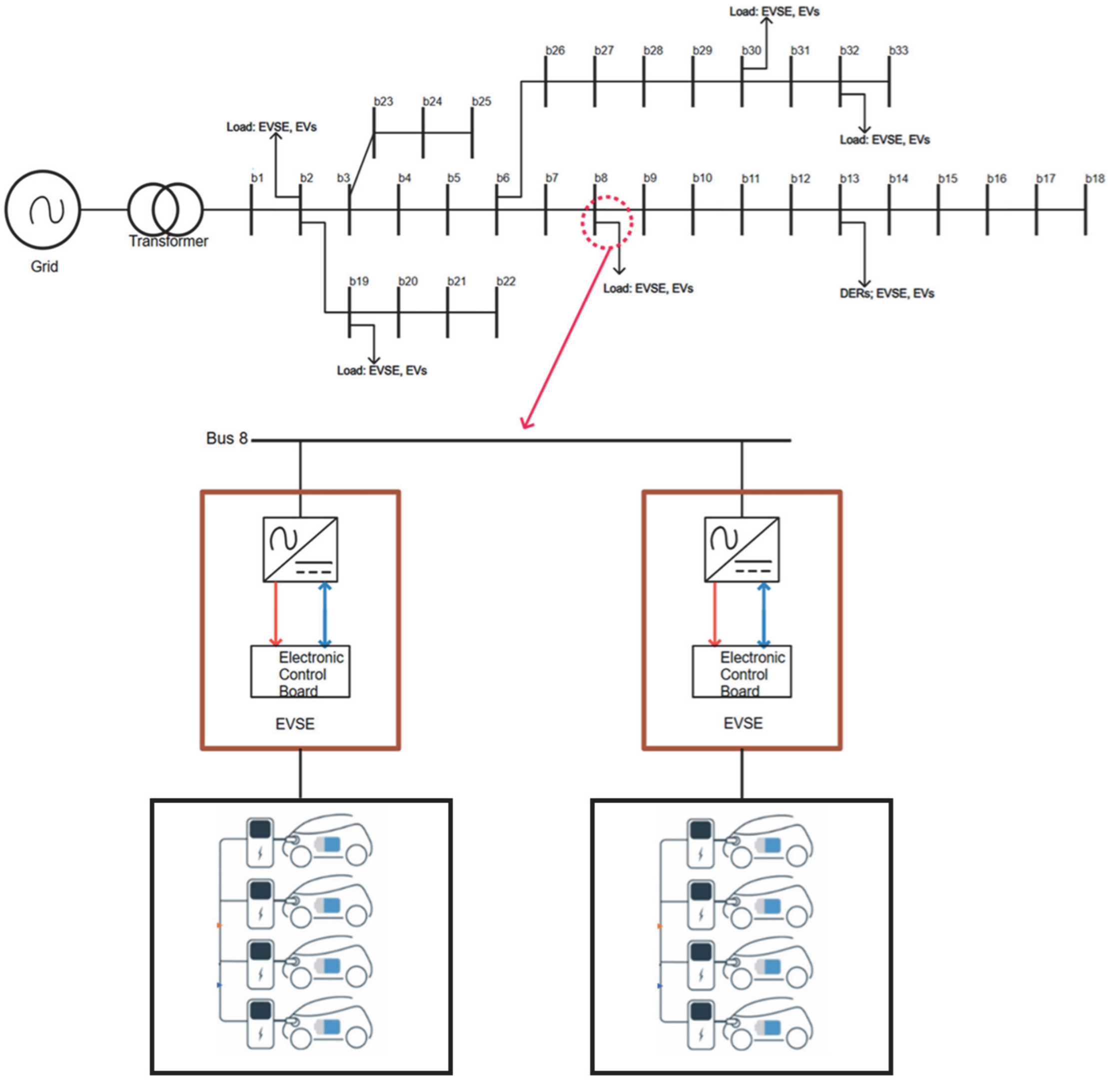


Figure 2. Modified IEEE 33-bus network single-line diagram with EV charging.

Table 2. Notations used in formulating the objective function to minimize EV energy consumption.

E_a (kWh) = represents the aggregate energy consumption for all EVs on the grid
N = aggregate number of EVs charging on the grid distribution network
x_i = sequence of EVs (x_1, x_2, x_3, … x_n) charging at random on the network
Ex_i (kWh) = i^{th} EV energy consumption in the sequence (x_i) of EVs $(x_1, x_2, x_3, \ldots x_n)$
t (h) = duration of time steps over a 24 h period (T)
T (h) = total time under consideration (24 h)
$\$_i(t)$ = energy price at time (t) for i^{th} EV
$\Delta n_i(t)$ = difference in i^{th} EV charging duration (t)
$P_i(t)$ (kW) = power supplied to i^{th} EV with constraint $P_i^{min}(t) \le P(t) \le P_i^{max}(t)$

3.2.2. Constraints

The problem space, which is characterized by large-scale, uncontrolled charging of EVs on the grid, imposes a number of conditions that limit the feasible solution. Some of the constraints are defined as follows.

(a) Rate of Charging Constraint:

To minimize the impact of EV stochastic energy demand during charging, the rate of charging EVs should be controlled in such a way that a limit or penalty is placed on any i^{th} EV energy consumption beyond a set value. Therefore, the EV charging rate in terms of power supplied (P) at time step (t) must be within the boundaries given by Equation (2), where $P_i^{min}(t)$ represents the minimum power consumed by i^{th} EV at time step (t) and $P_i^{max}(t)$ represents the maximum power an EV can consume at a given time (t) with respect to the total available power supplied (P) at any given time (t).

$$P_i^{min}(t) \leq P(t) \leq P_i^{max}(t) \tag{2}$$

which means that the variables P_i^{min} and P_i^{max} at any given time (t) for i^{th} EV energy consumption in the sequence (x_1, $x_2, x_3, \ldots x_n$) must be within the total power supplied as represented by Equation (3).

$$P(t) = \sum_{i=1}^{N} \Delta P_i(t) \tag{3}$$

where $\Delta P_i(t)$ is the difference between the P_i^{min} and P_i^{max} at any given time (t) for i^{th} EV.

(b) Bus Voltage Constraint

The constraints imposed on the distribution network bus voltage can be represented using Equation (4).

$$V_b^{min} \leq V_{b(t)}^n \leq V_b^{max} \tag{4}$$

where V_b^{min} is the minimum bus voltage, V_b^{max} is the maximum bus voltage, and $V_{b(t)}^n$ is the bus voltage at node n at any given time (t).

3.3. Data Curation and Identification

In this subsection, we provide details about the datasets and the process used in preparing the datasets. The term data points is used to denote the size of datasets used in this study. Over eighteen million data points were collected, which contained real-world, time-series datasets of EV charging sessions. Table 3 is presented to show sample raw datasets with some of the parameters recorded during the EV charging sessions. More than 18 different types of parameters have been captured and recorded during the EV charging sessions. However, to reduce the computational cost and time to analyze these large-scale datasets of EV charging sessions, the parameters utilized in this study include the power delivered for charging EVs, duration of charge, EV SoC, the voltage, and the current drawn from the grid by EVs. This is to enable us to approximate the impact of large-scale charging of EVs on the grid using the most important parameters that influence grid stability. It should be noted that the number of parameters omitted for the analysis in this case had a negligible impact on the EV charging profile when a sensitivity analysis was conducted as compared to when five or more parameters were used. The reason being that, to evaluate the impact of large-scale charging of EVs on the grid, this study takes into consideration the power delivered to charge EVs, the energy consumption by EVs vis-à-vis the amperage drawn by the EV charger, the voltage delivered by the EVSE, the duration required to charge EVs, and the aggregate number of EVs charging on the grid at any given time, as the parameters that have the most impacts on the power system capacity and grid stability. This is in contrast to previous studies [32,34,36,38] that have used travel data and EV mobility patterns to determine the load model of EVs and estimate their energy demand form the grid.

Table 3. Sample raw datasets with parameters.

Start Date Time	End_Date Time	Total Duration (h)	Charge Duration (h)	Energy kWh	Start SoC (%)	End SoC (%)	Flag ID
29 October 2019 18:17	29 October 2019 18:17	0.006	0.003	0.001	84.0	84.0	320
29 October 2019 19:04	29 October 2019 19:05	0.014	0.003	0.002	84.0	84.0	320
15 November 2019 17:57	15 November 2019 18:32	0.573	0.550	10.764	75.0	90.0	0
7 November 2019 9:49	7 November 2019 11:41	1.864	1.861	51.164	14.0	100.0	0
19 November 2019 8:38	19 November 2019 8:59	0.362	0.354	11.179	52.0	71.0	0
14 November 2019 11:42	14 November 2019 13:30	1.796	1.779	41.954	23.0	100.0	0
8 November 2019 10:24	8 November 2019 11:46	1.373	1.364	20.326	67.0	100.0	0
24 September 2020 12:13	24 September 2020 13:11	0.972	0.970	32.601	27.0	83.0	0

The real-world, time-series, historical datasets used in this study were based on an estimated 1,043,001 charging sessions from 2019 to 2022. The datasets contain the following identifications for the EV charging sessions: session ID, EVSE ID, connector ID, start date and time, end date and time, total duration, charge duration, energy consumed, start state of charge, end state of charge, and flag ID. Other parameters not included are the number of connectors on each EVSE and the connector (plug) types (i.e., J1772, Type 2, Type 2 Combo, and CHAdeMO). The flag ID in the datasets is error flags designed to provide insight into charging sessions that are inaccurate. As an example, the flag ID in the sample raw datasets of Table 3 may indicate negligible kWh of EV energy consumption, or zero energy consumption, or insignificant session length. During data normalization, these datasets including zero value data and null data were removed. From the sets of data collected, there were no data points provided for the grid power delivered (kW) to the EVSE for charging the EVs and not all charging sessions had battery SoC estimated. Based on these findings and to limit the computational cost in this study, we made calculations based on the existing parameters and were able to derive data points of approximate power delivered to the EVSE from the grid. We performed this by dividing the individual EV energy consumed by the charging duration of individual EVs. Some challenges regarding the number of datasets to be processed were encountered. And this was related to the computer processing capacity and the memory resource allocation to the threads of application required to analyze over eighteen million data points in MATLAB R2024b. The data source used throughout this study was from a public database [48] funded by the United States Department of Energy's Vehicle Technologies Office. This public database is operated and maintained by Pacific National Laboratory, Idaho National Laboratory, and National Renewable Energy.

3.4. Machine Learning Application

In this study, ML is employed in a computer simulation environment based on MATLAB. We carried out data visualization, modeling, and predictions of EV energy consumption. ML techniques used included fine tree regression, linear regression, linear SVM, and neural network. The reason for choosing these techniques is based on their ability to capture complex nonlinear relationships in datasets, low computational cost, flexibility of use, and easy interpretation. Other techniques like ensembled learning [44] are computationally expensive and less interpretable. The insights from the ML techniques we chose, as they learn directly from data, make it possible to discover variability in EV charging profiles. Moreover, they provide valuable insights into the characteristic behavior of distribution systems when large-scale charging of EVs consumes grid power, some of which includes load modulations on the grid and variations in bus voltages.

4. Simulations, Model Predictions, and Results

In this section, the analysis of EV charging sessions using the actual datasets from real-world EV charging operations is provided; we then define the metrics used to evaluate the performance of ML techniques. Finally, the simulation models and predictions of EV energy consumptions are conducted.

4.1. Electric Vehicle Charging Sessions Analysis

In this subsection, we studied and analyzed the increasing energy demand during EVs' charging sessions based on their energy consumption (kWh) profiles using the level 2 and DC fast chargers. We used the time-series datasets accounting for EV charging operations for the datasets collected from June 2019 to December 2022. Using Figure 3, we present a general energy outlook based on the actual energy consumption by EVs in 65 cities across the U.S. to show evidence of an increasing energy demand from EV charging on the national grid. Based on the literature studies [1,8–11,13], the exponential increase in grid energy consumption by the large-scale integration of EVs will continue to grow into future energy systems. With Figure 3, we try to show an estimated energy outlook for cumulative energy consumption by EV charging on the grid between Friday, 28 June 2019 and Saturday, 31 December 2022. The cumulative sum of the energy consumed by EV charging increased by 1422.67% for the periods indicated.

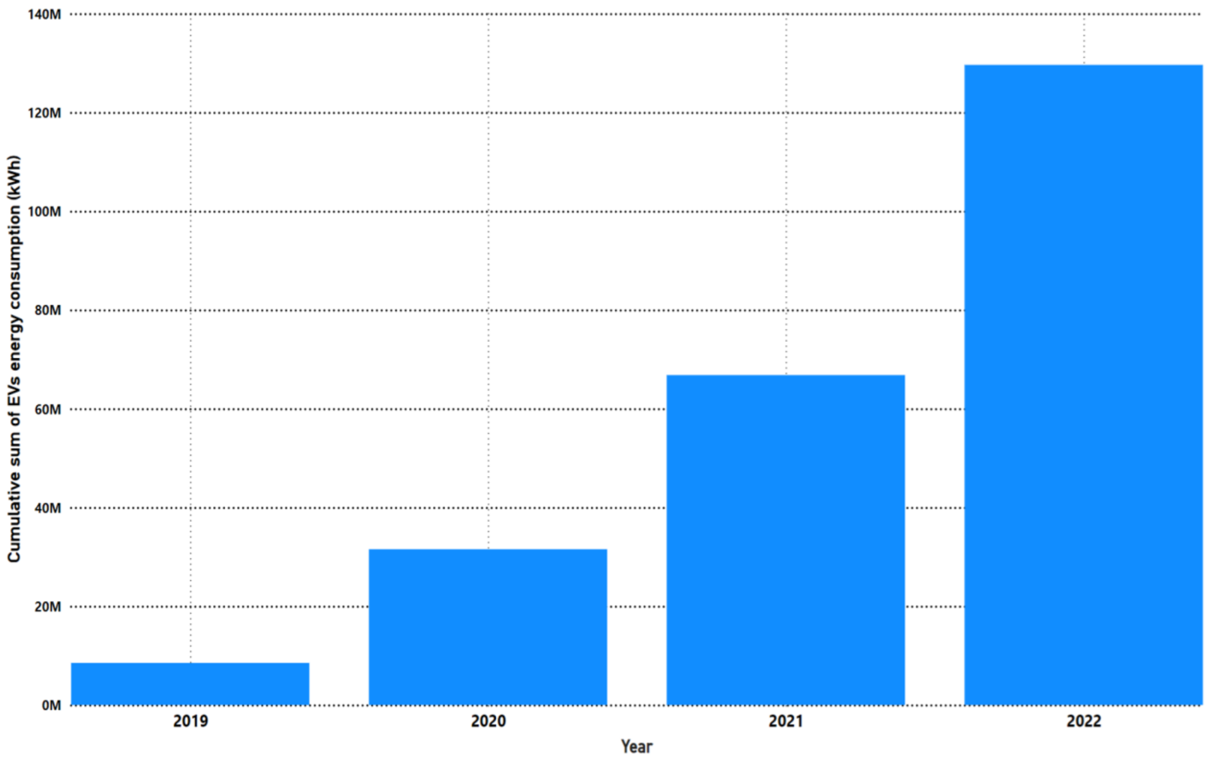


Figure 3. Energy outlook: cumulative sum of EV energy consumption (kWh).

Twelve Months' Case Study of Electric Vehicle Charging Sessions

In this subsection, we provide an in-depth analysis of twelve months' EV charging operations. To reduce the computational cost of processing large-scale datasets collected for this study, we limited the in-depth analysis of EV charging sessions to the California metro areas rather than the 65 cities across the USA. In this case, we provide twelve months' estimates of cumulative energy consumption by EV charging operations for the year 2022 starting from January to December. The chart provided in Figure 4 below shows an increasing trend in EV energy demand based on the temporal distributions of EV energy consumption profiles. The random nature of the energy consumption seen in Figure 4 is an indication of how uncontrolled charging of EVs on the grid will impact the distribution system with voltage variations that are likely to result in grid instability.

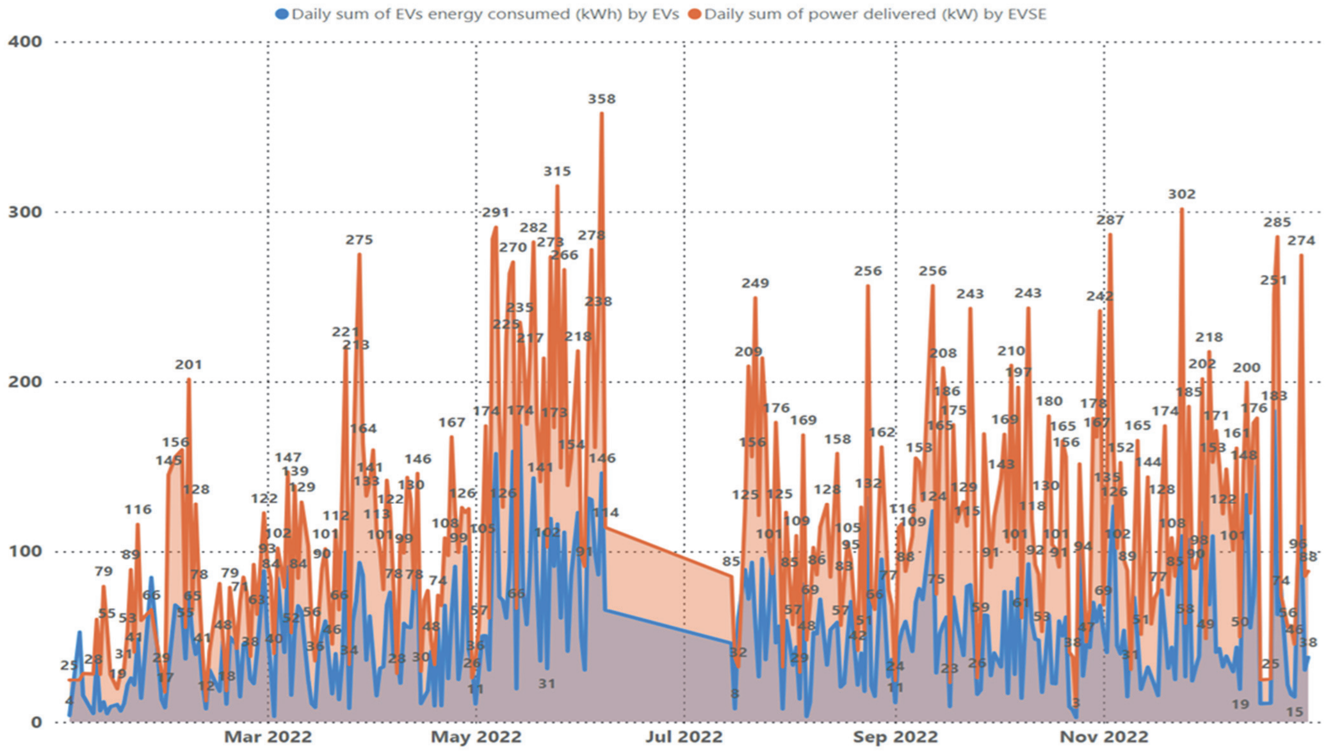


Figure 4. Temporal distributions of EV energy consumption profiles January–December 2022.

Insights from this data analysis show increasing trends in peak energy consumption profiles, which coincide with the new peaks generated on the grid distribution system by EVs. These uncontrolled peaks arising from the random charging of EVs will create power quality issues on the grid with large-scale EV penetration. The statistics provided by Figure 4 based on the datasets from [48] show an increase of 879.20% in EV energy consumption from the grid between 2 January 2022 and 31 December 2022. Similarly, the power delivered by the grid to charge these EVs also increased by 258.73%.

To show further insights into the variability in grid power delivered and the stochastic energy consumption from large-scale integration of EVs on the grid, we have included a chart in Figure 5 below based on the datasets from [48], to show the average state of charge (SoC) for all EVs' batteries upon arrival (before charging) at the EVSE. The characteristics of the EVs' battery SoC in relation to the EV energy consumption profiles provide a significant insight into how variable the amperage drawn by these EVs would be and the nature of the voltage variations that will be created by these EVs on the grid. By looking at the chart of Figure 5, we can confidently conclude and predict that the future power required from the grid to charge EVs will continue to rise unabatedly.

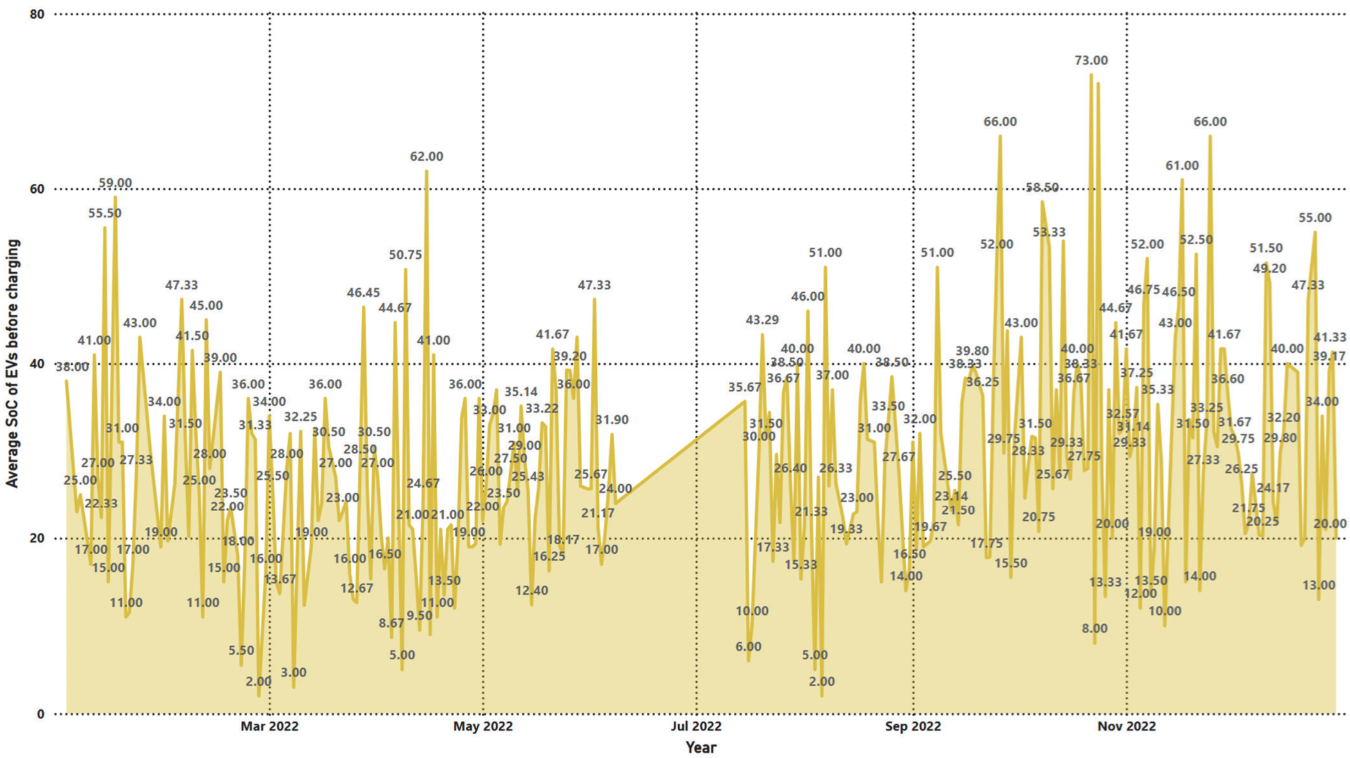


Figure 5. Average state of charge for all EVs before charging on the grid.

4.2. Performance Metrics for Evaluating the Models

To evaluate the performances of ML learning models that will be implemented for EV energy consumption, we define the following notations provided in Table 4.

Table 4. Description of notations used in the regression metrics.

$E\dot{v}$ = actual values of EV energy consumption
$E\overline{\ddot{v}}$ = the mean of the actual values of EV energy consumption
$E\ddot{v}$ = predicted values of EV energy consumption
N = the total number of observations
i = indicates the i^{th} element in the sequence of actual and predicted values

- Root Mean Squared Error (RMSE)

In this study, we applied the RMSE to determine the average of the squared difference that is observed between the actual values of EV energy consumption and the predicted values presented during the training of the model. Equation (5) depicts the RMSE used to evaluate the models in this study.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E\dot{v} - E\ddot{v}\right)^2} \cdot (\mathrm{kWh}) \tag{5}$$

- Mean Squared Error (MSE)

This is the performance function that enables us to measure how well the outcome variables (the predicted values) of the machine learning models match with the true response (actual values) of energy consumption by EVs. Equation (6) represents the MSE.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(E\dot{v} - E\ddot{v}\right)^2 \cdot (\mathrm{kWh}^2) \tag{6}$$

- Coefficient of Determination (R^2)

In this study, we have specifically chosen R^2, which can only be applied in regression models as a metric for measurement over the R-value that is more generalized for most linear relationships. The R^2 values are from 0 to 1, with higher values of R^2 closest to unity being preferred as these indicate a better goodness-of-fit for the trained model. Equation (7) represents the R^2 used in the regression analysis of this study.

$$R^2 = 1 - \frac{\left(\sum_{i=1}^{N} E\ddot{v} - E\dot{v}\right)^2}{\left(\sum_{i=1}^{N} E\dot{v} - E\bar{\dot{v}}\right)^2} \quad (7)$$

- Mean Absolute Error (MAE)

The MAE is the performance function that enables us to measure the average absolute error between the predicted EV energy consumption and the actual values of the EV energy consumption. In its calculations, it considers the position of the outliers around and far from the prediction line. Equation (8) represents the MAE.

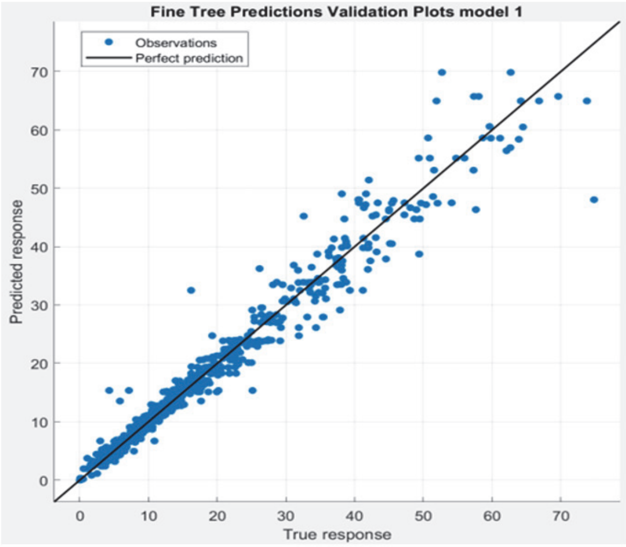
$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|E\dot{v} - E\ddot{v}\right| \text{ (kWh)} \quad (8)$$

4.3. Simulation Models and Predictions of EV Energy Consumption

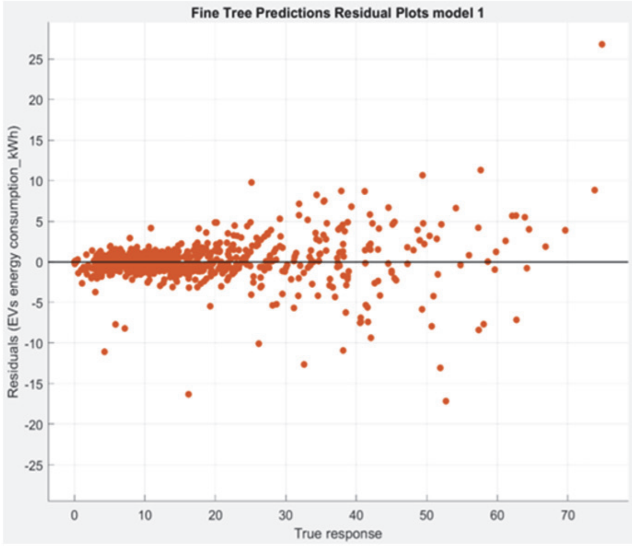
Using ML techniques in the MATLAB environment, we present simulation models of EV charging sessions based on the distribution of the load profiles generated with the datasets collected. We go further to predict EV energy consumption based on the grid power delivered using the level 2 and DC fast chargers. Input datasets (predictor variables) to the models are the amperage drawn by the EV charger, the voltage delivered by the EVSE, and the duration required to charge EVs. The output variable (predicted variable or response data) is the EV kWh energy consumption. We set up machine learning tools based on regression analysis models including fine tree regression, linear regression, support vector machine (SVM), and neural networks. The datasets used for the ML were split into 80% for training the models and 20% as a testing dataset for evaluating the performances of the models using loss functions (e.g., MSE). The model hyperparameters are fine-tuned; as an example, we included a cross-validation scheme, which protects against overfitting.

4.3.1. Fine Tree Regression Model

Fine tree regression is applied as an ML technique for the analysis, simulation, and predictions of the EV energy consumption profile. As a nonlinear predictive model, it uses the decision tree algorithm [49] to capture the relationships between the power delivered from the grid to charge the EVs, the profile of the grid power supplied, the energy consumption of EVs, and the load profiles of EVs charging on the grid. In Figure 6, we present the results of the fine tree regression model. This figure displays the simulation and prediction of EV energy consumption for the period January to December 2022. In this figure, the training of the datasets shows how the predicted values measure with the actual (true response) values.



(a). Validation plots: Fine Tree prediction model



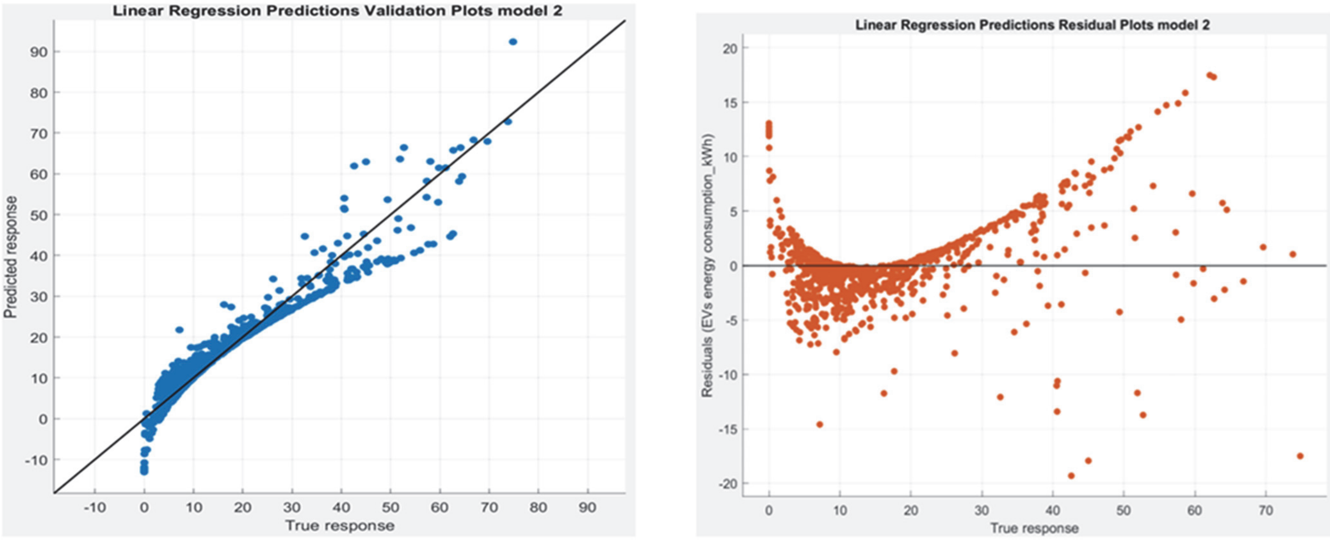
(b). Residual Plots: Fine Tree prediction model

Figure 6. Fine tree predictions of EV energy consumption.

The validation plots of the fine tree model are given as Figure 6a with the blue dots representing the observations while the forecast line shows how perfect the predictions are to the actual data. The performance of the validation plots is estimated with the following regression metrics showing results for the RMSE (2.525), R^2 (0.964), MSE (6.373), and MAE (1.356). Figure 6b, showing the residual plots in orange dots, is used to check the performance of the model. With Figure 6b, we investigated the influence of the predictor variables (amperage drawn by the EV charger, the voltage delivered by the EVSE, and the charging duration) on the outcome variables (EV kWh energy consumed). The purpose of this residual (error) plot would be to measure the accuracy of the fine tree model. This involves evaluating the difference between the real-world (i.e., true response) EV energy consumption datasets based on the charging sessions and the observed variables (predicted response) that we intend to achieve. To identify a good model, the residuals, which are the orange dots representing observed variables (EV energy consumption), should be scattered in such a way that they do not show any pattern and must be almost symmetrically distributed around 0 (the forecast line). With this data visualization in Figure 6b, our aim is to determine how valid our model is. Based on this, we used the testing datasets to evaluate the model accuracy, and we obtained the following results for the RMSE (2.201), R^2 (0.960), MSE (4.842), and MAE (1.033).

4.3.2. Linear Regression Model

Using liner regression as an ML technique, we applied the same datasets for the analysis, simulation, and predictions of EV energy consumption based on the charging sessions as already established. In this case, there is a clear pattern in the simulation plots presented in Figure 7 below, which is an indicator that the model is not a good fit.



(a). Validation plots: Linear Regression prediction model (b). Residual Plots: Linear Regression prediction model

Figure 7. Linear regression predictions of EV energy consumption.

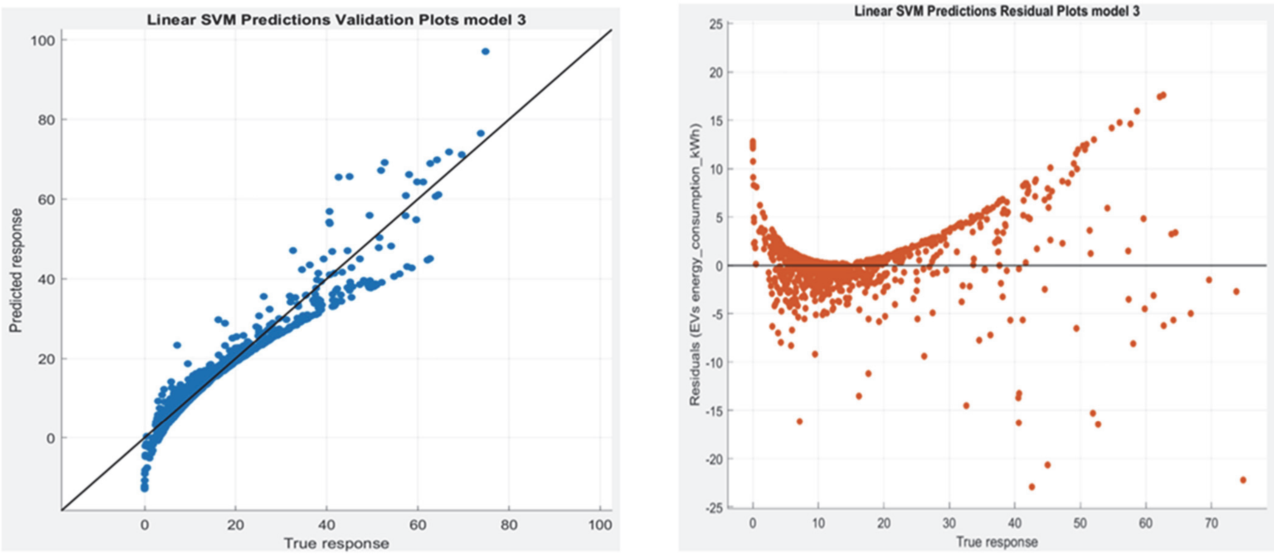
Based on the validation plots in Figure 7a showing the predicted versus the actual (true response) energy consumption by EVs, the blue dots show a clear pattern that the validation plots have a significant deviation from the forecast line, meaning that the predictions are not a perfect fit when compared to the real-world actual datasets that we intend to predict. To support this argument, the validation plots are estimated using the following regression metrics with the results showing the RMSE (3.927), R^2 (0.914), MSE (15.422), and MAE (2.483). To evaluate the performance of the linear regression model, the residual plots in Figure 7b are presented. Similarly, we investigate the influence of the predictor variables (amperage drawn by the EV charger, the voltage delivered by the EVSE, and the charging duration) on the outcome variables (EV kWh energy consumed). Given the observation as seen in the residual plots, there is a significant deviation in the actual datasets of EV energy consumption. Using the testing datasets to evaluate the performance of this second model, we obtained the following results based on the regression metrics of the RMSE (2.803), R^2 (0.935), MSE (7.859), and MAE (1.765).

4.3.3. Linear SVM Model

A third model known as linear SVM [50] was implemented and represented as Figure 8.

From the diagrams presented, the linear SVM validation plots show the predicted values versus the actual (true response) values of EV energy consumption. There is a similarity between the linear regression plots of Figure 7 with the observations made with Figure 8, which shows a clear pattern and significant deviation from the forecast line. Hence, the predictions are not a perfect fit when compared to the real-world actual datasets.

The results from the validation plots of Figure 8a show the regression metrics with the RMSE (4.017), R^2 (0.910), MSE (16.136), and MAE (2.384). It is observed that the residual plots in Figure 8b show the predicted response of EV energy consumption having outliers. Furthermore, the residual plots are not symmetrical to the forecast line, which is an indication that the plot is a bad model. To evaluate the performance of this third model, the testing datasets were used with regression metrics showing the RMSE (2.503), R^2 (0.948), MSE (6.267), and MAE (1.542).



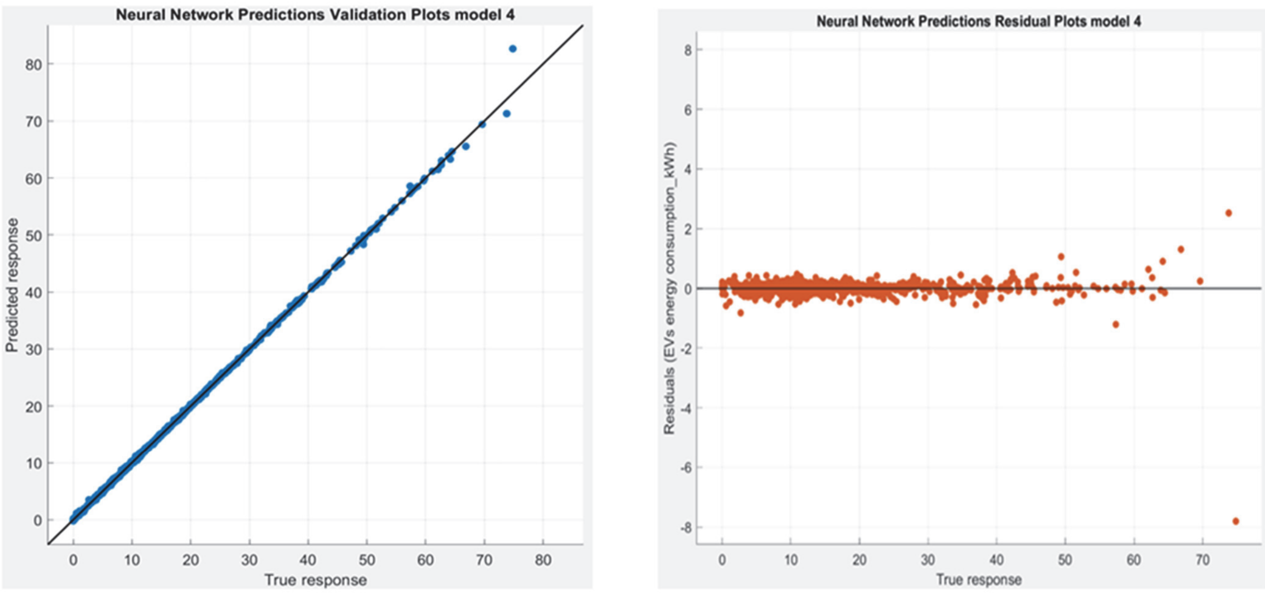
(a). Validation plots: Linear SVM prediction

(b). Residual Plots: Linear SVM prediction

Figure 8. Linear SVM predictions of EV energy consumption.

4.3.4. Neural Network Model

The fourth model is based on an artificial neural network [51], a universal approximator with the capability for supervised and unsupervised learning. Using supervised learning, we applied a feedforward neural network with multilayer perceptron and a training process based on the Levenberg–Marquardt (LM) backpropagation algorithm. The hidden layer has 25 neurons, three input layers, and one output layer. A tuning parameter of 0.1 was set to avoid oscillation in the training process. The validation plots for this model show a high correlation between the predicted values and the actual datasets of EV energy consumption as indicated by the symmetry around the forecast line in Figure 9a. The regression metrics for the validation plots have an RMSE (0.325), R^2 (0.999), MSE (0.106), and MAE (0.130).



(a). Validation plots: Neural Network prediction

(b). Residual Plots: Neural Network prediction

Figure 9. Neural network predictions of EV energy consumption.

To check the performance of the neural network model, Figure 9b is presented as the residual plots. This shows how the predictor variables of the amperage drawn by the EV charger, the voltage delivered by the EVSE, and the duration required to charge the EVs influence the output variable of the EV kWh energy consumption. The observation made based on this model indicated a good fit with the neural network accurately predicting EV energy consumption. Using the testing datasets, the performance of the neural network model is evaluated with the regression metrics of the RMSE (0.074), R^2 (1.000), MSE (0.005), and MAE (0.052).

5. Results Discussion and Comparison

In this section, the results from the analysis, simulation, and predictions of the applied machine learning models are discussed. Subsequently, we will compare our study results with the works of other authors in [44].

5.1. Machine Learning Models and Their Performances

From the diagrams in Figures 7 and 8, observations can be made that the linear regression model with the linear SVM regression model have similar patterns showing deviations from the forecast line. The implications with the models of Figures 7 and 8 are poor predictions and a lack of correlation between the predicted values and the actual values of EV energy consumption, whereas the fine tree model of Figure 6 and the neural network model of Figure 9 have better and more accurate predictions. Above all, the neural network model has the best and most accurate prediction with good symmetry around the forecast line. Using Table 5, we present a summarized view of the validation results from the four machine learning regression models used in our study, while Table 6 summarizes the test results based on the performance evaluation for all the models.

Table 5. Comparing validation results for all models.

Models	RMSE (kWh)	R^2	MSE (kWh^2)	MAE (kWh)
Fine Tree	2.525	0.964	6.373	1.356
Linear Reg.	3.927	0.914	15.422	2.483
Linear SVM	4.017	0.910	16.136	2.384
Neural Net.	0.325	0.999	0.106	0.130

Table 6. Comparing test results for all models.

Models	RMSE (kWh)	R^2	MSE (kWh^2)	MAE (kWh)
Fine Tree	2.201	0.960	4.842	1.033
Linear Reg.	2.803	0.935	7.859	1.765
Linear SVM	2.503	0.948	6.267	1.542
Neural Net.	0.074	1.000	0.005	0.052

From Tables 5 and 6, we can deduce that the performance of the neural network regression model has far more significant accuracy of predictions to the actual and real-world EV energy consumption predictions than we hope to achieve. The goodness-of-fit exhibited by the neural network model using the coefficient of determination (R^2) gives a better prediction accuracy for EV energy consumption. The next best model is the fine tree regression model, while the metrics of the linear regression and the linear SVM show extremely high numbers of outliers, which are an indication of non-symmetry of prediction around the forecast line. The high values in the MSE results for the linear regression and the linear SVM regression models also show their sensitivity to outliers, resulting in the inflation of errors. The increasing values of the mean absolute error (MAE) indicated in the result of the linear regression and the linear SVM models also show that their performances are less optimal and have more errors as compared to the neural network and the fine tree models. So, both the fine tree and the neural network model are good options for modeling and predictions based on this study. In submission, the neural network model showing the most accurate performance and predictions is the best and preferred option.

5.2. Performance Comparison of This Study with the Works of Other Authors

In Table 7, we provide the results from the works of other authors in [44] as a summary, and we compare the performances of their machine learning models with the results from our study. This comparison is performed based on the predictions made for EV energy consumption from the test simulations using the regression metrics of the RMSE, MAE, and $R^{2,}$ which are common to both studies.

Table 7. Performance comparison between this study and the study in [44] using test results.

Results from This Study			
Models	**RMSE (kWh)**	**R^2**	**MAE (kWh)**
Fine Tree	2.201	0.960	1.033
Linear Reg.	2.803	0.935	1.765
Linear SVM	2.503	0.948	1.542
Neural Net.	0.074	1.000	0.052
Results from authors in [44]			
RF	5.50	0.54	3.39
SVM	5.69	0.51	3.54
XGBoost	5.61	0.51	3.48
Deep ANN	5.65	0.55	3.55

From the results in Table 7, the ML regression models from our study show better performances in terms of the predictions made for the EV energy consumption when compared with the results in [44]. Even though the authors in [44] used a 10-fold cross-validation, we used 5-fold cross-validation to achieve improved learning outcomes and better results. In choosing our ML models over other models, and the cross-validation scheme used, we considered the benefits of simplicity, fast training, and memory efficiency in terms of computational resources, unlike ensembled methods, which require higher computational resources, longer training, and extended prediction time.

6. Conclusions and Future Work

6.1. Conclusions

In this study, we investigated large-scale penetration of EVs on the grid and observed a significant impact of uncontrolled charging on the grid distribution system. Using large-scale datasets, we analyzed EV charging sessions and studied EV energy consumption profiles. From the charts of Figures 3 and 4, which display EV energy consumption profiles based on real-world datasets, we established that EV energy consumption has an increasing demand from the grid. This insight shows that the increasing demand for grid electric power required to charge EVs will have a significant impact on grid stability. Using real-world charging session datasets, we trained four different ML regression models to predict EV energy consumption. The results from our predictions indicated better accuracy when compared with the results from the work of other authors in [44]. Unlike previous work that used 10-fold cross-validation, we implemented a 5-fold cross-validation scheme in our machine learning application to protect against overfitting and we achieved improved learning outcomes with better performance. As part of this study's contributions, we developed quantitative analysis and load models of EV charging sessions based on real-world datasets of energy consumption by EVs. These efforts provide a realistic assessment of EV charging scenarios that is useful for load flow analysis, impact assessment of charging EVs on the grid, and for planning future energy supply to distribution systems with large-scale charging of EVs. Furthermore, the findings and results from this study imply that the increase in grid energy consumption can be curtailed by using charging session datasets to understand EV charging patterns. With this insight, operational decisions on grid energy management and infrastructure planning in terms of charging station placement to handle peak energy demand can be positively influenced. Similarly, it provides insight for stakeholders to make policy decisions around incentive programs that influence EV charging based on tariffs and environmental impact.

6.2. Future Work Recommendations

The optimization of EV charging on grid distribution systems offers an interesting research area that is still evolving. Further research in scheduling algorithms with meta-heuristics capacity that significantly improve the search process in grid power allocation for large-scale, uncontrolled charging of EVs is crucial. Specifically, we recommend the concept of a topology-aware charging control framework that will improve the operational reliability of the grid and minimize uncontrolled energy consumption from EVs.

Author Contributions: Conceptualization, R.O.K.; methodology, R.O.K.; software, R.O.K.; validation, R.O.K. and T.O.O.; formal analysis, R.O.K.; investigation, R.O.K.; resources, R.O.K. and T.O.O.; data curation, R.O.K.; writing—original draft preparation, R.O.K.; writing—review and editing, R.O.K. and T.O.O.; visualization, R.O.K.; supervision, T.O.O.; project administration, R.O.K. and T.O.O. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

AC	Alternate Current
ACN	Adaptive charging network
ANN	Artificial neural network
BEVs	Battery electric vehicles
DC	Direct current
EVs	Electric vehicles
EVSE	Electric vehicle supply equipment
ETAP	Electrical Transient Analyzer Program
GHG	Greenhouse gas
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
LADWP	Los Angeles Department of Water and Power
LM	Levenberg–Marquardt
MAE	Mean absolute error
ML	Machine learning

MSE	Mean squared error
PEVs	Plug-in electric vehicles
PHEVs	Plug-in hybrid electric vehicles
RMSE	Root mean squared error
SDG	Sustainable Development Goal
SMAPE	Symmetric Mean Absolute Percentage Error
SLD	Single-line diagram
SoC	State of charge
SVM	Support vector machine
V2G	Vehicle-to-grid
XGBoost	Extreme gradient boosting

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