energies

MDPI

Article

Smart Charging Recommendation Framework for Electric Vehicles: A Machine-Learning-Based Approach for Residential Buildings

Nikolaos Tsalikidis [1], Paraskevas Koukaras [1,2,*], Dimosthenis Ioannidis [1] and Dimitrios Tzovaras [1]

[1] Information Technologies Institute, Centre for Research & Technology, 6th km Charilaou-Thermi, 57001 Thessaloniki, Greece; ntsalikidis@iti.gr (N.T.); djoannid@iti.gr (D.I.); dimitrios.tzovaras@iti.gr (D.T.)
[2] School of Science and Technology, International Hellenic University, 14th km Thessaloniki-Moudania, 57001 Thessaloniki, Greece
* Correspondence: p.koukaras@iti.gr

Abstract: The transition to a decarbonized energy sector, driven by the integration of Renewable Energy Sources (RESs), smart building technology, and the rise of Electric Vehicles (EVs), has highlighted the need for optimized energy system planning. Increasing EV adoption creates additional challenges for charging infrastructure and grid demand, while proactive and informed decisions by residential EV users can help mitigate such challenges. Our work develops a smart residential charging framework that assists residents in making informed decisions about optimal EV charging. The framework integrates a machine-learning-based forecasting engine that consists of two components: a stacking and voting meta-ensemble regressor for predicting EV charging load and a bidirectional LSTM for forecasting national net energy exchange using real-world data from local road traffic, residential charging sessions, and grid net energy exchange flow. The combined forecasting outputs are passed through a data-driven weighting mechanism to generate probabilistic recommendations that identify optimal charging periods, aiming to alleviate grid stress and ensure efficient operation of local charging infrastructure. The framework's modular design ensures adaptability to local charging infrastructure within or nearby building complexes, making it a versatile tool for enhancing energy efficiency in residential settings.

Keywords: electric vehicle charging; recommender system; dynamic load management; smart grid; forecasting; machine learning

check for updates

Academic Editor: Hassam Ur Rehman

Received: 24 February 2025
Revised: 17 March 2025
Accepted: 18 March 2025
Published: 19 March 2025

Citation: Tsalikidis, N.; Koukaras, P.; Ioannidis, D.; Tzovaras, D. Smart Charging Recommendation Framework for Electric Vehicles: A Machine-Learning-Based Approach for Residential Buildings. *Energies* **2025**, *18*, 1528. https://doi.org/10.3390/en18061528

1. Background

1.1. Introduction

The effects of climate change have heightened awareness about the need for energy sector decarbonization. This transition towards decarbonization is already reshaping the ways energy is produced, distributed, and consumed globally. The development of Renewable Energy Sources (RESs) and intelligent grid systems, coupled with the widespread adoption of Electric Vehicles (EVs), has made electric power system planning, scheduling, and operation central components of sustainability initiatives. EVs have become an established alternative to Internal Combustion Engine Vehicles (ICEVs), as policymakers worldwide incentivize a push towards realizing carbon neutrality [1,2]. In 2023, approximately 40 million electric passenger cars were in operation globally, with new EV sales surpassing the previous year by 3.5 million, accounting for 18% of all new vehicle sales [3]. At the same time, the growing adoption of smart building technologies, enabled by Internet of Things (IoT) technology and advanced data analytics, has revolutionized energy management strategies [4]. This shift is vital for enhancing overall energy efficiency and facilitating the effective integration of RESs into existing grids [5–7]. Looking ahead, smart residential buildings are envisioned to become proactive [8], integrating advanced sensor networks and communication technologies, thereby enabling seamless, bidirectional interaction with energy distribution systems and fostering more efficient, adaptive energy management [9–11]. Assessment tools such as the Smart Readiness Indicator (SRI) play a key role in evaluating a building's capacity to optimize energy consumption through the integration of smart technologies. By quantitatively assessing factors like energy efficiency, grid interaction, and occupant requirements, the SRI facilitates more informed decision-making across various building types [12–14]. In smart building environments and EV charging scenarios, the integration of the SRI encourages adaptive energy strategies [15–17], ensuring grid-friendly charging and improved system resilience [18].

The primary objective of this research was to develop a smart charging recommendation framework that enhances the decision-making process for residents. This framework was contextualized through a real-world case study in Norway, where it leveraged residential EV charging session data alongside local passenger car mobility patterns. Our work initially focused on a comprehensive analysis of charging session characteristics, which informed the development of ML algorithms for predicting localized EV charge loads. These forecasting results were subsequently integrated into the recommender system, which identified prospective periods of both low national grid-level electricity demand and local charging demand. This approach contributes to optimizing grid flexibility and ensures the smooth operation of local charging infrastructure, mitigating the risk of overloads. Additionally, it potentially promotes cost-effectiveness and enhanced energy efficiency by aligning charging with off-peak periods for residential users. Beyond its immediate operational benefits for residential EV charging, our proposed recommendation framework distinguishes itself through its customizability and adaptability:

- The modular design of the ML-based forecasting engine facilitates the integration of additional data streams—such as national grid energy flows—ensuring that the system remains responsive to evolving energy market dynamics as well as user requirements.
- The framework employs a dynamic weighting mechanism for the forecast values, which underpins the generation of a probabilistic recommendation. This flexible mechanism can be recalibrated based on local and regional/national data streams, thereby optimizing energy usage recommendations across a broader spectrum of operational scenarios.

1.2. EV Charging Operations

EV charging operations pose significant challenges to the stability of local power substations, national grids, and electrical grids. One approach to addressing these challenges is Smart Charging (SC) [19–21]. SC can be implemented in two main ways: User-Managed Charging (UMC), where users independently decide when and for how long to charge based on available information and pricing policies, or Supplier-Managed Charging (SMC), where the charging process is controlled by the system operator using data provided by the user [22]. Our focus is on UMC, where users/residents can adopt more flexible energy consumption patterns supported by systems that provide signals to encourage them to make more intelligent decisions about their energy use. Coupled with the emergence of smart grids in urban areas [23,24] and the integration of building smart energy management systems [25], this has elevated the significance of enhanced decision-making in charging operations [26,27].

Understanding EV energy demands and charging patterns is crucial for developing accurate forecasting methods and optimizing charging infrastructure management [28,29]. Two major factors are involved: the quantity of energy required, and the timing of the charging activity [30]. However, the frequent unpredictability of users' charging habits and behaviors—including variations in start time, duration, and energy demand—complicates the scheduling and optimization of charging sessions [31–33]. Consequently, the integration of EVs into existing power grids poses significant challenges to stability, necessitating the development of advanced forecasting and Demand Side Management (DSM) strategies that can dynamically adjust to real-time demand fluctuations [34]. The study of [35] reviewed various DSM strategies (load shifting, peak shaving), while also addressing the challenges of systemic uncertainties. It examined diverse modeling and optimization methods, including linear programming, metaheuristic algorithms (such as PSO), and hybrid approaches—used to enhance EV scheduling and energy management.

In the residential context, EV charging behavior can be generally categorized into three distinct patterns:

- Peak Charging: Occurring when vehicle owners charge their vehicles immediately after work, coinciding with periods of heightened residential electricity demand. The simultaneous increase in residential electricity consumption and EV charging can significantly elevate grid load peaks, potentially requiring DSM interventions such as load-shifting strategies.
- Off-Peak Charging: Involving delayed or controlled charging, this pattern typically occurs during night hours when electricity rates are lower and overall demand is reduced. Off-peak charging offers the opportunity to flatten the load curve and improve grid stability by shifting energy consumption to periods with surplus generation capacity.
- Stochastic Charging: Characterized by sporadic charging events based on immediate needs or personal habits, this pattern is the most unpredictable. Its random nature complicates accurate forecasting. Nonetheless, such charging behavior tends to be less prevalent in residential scenarios compared to public charging in commercial areas.

1.3. Related Work

Advanced forecasting methods are essential to predict such charging patterns effectively, as they enable better optimization of the probabilistic profile of the EV charge load. The widespread deployment of EV charging stations—encompassing public networks as well as private facilities at residences and workplaces—has resulted in an extensive accumulation of charging-related data [36]. Traditionally, load forecasting has relied on statistical-based algorithms. However, with this exponential increase in available data, emerging studies suggest that data-driven algorithms demonstrate more robust behavior compared to conventional statistical methods for load forecasting [37–39]. Specifically, the shift towards ML and DL approaches reflects their enhanced ability to capture the complex, non-linear relationships and temporal dependencies inherent in EV charging data [40,41]. Recent research has focused on smart charging techniques that leverage data-driven methodologies and optimization algorithms to dynamically optimize charging schedules, mitigate grid stress, and enhance the integration of RES. In this section, we highlight key relevant studies.

Kara et al. [42] utilized charging events, encompassing EV arrival and departure times and charging power levels, to estimate EV charge load and assess the advantages of smart charging strategies. Their framework evaluated two case studies: one demonstrated that behind-the-meter EV aggregations could reduce monthly electricity costs by up to 24.8% under time-of-use pricing, and another showed that controlled charging reduced the EV peak load contribution by a median of 37%, shifting approximately 0.25 kWh ($\approx$2.8%) per session from peak to off-peak periods.

Brady et al. [43] applied a stochastic simulation approach to generate schedules for daily travel and charging profiles. Their probabilistic charging decision model calculates the likelihood of an EV being charged upon arrival at a destination, taking into account the current State of Charge (SoC), available parking time, and the specific journey in progress.

The work of [44] proposed a hybrid CNN-LSTM model for multi-step EV charge load forecasting in smart buildings, outperforming traditional methods. By leveraging convolutional layers to extract localized temporal features and LSTM layers to capture long-term dependencies, the model effectively addresses complex dynamics, achieving high accuracy.

The work in [45] assessed the impact of ambient temperature, traffic conditions (e.g., congestion), and spatiotemporal distribution on EV charge load forecasting, utilizing Monte Carlo simulations. In particular, by incorporating ambient temperature and traffic condition factors, the forecasting accuracy was improved by around 38%.

In [46], a novel multilayer iterative stochastic dynamic programming (MISDP) framework was introduced for optimizing energy management in residential settings with integrated electric vehicles. The approach decomposes the problem into two iterative layers: an external layer that adapts to stochastic fluctuations in electricity prices and residential demand, and an internal layer that fine-tunes real-time EV battery charging and discharging strategies. This dual-layer scheme minimizes energy costs, while extending battery life and maintaining grid stability.

To enhance grid stability amid rising EV charging demands, researchers in [47] proposed an innovative integration strategy that leverages dynamic scheduling and control algorithms. By fusing real-time data—such as battery state-of-charge, arrival/departure times, and real-time pricing—from both distribution system operators and EV owners, the system continuously refines its charging and discharging schedules. This iterative optimization identifies optimal energy injection moments, reducing peak loads, improving voltage profiles, and minimizing losses, while maximizing the financial benefits for EV owners.

The work of [48] introduced a novel valley-filling heuristic for optimizing electric vehicle charging to enhance grid stability. It presented a Load Conservation Valley-Filling (LCVF) method that builds on classical and optimistic valley-filling strategies by preserving EV load allocation states across iterations, thereby reducing oscillatory behavior. Evaluated across various scenarios, LCVF achieved up to a 20% reduction in peak demand compared to traditional methods, demonstrating improved energy efficiency and grid reliability.

This paper [49] presents an integrated approach to optimize the sizing of battery energy storage systems (BESS) for residential households, specifically addressing the energy requirements of EV charging infrastructure in conjunction with PVs. Using LSTM to forecast monthly load profiles, the approach identifies the optimal BESS capacity needed to capture surplus solar energy and perform peak shaving. The integration of real-time pricing further refines energy management, reducing both operational costs and installation size.

The work in [50] presented a novel charging method that exploits a building's idle power capacity to manage EV charging efficiently. Central to this solution is an intelligent scheduling and control algorithm that dynamically adjusts the charging current for each EV. By incorporating user-specific inputs (e.g., SoC, available charging time), the system formulates a non-linear minimization problem. The objective is to minimize the gap between the time needed to reach the desired SoC and the time available for charging, while also respecting the building's power limitations. The algorithm employs a Sequential Least Squares Programming (SLSQP) method to iteratively determine the optimal charging current allocation for each vehicle, ensuring efficient power usage and overall system safety.

2. Methodology

2.1. Data Description

Our case study focuses on residential buildings with EV charging infrastructure, as detailed in [51]. The Risvollan housing complex in Trondheim, Norway, accommodates 2400 residents across 1113 apartments. Its EV charging network includes up to 764 Charging Points (CPs) in private and shared parking areas. CPs are located in individual parking spots for residents or shared parking zones.

The charging infrastructure balances the EV demand in each garage, ensuring they remain within the specified overall power limit. All charging sessions registered include plug-in times, plug-out times, and charged energy. From January 2019 to January 2020, 6878 charging sessions were registered. The EVs can charge at 24 different parking locations, each with an Advanced Measurement System (AMS) type of meter measuring the aggregated EV charge load. We focused on data from two main garages (Bl2 & A1), as more than 35% of the total charging sessions of the housing complex occurred in these garages. We also incorporated the hourly traffic flow data of passenger cars in six nearby traffic locations. The data were collected from a web portal [52], and more details can be found in this study [53]. The overall elements of the final dataset utilized in our work are described in Table 1.

Table 1. Dataset description.

Field	Description	Units
Charging sessions		
session_ID	Unique charging session ID	–
Garage_ID	Garage address identifier	–
User_ID	User identifier	–
User_type	Charger ownership (Private/Shared)	–
Start_plugin	Plug-in date and time	DateTime
Start_plugin_hour	Hour of plug-in (00–23)	–
End_plugout	Plug-out date and time	DateTime
El_kWh	Charged energy	kWh
Duration_hours	EV connection duration	Hours
weekdays_start	Plug-in weekday	Monday–Sunday
Plugin_category	3-h interval category	e.g., morning, afternoon
EV charge load (Garages B12 & A1)		
date_from	Start time	DateTime
date_to	End time	DateTime
AMS_kWh	Hourly aggregated load	kWh
Local traffic flow		
date_from	Start time	DateTime
date_to	End time	DateTime
Nearby Locations	Hourly number of vehicles	Count
Net energy exchange (Norway)		
date	Timestamp	DateTime
Net energy exchange	Amount of electric energy imported/exported	MWh

Table 2 provides descriptive statistics for EV charge load for both garages. To provide a more intricate view of the dataset, a set of key figures was produced to visualize the notable patterns in EV charging behavior. Figure 1 presents a frequency histogram depicting the distribution of charging session durations, while Figure 2 shows the daily distribution of plug-in and plug-out times. Figure 3 shows the connection time, private and shared, for all CP sessions of the Risvollan complex.

Table 2. Descriptive statistics for EV charge load (kWh).

Descriptive Statistics	Garage B12	Garage A1
Count	9424	8285
Mean	2.9772	1.0314
Std.	4.2723	2.0760
Min.	0.0000	0.0280
25th Percentile	0.0500	0.0290
Median	0.4000	0.0290
75th Percentile	4.5000	0.6400
Max.	26.4588	18.2180

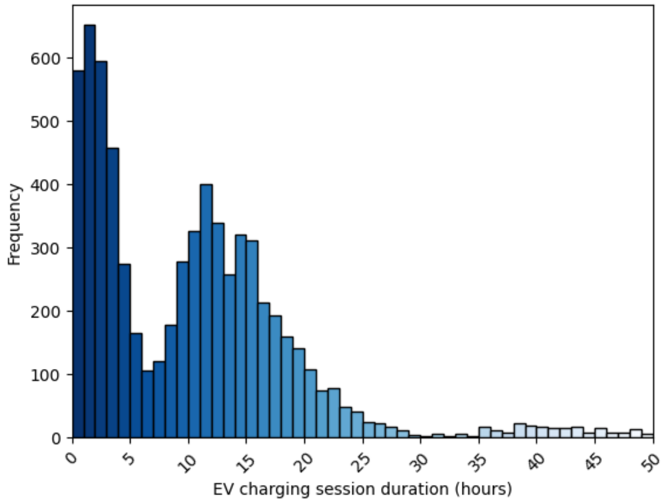
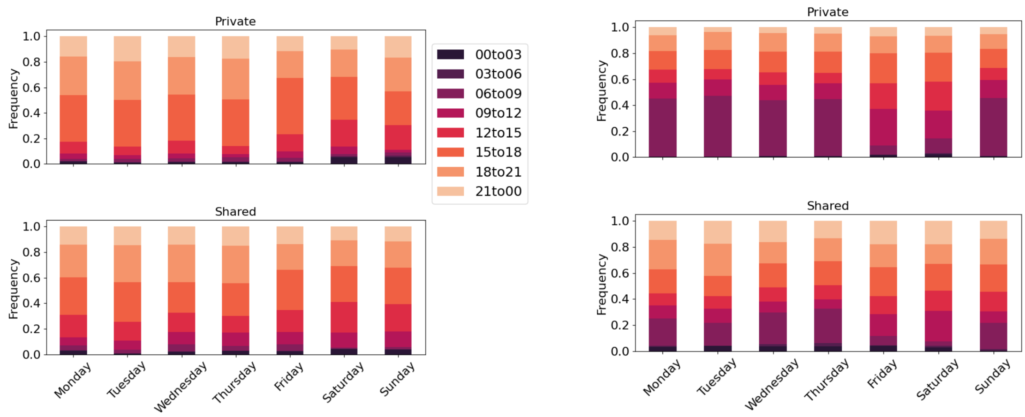
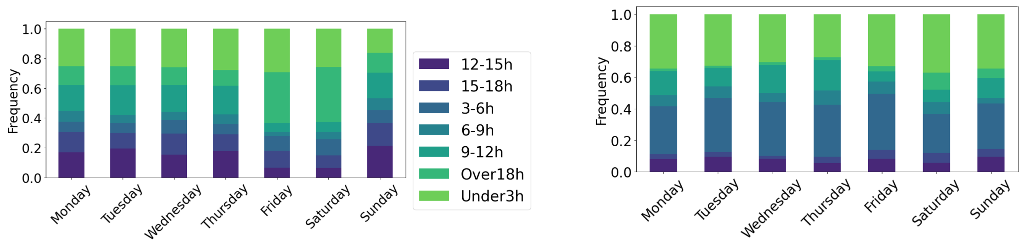


Figure 1. Frequency histogram of EV charging session duration framework (lighter shades of blue correspond to longer charging durations).



(**a**) Plug-in time (**b**) Plug-out time

Figure 2. Daily distributions of plug-in and plug-out times (All CPs).



(**a**) Connection time (Private) (**b**) Connection time (Shared)

Figure 3. Daily distributions of charging connection time (All CPs).

Most charging sessions lasted fewer than five hours; however, a secondary peak in the 10–15 h range suggests that a subset of users intentionally left their vehicles plugged in for extended periods, such as overnight charging. There were clear differences between shared and private sessions with regard to plug-in and plug-out times. For private users, plug-in times for their vehicles primarily occurred during the afternoon (i.e., 3–9 PM), while shared chargers exhibited increased activity during the morning to early afternoon period (9 AM to 3 PM), especially on weekdays. Regarding plug-out times, the highest proportion of private users disconnected their vehicles between 6 and 9 AM, most likely to commence their daily commute. In contrast, shared chargers displayed a more balanced distribution of plug-out times. This suggests that shared chargers may be utilized by a broader range of residents (not solely those commuting to work), thereby allowing greater flexibility for charging during working hours, as seen with work-from-home residents.

Regarding connection times, in private charging arrangements, vehicle owners typically do not face external constraints when disconnecting once charging is complete. Consequently, vehicles often remain plugged in for extended periods (especially overnight). This contributed to the secondary peak in connection durations of 10–15 h (Figure 1). In shared charging, there is an expectation that users free up the charging station as soon as the SoC is sufficient, which generally encourages more targeted and shorter charging sessions.

2.2. Net Energy Exchange Data (Norway)

Norway, a leading renewable energy producer in the EU, relies heavily on hydroelectric power, leading to grid variations influenced by integration with renewable energy sources (RES). A notable characteristic of Norway's hydropower system is its substantial storage capacity. The country accounts for half of Europe's reservoir storage capacity, and over 75% of its production capacity is flexible [54]. This flexible system stores water during low demand, optimizing resource allocation during peak demand periods. A key metric of energy demand trends is the total net energy exchange, representing imports (negative values) and exports (positive values) on the national grid [55]. Day-ahead pricing data show electricity costs fluctuate within a 24 h cycle, typically lowest at night and weekends, and highest during the day [56]. This pattern aligns with hydropower operational practices, where plants often disengage from the energy grid during low-demand periods, typically during late-evening and night-time hours, to store water, ensuring there are sufficient reserves to be used for daytime peaks in energy demand. During these periods, the grid relies more on energy imports from neighboring countries' thermal power plant-based output, which provides low-cost electricity during off-peak periods [55], hence driving the end-consumer electricity pricing downward. Figure 4 illustrates this operational strategy by highlighting the temporal variations in grid exchange. Negative values denote energy imports, while positive values indicate exports.

Specifically, selected days in 2019 reveal two distinct net energy exchange peaks—one occurring in the early morning (approximately 7–8 AM) and another in the late afternoon (around 5–6 PM). In contrast, during nighttime hours (i.e., from 10 PM to approximately 5–6 AM), the net energy exchanges trend toward zero and negative values, reflecting a period of increased reliance on energy imports.

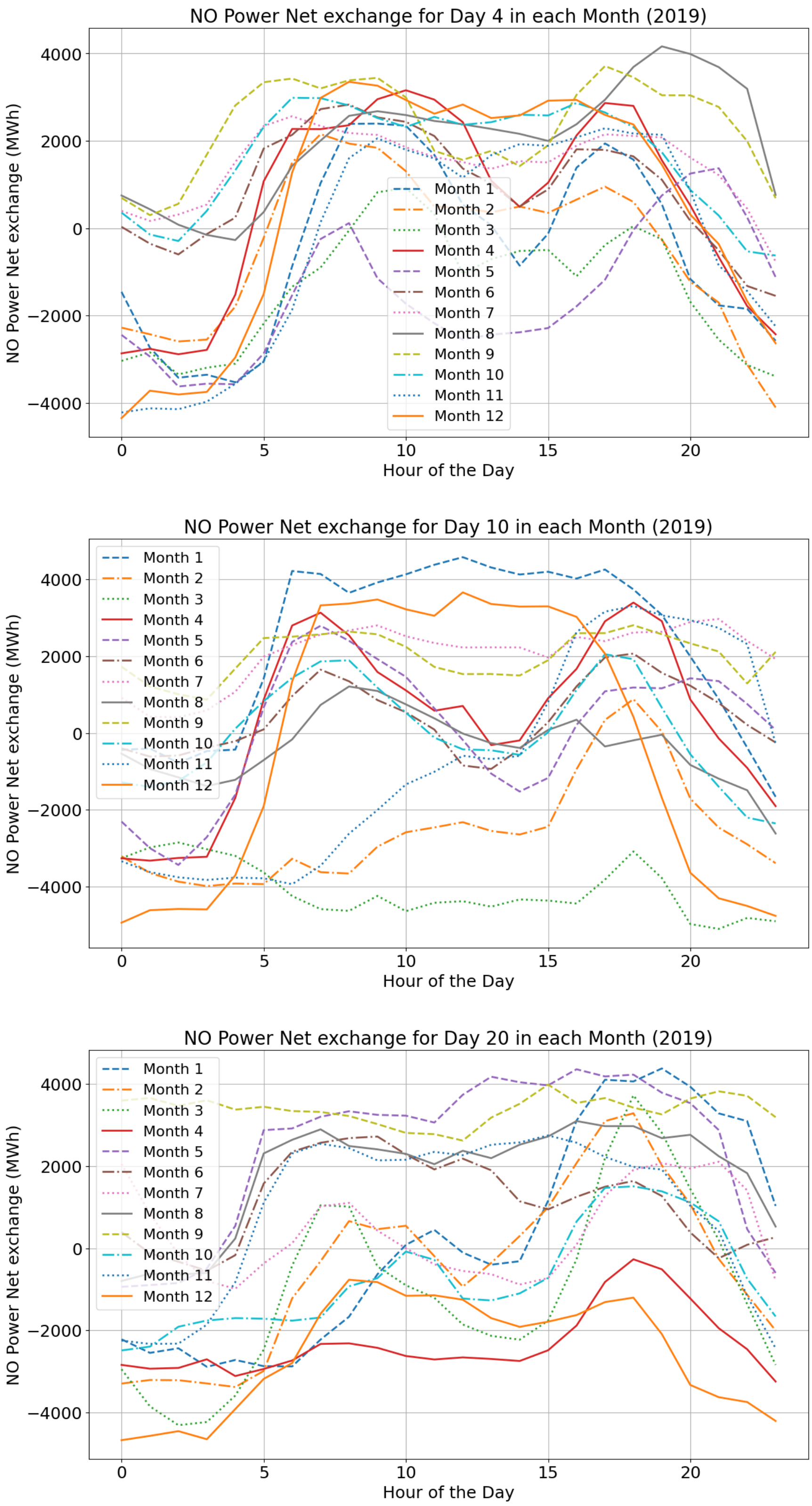


Figure 4. Hourly net energy exchange flow in Norway.

2.3. Preprocessing and Feature Engineering

Since the target variable (EV charge load) exhibited differing magnitudes between the two garages (Table 2), normalization was applied using Min-Max scaling to rescale the target values to a common range, ensuring consistency for model training. Outliers exceeding the 99.99th percentile were capped at their respective maximum values to mitigate the influence of extreme observations. Additionally, time-based interpolation was used to fill in any missing values, thereby maintaining the continuity of the dataset for model training.

- Temporal features: Seasonality features were generated by partitioning timestamps into categorical variables (e.g., hour, day, week, and month). Additional features, such as off-peak hours, were synthesized to better capture variations in charging and traffic patterns. Then, a sinusoidal positional encoding method was utilized to preserve the inherent periodicity of these features. For a given temporal feature x (e.g., the hour of the day) with a known maximum value $x_{\max}$ (for instance, 24 for hours), cyclical encoding is defined by the following transformations:

$$x_{\sin} = \sin\left(\frac{2\pi x}{x_{\max}}\right), \quad x_{\cos} = \cos\left(\frac{2\pi x}{x_{\max}}\right).$$

  This mapping projects the value x onto the unit circle, ensuring that values near the cycle boundaries (e.g., 23:00 and 00:00) are close in the transformed space.
- Other features: Two additional exogenous features were included in the dataset:
  - Public/Private Charging Share: Charging sessions were classified into shared and private categories. The hourly proportion for each category was computed by aggregating the session durations, which were first recorded on a minute-by-minute basis and subsequently summed to obtain an hourly total.
  - Local Traffic Flow Indicator: This feature quantifies the variability of local traffic patterns by employing dimensionality reduction. Specifically, Principal Component Analysis (PCA) was applied to traffic flow data collected from six nearby locations (Figure 5) over the preceding eight hours. The data were then projected onto the first principal component, which was subsequently utilized as a training feature.

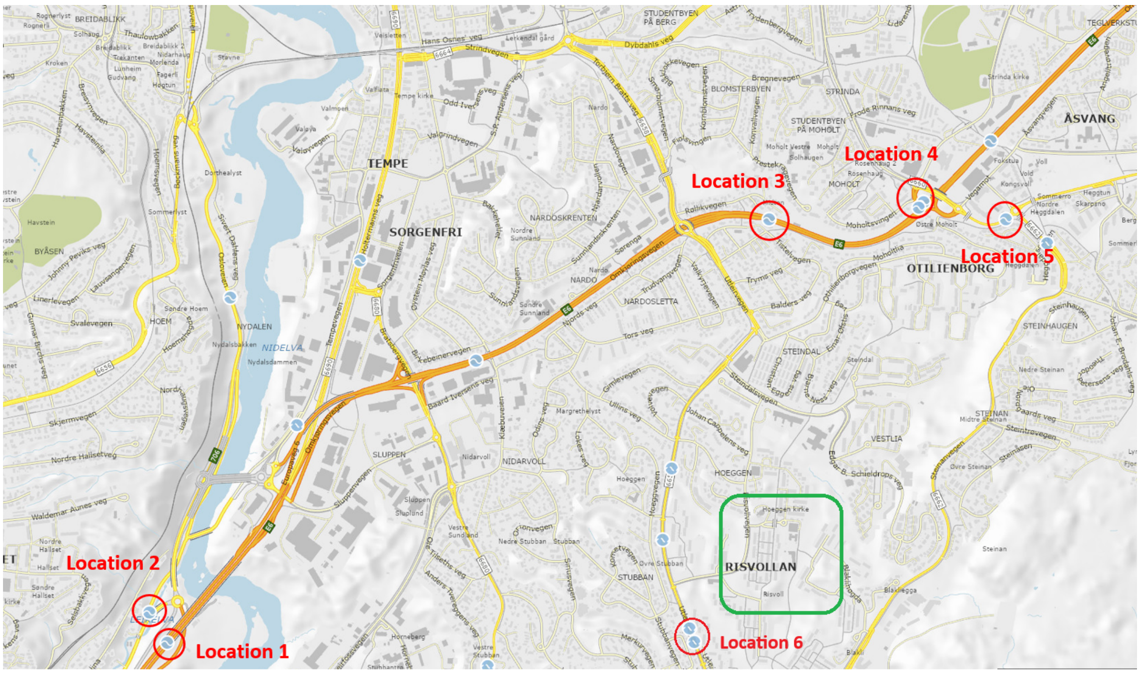


Figure 5. Locations of measured traffic flow near the Risvolan area.

2.4. Forecasting Approach

During implementation, various ML and DL algorithms were trained and tested for one-step-ahead forecasting, with the best-performing models selected for further tuning. The evaluation included tree-based and non-tree-based ML algorithms, as well as Recurrent Neural Networks (RNNs), which are well-suited for time series forecasting. Before applying regression techniques, data standardization was performed, since non-tree-based algorithms and RNNs require scaled features.

The final feature matrix was constructed using the Sliding Window (SW) technique [57], which creates lagged variables by shifting data in 24 h increments. Let

$$\{\mathbf{x}_t\}_{t=1}^{T}, \quad \mathbf{x}_t \in \mathbb{R}^F,$$

denote the original time series data, where F is the number of features per time step. To generate lagged variables with a 24 h shift, a sliding window of length L is applied. Specifically, for the ith sample, the sliding window is defined as

$$\mathbf{X}_i = \begin{bmatrix} \mathbf{x}_i \\ \mathbf{x}_{i+24} \\ \vdots \\ \mathbf{x}_{i+(L-1)\cdot 24} \end{bmatrix} \in \mathbb{R}^{L\times F}.$$

For RNN models, the entire dataset was organized as a three-dimensional tensor:

$$\mathcal{X} \in \mathbb{R}^{N\times L\times F},$$

where N is the total number of samples, L represents the number of time steps (lagged observations), and F is the number of features. For models that do not explicitly capture temporal dependencies (such as tree-based models), the sliding window samples are flattened into a two-dimensional feature matrix, where the time steps are concatenated along the feature dimension.

In our work, the window length L was chosen as 24, corresponding to 24 h. This decision was motivated by empirical knowledge and the observed daily cyclical patterns in residential EV charging behavior. Experiments confirmed that a 24 h lag effectively captured the daily recurring patterns in EV load, maximizing forecasting performance, while avoiding unnecessary expansion of the feature space.

The forecasting approach is specifically tailored to one-step-ahead prediction, where the model forecasts the immediate subsequent value based on historical data. This targeted strategy ensures timely and precise predictions, which are critical for dynamic EV charging recommendation, as it enables rapid updates with the most recent information, reducing forecast uncertainty. The overall forecast modeling methodology is illustrated in Figure 6.

2.4.1. EV Charge Load Forecasting

Based on empirical experience, for the forecast of the next hour EV charge load, we tested different key base ML regressors such as LightGBM (LGBM), HistGradientBoosting (HGB), XGBoost (XGB), CatBoost (CB), Gradient Boosting (GB), Extra Trees (ET), Huber Regressor (HR), and Lasso Lars CV (LLCV). Our strategy was to evaluate these base models and select the best-performing ones in terms of accuracy, to develop a meta-ensemble regressor that utilized both stacking and voting strategies. The selected models were hyperparameter-tuned using empirical knowledge and the grid search method.

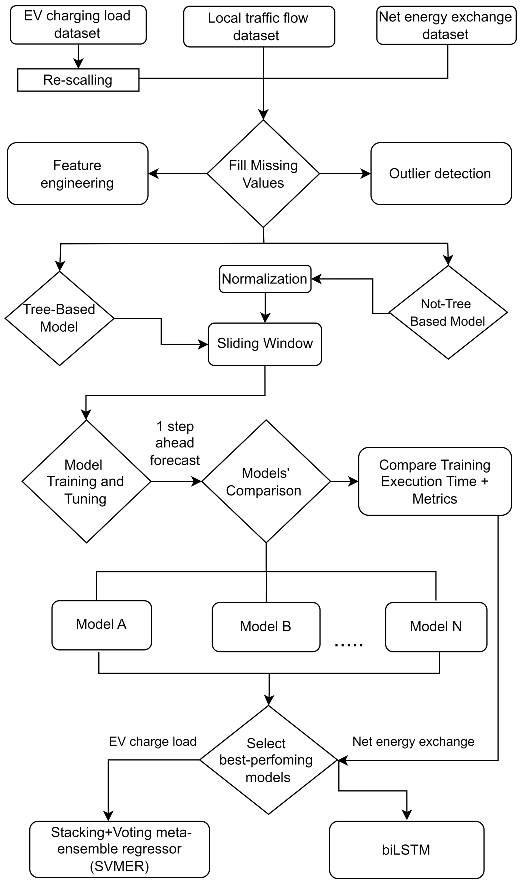


Figure 6. Overview of the forecasting approach.

Let $f_1, f_2, \ldots, f_M$ denote a set of M base regressors trained to forecast the next hour's EV charge load. For an input x, each base model produces a prediction

$$\hat{y}_j(x) = f_j(x), \quad j = 1, 2, \ldots, M.$$

Stacking Strategy: In stacking, the forecasts of the selected base regressors are used as training features to form the vector:

$$\hat{\mathbf{y}}(x) = \begin{bmatrix} \hat{y}_1(x) \\ \hat{y}_2(x) \\ \vdots \\ \hat{y}_M(x) \end{bmatrix},$$

Then, a meta-learner g maps these features to the final output:

$$\hat{y}(x) = g\big(\hat{y}_1(x), \hat{y}_2(x), \ldots, \hat{y}_M(x)\big).$$

Voting Strategy: In this case, the final forecast is computed as the weighted average of the base regressors' forecasts:

$$\hat{y}(x) = \sum_{j=1}^{M} \alpha_j \, \hat{y}_j(x),$$

subject to

$$\sum_{j=1}^{M} \alpha_j = 1 \quad \text{and} \quad \alpha_j \geq 0, \quad \forall\, j.$$

The weights α_j are chosen based on the relative performance of the base models.

Stacking and Voting Meta-Ensemble Regressor (SVMER): In our approach, we selected the best-performing base models based on their observed accuracy. Their predictions were then combined in the stacking framework, where the meta-learner was implemented as a voting regressor:

$$\hat{y}(x) = g\big(\hat{y}_1(x), \ldots, \hat{y}_M(x)\big) = \sum_{j=1}^{M} \alpha_j\, \hat{y}_j(x).$$

For the meta-learner, we selected a combination of linear (LLCV) and tree-based regressors (ET, GB). This selection enables the ensemble to capture both linear trends and potential nonlinear interactions among the base forecasts. To ensure robustness and mitigate overfitting, we employed a 5-fold Cross-Validation (CV) strategy during the meta-learning phase. Specifically, the training data were divided into five equal parts; for each fold, the base regressors were trained on four parts and used to generate predictions on the remaining part. These out-of-fold forecasts served as unbiased inputs for training the voting regressor. Since each forecast is produced by a model that has not been exposed to the corresponding subset of data, this approach yields more reliable estimates of model performance and enhances the overall generalization.

2.4.2. Net Energy Exchange Forecasting

Similarly to the localized EV charge load time series, based on the available historical data, we developed a forecasting model for Norway's net electric energy exchange. Considering that the net energy exchange data comprise a large univariate time series spanning four years (2019–2023), a dataset substantially larger than that used for the local EV charge load, we opted to experiment with DL methods. In particular, RNN architectures were selected, due to their proven ability to capture long-term temporal dependencies in sequential data, especially when trained on extensive datasets. We developed and evaluated three established RNN-based models: Long Short-Term Memory (LSTM), its bidirectional variant (biLSTM), and Gated Recurrent Unit (GRU).

A comprehensive exploration of various network architectures and hyperparameter settings was conducted to optimize the one-step-ahead forecasting accuracy. Key hyperparameters were carefully optimized to balance model complexity and generalization ability. All three models employed a shared stacked architecture consisting of three recurrent layers with dropout regularization. In our configuration, each recurrent layer was set to 24 hidden units, and a dropout rate of 0.2 was applied to mitigate overfitting. We adopted the ReLU activation function and the Adam optimizer.

2.5. Smart Charging Recommendation Framework

In our recommendation framework, we integrate local EV charge load data with Norway's net electric energy fluctuation profile to generate smart charging recommendations. Benefiting the outcomes of the two developed forecasting models, the framework is designed to be reproducible and easily adaptable to diverse use cases and building configurations, making it a versatile tool for residents and EV users to optimize their charging decisions.

The framework determines a confidence level that assesses the energy efficiency of EV charging within the next hour based on the forecast EV charge load and the national net energy exchange. Confidence levels are calculated using a weighting mechanism applied to the forecast values. The weighting is guided by boundary conditions, which are defined based on the data distribution; in particular, the quartiles extracted for the period analyzed (2019). Lower values (below $Q1$) for both the EV charge load and net energy exchange are assigned higher weights, while higher values are penalized. These weights, combined with the forecasting model accuracies (R^2), yield the final confidence level.

We define the forecast variables as follows:

$$F_{\text{EV}} = \text{Forecast EV charging load (kWh)},$$
$$F_{\text{NEE}} = \text{Forecast net energy exchange (MWh)}.$$

The historical quartiles are denoted by

$$Q_{1,\text{EV}}, \quad Q_{3,\text{EV}} \quad (\text{for EV charge load}),$$
$$Q_{1,\text{NEE}}, \quad Q_{3,\text{NEE}} \quad (\text{for net energy exchange}).$$

For any forecast value x (either F_{EV} or F_{NEE}) with corresponding quartiles Q_1 and Q_3, define the weight function as

$$\omega(x; Q_1, Q_3) = \begin{cases} 1, & \text{if } x \leq Q_1, \\ \dfrac{Q_3 - x}{Q_3 - Q_1}, & \text{if } Q_1 < x < Q_3, \\ 0, & \text{if } x \geq Q_3. \end{cases} \tag{1}$$

Thus, the weights for the forecasts are

$$\omega_{\text{EV}} = \omega(F_{\text{EV}}; Q_{1,\text{EV}}, Q_{3,\text{EV}}),$$
$$\omega_{\text{NEE}} = \omega(F_{\text{NEE}}; Q_{1,\text{NEE}}, Q_{3,\text{NEE}}).$$

Let the forecasting accuracies (R^2 values) be:

$$A_{\text{EV}} = \text{Accuracy for the EV charge load model},$$
$$A_{\text{NEE}} = \text{Accuracy for the net energy exchange model}.$$

Using a balancing parameter $\lambda \in [0, 1]$, the overall confidence score C is computed as

$$C = \lambda\, (\omega_{\text{EV}} \cdot A_{\text{EV}}) + (1 - \lambda)\, (\omega_{\text{NEE}} \cdot A_{\text{NEE}}) \tag{2}$$

Finally, the continuous confidence score C is mapped to five discrete probability classes, ranging from 'Very Low' to 'Very High'. These categories aim to provide a qualitative assessment of the confidence in energy-efficient EV charging.

$$\text{Confidence Level} = \begin{cases} \text{Very High}, & \text{if } C \geq 0.8, \\ \text{High}, & \text{if } 0.6 \leq C < 0.8, \\ \text{Medium}, & \text{if } 0.4 \leq C < 0.6, \\ \text{Low}, & \text{if } 0.2 \leq C < 0.4, \\ \text{Very Low}, & \text{if } C < 0.2. \end{cases} \tag{3}$$

The overall methodological concept of the residential recommendation framework is depicted in Figure 7.

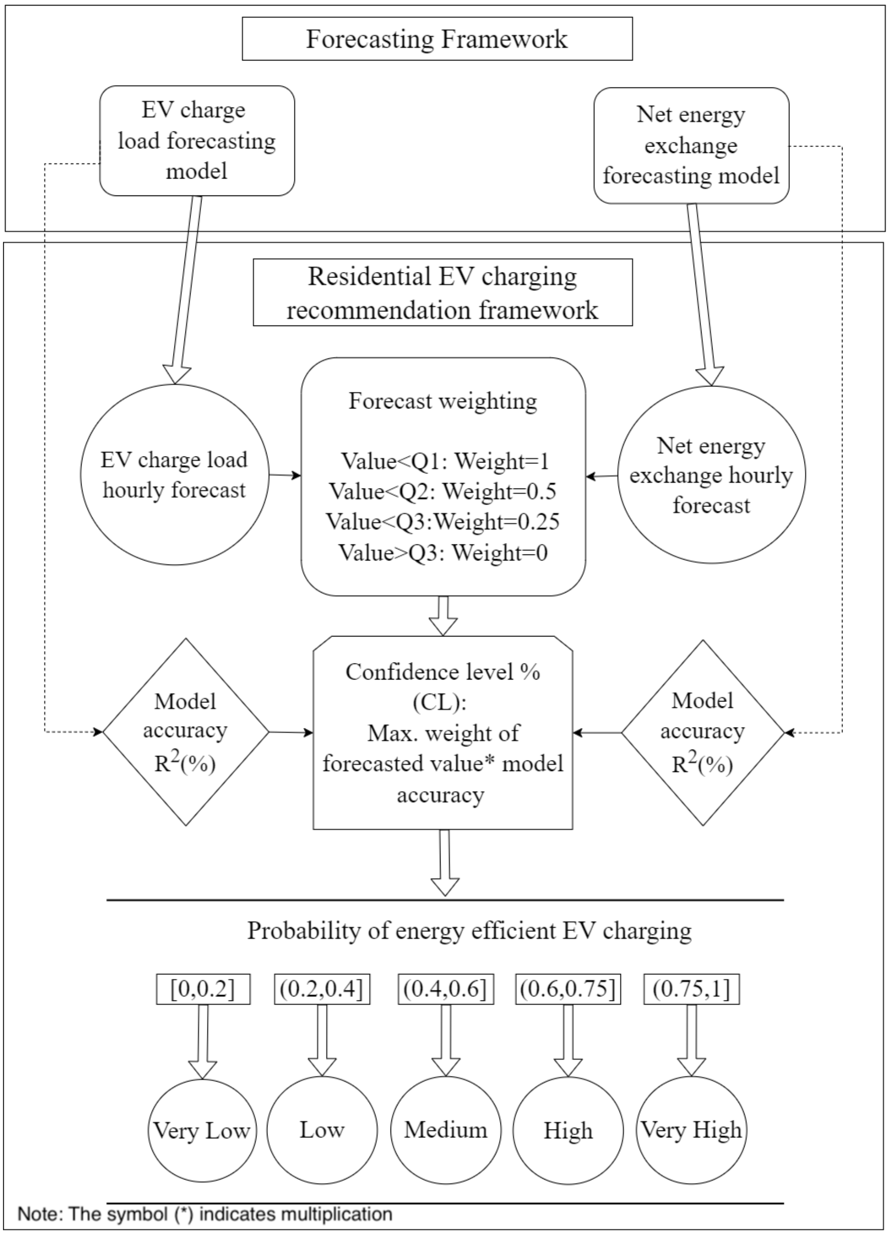


Figure 7. Design overview of the residential EV recommendation framework, based on Equations (1)–(3).

Utilizing the forecasts generated by the trained models and the developed smart charging recommendation methodology, residents and EV users can be promptly notified of favorable charging conditions. These conditions are determined based on two main factors:

- A lower national energy demand, which typically correlates with reduced electricity costs for residential users.
- A short-term assessment of the anticipated charging load, ensuring that the cumulative demand remains within the normal operating power limit of the residential block's charging infrastructure and serving as an indicator of increased availability of shared CP.

3. Experimental Results and Discussion

3.1. Forecasting Results

This research demonstrates a step-by-step approach for forecasting EV charge load and national net energy exchange using both ML and DL models. The experimental results validated the proposed methods, with high forecasting accuracy achieved for both targets. The developed smart charging recommendation framework shows promising potential for guiding EV users to charge during periods of lower grid demand, thereby enhancing energy efficiency and reducing electricity costs. Seasonal variations and external factors (such as weather conditions and traffic diversions) may influence the variability in forecast outcomes.

Table 3 illustrates the base regression models utilized and tested against the SVMER. The results indicate that the developed SVMER model clearly outperformed the base models, providing more accurate forecasts. By combining multiple models, SVMER can aggregate their strengths, reducing the risk that an error in a single base model will disproportionately affect the final prediction and mitigate their weaknesses, leading to improved overall performance.

Table 3. EV charge load forecasting model performance metrics (best values shown in bold).

Model	R^2	RMSE	MAE	CVRMSE	NRMSE
Test data-Garage B12					
SVMER	**0.798**	**1.950**	**1.201**	**0.642**	**0.079**
LGBM	0.758	2.105	1.257	0.708	0.088
HGBR	0.757	2.111	1.266	0.710	0.088
CB	0.763	2.085	1.286	0.701	0.087
XGB	0.735	2.201	1.331	0.740	0.092
DTR	0.696	2.358	1.392	0.793	0.098
KNN	0.655	2.514	1.598	0.845	0.105
RF	0.753	2.127	1.257	0.715	0.089
HR	0.688	2.389	1.352	0.803	0.100
Test data-Garage A1					
SVMER	**0.809**	**0.933**	**0.467**	**0.908**	**0.056**
LGBM	0.775	0.955	0.477	0.932	0.066
HGBR	0.772	0.961	0.485	0.937	0.066
CB	0.776	0.952	0.490	0.928	0.066
XGB	0.750	1.007	0.504	0.982	0.070
DTR	0.719	1.067	0.525	1.041	0.074
KNN	0.524	1.390	0.765	1.355	0.096
RF	0.770	0.965	0.475	0.941	0.067
HR	0.712	1.081	0.494	1.054	0.075
Train data					
SVMER (Garage B12)	0.827	1.417	0.903	0.477	0.059
SVMER (Garage A1)	0.839	0.738	0.389	0.725	0.041

Based on the experimental modeling results, we selected the best-performing base models to develop a meta-ensembling learner (SVMER). The selected models and overall structure of the meta-ensembling learner are depicted in Figure 8.

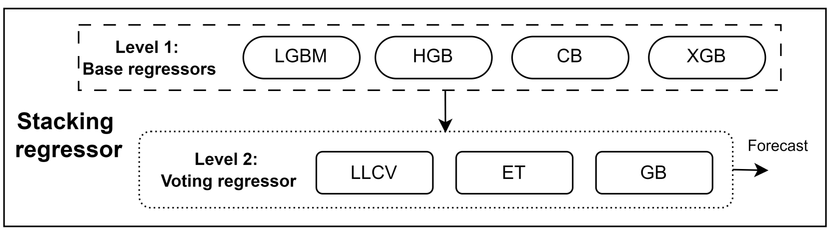


Figure 8. SVMER model primary structure.

For the net energy exchange case, the RNNs proved more accurate than traditional ML algorithms. The results of the tested RNN models showed that all models achieved high forecasting accuracies in predicting the next hour's net energy exchange (Table 4). The observed high forecasting accuracy can be attributed to the clear periodic pattern exhibited by the net energy exchange between daytime and nighttime. This recurring cycle was effectively captured by the implemented RNNs, showcasing their ability to discern and replicate complex temporal dependencies. This was further enhanced by the substantial volume of data used for training (about three years of historical data). The biLSTM model had a slightly better performance, most likely due to its ability to capture both past and future contextual information—a critical factor for modeling complex sequential dependencies. Hence, it was finally chosen to predict the values to be fed into the recommendation framework.

Table 4. Net energy exchange model performance metrics.

Model	R^2	RMSE	MAE	CVRMSE	NRMSE
Test data					
LSTM	0.9617	0.031	0.023	0.061	0.043
biLSTM	0.9624	0.031	0.023	0.06	0.043
GRU	0.9567	0.033	0.024	0.064	0.046

Concerning potential overfitting effects, as illustrated in Figure 9, the training and validation metrics remained closely aligned throughout the training process, showing no significant deviations that would suggest overfitting. Both curves steadily decreased and eventually converged to stable values, indicating that the model was effectively learning underlying patterns in the data, while maintaining a robust generalization performance.

3.2. Charging Recommendations

We selected indicative results for most hours of the day to showcase the outcome of the developed charging recommendation framework, as depicted in Table 5. Initially, we noticed that in certain instances—such as the case on 16 March 2019 at 12:00:00—the probability of efficient charging remained low or medium, despite a negative net energy forecast. This apparent inconsistency is attributable to the balancing parameter, λ, which was set to 0.5 in our study. By assigning equal weight to the net energy forecast and the local EV charge load, the framework allows for the possibility that a high local load, even in the presence of a negative net energy forecast, may moderate the overall recommendation probability.

From a 24 h periodic point of view, during late night hours and very early morning hours, the probability of a more efficient charge was high, likely due to the lower power demand, highlighted by the energy imports. For mid-day and afternoon hours, there was an indication of a low probability of an efficient charge. This can probably be attributed to the fact that these are mostly peak hours in terms of energy consumption on the national grid level and to the high number of EV plug-ins.

Concerning the morning hours (i.e., 06:00–11:00), the patterns seemed less clear in terms of consistency. There were mornings with a low-to-medium probability of efficient charging, but there were also cases with an indication for more efficient charging. This could be partly attributed to fluctuations in the net energy exchange, potentially influenced by weather conditions and seasonal shifts, such as increased solar energy in summer or reduced hydropower during freezing conditions.

Table 5. Smart charging recommendation framework selected results.

Time (Local)	Net Energy Forecast (MWh)	EV Charge Load Forecast (kWh)	Probability of Efficient Charge
2019-03-01 06:00:00	1746.58	0.32	Low
2019-03-01 07:00:00	−815.20	0.70	Medium
2019-03-01 08:00:00	164.16	0.63	Medium
2019-08-16 09:00:00	2744.52	0.35	Low
2019-08-16 10:00:00	1704.57	9.09	Very Low
2019-08-16 11:00:00	1550.41	0.22	Low
2019-03-16 10:00:00	−3436.45	0.22	Very High
2019-03-16 11:00:00	−3389.84	0.19	Very High
2019-03-16 12:00:00	−3494.69	10.05	Medium
2019-04-07 12:00:00	1760.57	0.49	Low
2019-04-07 13:00:00	−1290.92	3.25	Low
2019-04-07 14:00:00	−453.22	6.05	Low
2020-01-29 12:00:00	3130.09	0.13	Low
2020-01-29 13:00:00	2941.38	0.41	Low
2020-01-29 14:00:00	2765.86	6.32	Very Low
2019-07-16 14:00:00	−221.96	0.29	Medium
2019-07-16 15:00:00	−1757.87	0.93	Medium
2019-07-16 16:00:00	1744.21	4.54	Low
2019-07-16 17:00:00	362.66	3.30	Low
2019-07-16 18:00:00	1059.23	4.66	Low
2019-05-08 19:00:00	2462.33	4.67	Very Low
2019-05-08 20:00:00	2168.85	8.59	Very Low
2019-05-08 21:00:00	1986.10	9.89	Very Low
2019-06-01 23:00:00	−2897.51	1.03	Very High
2019-06-02 00:00:00	−2798.59	4.67	High
2019-06-02 01:00:00	−2558.05	0.22	Very High
2019-05-05 02:00:00	−2722.13	5.03	High
2019-05-05 03:00:00	−2584.82	0.17	Very High
2019-05-05 04:00:00	−2490.52	5.75	High
2019-05-05 05:00:00	−2592.87	0.19	Very High

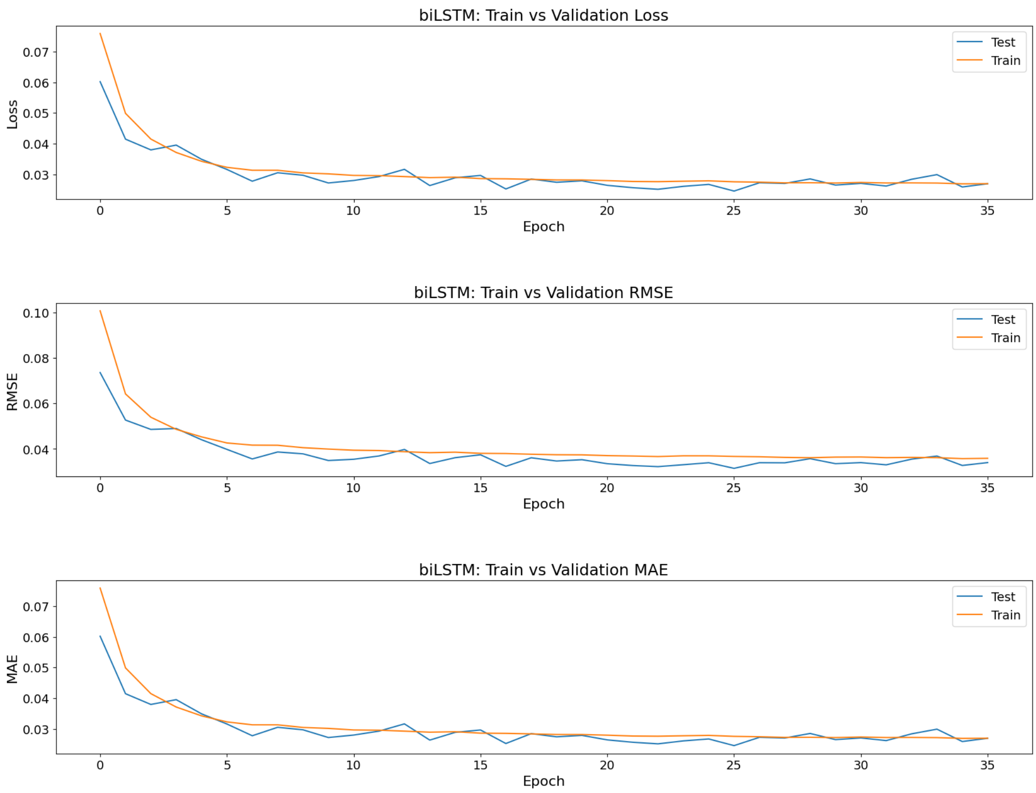


Figure 9. Net energy exchange biLSTM model train–validation metrics.

4. Conclusions

Smart EV charging, empowered by data-driven forecasting methods, has the potential to enhance user decision-making and ensure the optimal operation of local charging infrastructure, while providing the flexibility needed to alleviate peak electricity demand on the grid. This study investigated the time series forecasting of EV charge load and net energy exchange, two critical inputs for a smart EV charging recommendation framework designed to assist residents in making informed charging decisions.

The first step was a one-step time series forecasting of EV charge load and net energy exchange. A variety of ML and DL models were tested, and the best-performing models were selected. In particular, for forecasting EV charge load, a robust meta-learner—referred to as the Stacking and Voting Meta-Ensemble Regressor (SVMER)—was developed by combining multiple base models using stacking and voting strategies. This ensemble approach leveraged the diversity of models to generalize better to unseen data, a crucial aspect in time series forecasting, where future conditions may diverge from historical data.

The second step was to develop a data-driven charging recommendation mechanism. This mechanism suggests optimal strategies for residents to charge their EVs based on the forecasting engine output. It probabilistically identifies prospective periods of low grid-level electricity and local charging demand and advises EV users to charge their vehicles within the next hour. In alignment with the SRI's primary objectives, this empowers residents to optimize energy efficiency by responding to dynamic grid signals, thereby enhancing the overall intelligence and energy performance of their smart homes.

The experimental results revealed that efficient EV charging was typically highest when a negative net energy forecast, indicating a surplus of energy, aligned with a low local EV charge load. In accordance with that, charging efficiency was generally higher during off-peak hours (late night and early morning) and lower during peak periods (mid-day and afternoon). That said, although some recommendations indicated high efficiency, others only achieved moderate or low efficiency, even under favorable grid conditions. This variation is largely driven by the balancing parameter λ, which in our study was set to equally weight the net energy forecast and local EV charge load. Under this configuration, a high local load affects the overall recommendation probability, even when surplus energy is available. The framework also prioritizes the optimal performance of the local charging infrastructure, mitigating the risk of overloading. Additionally, the charging efficiency was generally higher during off-peak hours (late night and early morning) and lower during peak periods (mid-day and afternoon), with some morning variability likely due to weather and seasonal effects.

The added value of our recommendation framework is its inherent adaptability and modular design. Designed to accommodate evolving energy market dynamics, the framework allows seamless integration of additional data streams, such as energy flows from the national grid. This adaptability ensures that the system remains responsive to regional energy variations and policy changes, and thus adaptable to a wide range of geographical locations. Importantly, the framework functions as a decision-making indicator system for residential users, guiding them toward optimal charging times, without attempting to synchronize EV charging with intermittent RESs on a national scale, a task better suited to top-down grid-level management.

4.1. Implications

The outcomes of this study have several broader implications for stakeholders, with a particular focus on benefiting the end-user:

1. Residents of future smart buildings who also drive EVs. The proposed framework offers a user-centric decision support tool that enables them to optimize their charging schedules.
2. Charge Point Operators (CPOs) can offer personalized recommendations to users and implement dynamic pricing and service strategies. For instance, during peak grid

demand, prices at certain charging points might increase to incentivize users to charge at off-peak times or locations with lower grid stress.

3. If implemented on a larger scale, Distribution System Operators (DSOs) and CPOs can collaborate to create more efficient Demand Response (DR) solutions. The predictive capabilities not only support the synchronization of local charging decisions with broader grid conditions but can also help facilitate the incorporation of RESs and Vehicle-to-Grid (V2G) technologies.

4.2. Limitations and Future Work

This work has certain limitations that need to be acknowledged. Starting from the training process, the training dataset was confined to charging data from only two garages, which may not adequately capture the diverse patterns and variations inherent in broader time series datasets. The forecasting engine's predictive performance could benefit from incorporating additional data from a diverse range of case study building complexes with EV infrastructure. This enrichment would ensure that the model more accurately reflects local conditions. In certain cases, the framework produced inconsistent recommendations and lacked a concrete pattern. These findings underscore the need for further research. Potential areas of future expansion involve the following main aspects:

- A more detailed sensitivity analysis of the balancing parameter, λ. Future work should explore the development of an adaptive weighting scheme that dynamically adjusts based on real-time grid conditions and local charging infrastructure constraints, which could further enhance the robustness of the recommendations.
- Enhance the methodology by incorporating multi-step ahead forecasting and expanding the training dataset to include additional charging data and longer timeframes. Validate the models on new data and investigate their improvement in terms of forecasting accuracy and generalization.
- Regarding the cost-effectiveness aspect, the framework could be further enhanced by incorporating Day-ahead Market (DAM) energy price data. This enhancement would enable the framework to provide more accurate recommendations during periods of low electricity pricing. This could contribute to establishing economic incentives for EV users with respect to charging operations.

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

Funding: This research was funded by the EU's LIFE Programme program under grant agreement No. 101077169.

Data Availability Statement: The datasets used for modeling in this study are openly available and can be extracted. EV charge load: Available in Mendeley Data at https://data.mendeley.com/datasets/jbks2rcwyj/1 under the **Creative Commons Attribution (CC BY 4.0)** license (accessed on 10 December 2024). Traffic flow: Can be retrieved from Norwegian Public Roads Administration, Trafikkdata website [52]. Net energy exchange (import/export): Can be retrieved from Statnett [55].

Acknowledgments: The authors would like to thank all the data providers and institutions whose open data repositories made this study possible.

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

Abbreviations

The following abbreviations are used in this manuscript:

A_{EV}	Accuracy (R^2) of the EV charging load forecasting model
A_{NEE}	Accuracy (R^2) of the net energy exchange forecasting model
AMS	Advanced Measurement Systems
biLSTM	bidirectional Long Short-Term Memory
BESS	Battery Energy Storage System
CB	CatBoost
CNN	Convolutional Neural Network
CP	Charging Point
CV	Cross-Validation
CVRMSE	Coefficient of Variation in the Root Mean Square Error
DAM	Day-ahead Market
DR	Demand Response
DSM	Demand Side Management
DL	Deep Learning
DSO	Distribution System Operator
DTR	Decision Tree Regressor
EV	Electric Vehicle
ET	Extra Trees
F_{EV}	Forecast EV charge load (kWh)
F_{NEE}	Forecast net energy exchange (MWh)
GB	Gradient Boosting
GRU	Gated Recurrent Unit
HGBR	HistGradientBoosting Regressor
HR	Huber Regressor
ICEV	Internal Combustion Engine Vehicle
IoT	Internet of Things
KNN	K-Nearest Neighbors
λ	Balancing factor between local charge load & net energy exchange forecasts ($0 \leq \lambda \leq 1$)
LCVF	Load Conservation Valley-Filling
LGBM	LightGBM
LLCV	Lasso Lars Cross-Validation
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MISDP	Multilayer Iterative Stochastic Dynamic Programming
ML	Machine Learning
MLP	Multi-Layer Perceptron
NEE	Net Energy Exchange
NRMSE	Normalized Root Mean Square Error
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
$Q_{1,\text{EV}}$	First quartile of EV charging load
$Q_{1,\text{NEE}}$	First quartile of net energy exchange
PV	Photovoltaics
R2	Coefficient of Determination
RF	Random Forest
RNN	Recurrent Neural Network
RES	Renewable Energy Sources
SC	Smart Charging
SLSQP	Sequential Least Squares Programming
SRI	Smart Readiness Indicator
SVMER	Stacking and Voting Meta-Ensemble Regressor

UMC	User-managed Charging
V2G	Vehicle-to-Grid
XGB	XGBoost

References

1. Alanazi, F. Electric Vehicles: Benefits, Challenges, and Potential Solutions for Widespread Adaptation. *Appl. Sci.* **2023**, *13*, 6016. [CrossRef]
2. Farzaneh, F.; Jung, S. Lifecycle carbon footprint comparison between internal combustion engine versus electric transit vehicle: A case study in the U.S. *J. Clean. Prod.* **2023**, *390*, 136111. [CrossRef]
3. International Energy Agency. *Global EV Outlook 2024: Moving Towards Increased Affordability*; Technical Report; IEA: Paris, France, 2024.
4. Olatomiwa, L.; Mekhilef, S.; Ismail, M.; Moghavvemi, M. Energy management strategies in hybrid renewable energy systems: A review. *Renew. Sustain. Energy Rev.* **2016**, *62*, 821–835. [CrossRef]
5. Ukoba, K.; Olatunji, K.O.; Adeoye, E.; Jen, T.C.; Madyira, D.M. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy Environ.* **2024**, *35*, 3833–3879.
6. Barman, P.; Dutta, L.; Bordoloi, S.; Kalita, A.; Buragohain, P.; Bharali, S.; Azzopardi, B. Renewable energy integration with electric vehicle technology: A review of the existing smart charging approaches. *Renew. Sustain. Energy Rev.* **2023**, *183*, 113518. [CrossRef]
7. Saxena, V.; Manna, S.; Rajput, S.K.; Kumar, P.; Sharma, B.; Alsharif, M.H.; Kim, M.K. Navigating the complexities of distributed generation: Integration, challenges, and solutions. *Energy Rep.* **2024**, *12*, 3302–3322. [CrossRef]
8. Koukaras, P.; Dimara, A.; Herrera, S.; Zangrando, N.; Krinidis, S.; Ioannidis, D.; Fraternali, P.; Tjortjis, C.; Anagnostopoulos, C.N.; Tzovaras, D. Proactive Buildings: A Prescriptive Maintenance Approach. In Proceedings of the Artificial Intelligence Applications and Innovations. AIAI 2022 IFIP WG 12.5 International Workshops, Crete, Greece, 17–20 June 2022; Maglogiannis, I., Iliadis, L., Macintyre, J., Cortez, P., Eds.; Springer: Cham, Switzerland, 2022; pp. 289–300.
9. Boasso, E.; Manganelli, M.; Martirano, L. Impact of EV Charging on the Electric Load of Smart Buildings and Energy Communities. In Proceedings of the 2021 IEEE Industry Applications Society Annual Meeting (IAS), Vancouver, BC, Canada, 10–14 October 2021; pp. 1–7. [CrossRef]
10. Muñiz, R.; del Coso, R.; Nuño, F.; Villegas, P.J.; Álvarez, D.; Martínez, J.A. Solar-Powered Smart Buildings: Integrated Energy Management Solution for IoT-Enabled Sustainability. *Electronics* **2024**, *13*, 317. [CrossRef]
11. Rodriguez-Gil, J.A.; Mojica-Nava, E.; Vargas-Medina, D.; Arevalo-Castiblanco, M.F.; Cortes, C.A.; Rivera, S.; Cortes-Romero, J. Energy management system in networked microgrids: An overview. *Energy Syst.* **2024** . [CrossRef]
12. Chatzikonstantinidis, K.; Giama, E.; Fokaides, P.A.; Papadopoulos, A.M. Smart Readiness Indicator (SRI) as a Decision-Making Tool for Low Carbon Buildings. *Energies* **2024**, *17*, 1406. [CrossRef]
13. Siddique, M.T.; Koukaras, P.; Ioannidis, D.; Tjortjis, C. A Methodology Integrating the Quantitative Assessment of Energy Efficient Operation and Occupant Needs into the Smart Readiness Indicator. *Energies* **2023**, *16*, 7007. [CrossRef]
14. Märzinger, T.; Österreicher, D. Supporting the Smart Readiness Indicator—A Methodology to Integrate A Quantitative Assessment of the Load Shifting Potential of Smart Buildings. *Energies* **2019**, *12*, 1955. [CrossRef]
15. Mu, C.; Liu, W.; Xu, W. Hierarchically Adaptive Frequency Control for an EV-Integrated Smart Grid With Renewable Energy. *IEEE Trans. Ind. Informatics* **2018**, *14*, 4254–4263. [CrossRef]
16. Sidharthan, V.P.; Kashyap, Y.; Kosmopoulos, P. Adaptive-Energy-Sharing-Based Energy Management Strategy of Hybrid Sources in Electric Vehicles. *Energies* **2023**, *16*, 1214. [CrossRef]
17. Korkas, C.D.; Baldi, S.; Yuan, S.; Kosmatopoulos, E.B. An Adaptive Learning-Based Approach for Nearly Optimal Dynamic Charging of Electric Vehicle Fleets. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 2066–2075. [CrossRef]
18. Johnsen, D.; Ostendorf, L.; Bechberger, M.; Strommenger, D. Review on Smart Charging of Electric Vehicles via Market-Based Incentives, Grid-Friendly and Grid-Compatible Measures. *World Electr. Veh. J.* **2023**, *14*, 25. [CrossRef]
19. Henriksen, I.M.; Throndsen, W.; Ryghaug, M.; Skjølsvold, T.M. Electric vehicle charging and end-user motivation for flexibility: A case study from Norway. *Energy Sustain. Soc.* **2021**, *11*, 44. [CrossRef]
20. Ahmad, A.; Khalid, M.; Ullah, Z.; Ahmad, N.; Aljaidi, M.; Malik, F.A.; Manzoor, U. Electric Vehicle Charging Modes, Technologies and Applications of Smart Charging. *Energies* **2022**, *15*, 9471. [CrossRef]
21. Pareek, S.; Sujil, A.; Ratra, S.; Kumar, R. Electric Vehicle Charging Station Challenges and Opportunities: A Future Perspective. In Proceedings of the 2020 International Conference on Emerging Trends in Communication, Control and Computing (ICONC3), Lakshmangarh, India, 21–22 February 2020; pp. 1–6. [CrossRef]
22. Libertson, F. Requesting control and flexibility: Exploring Swedish user perspectives of electric vehicle smart charging. *Energy Res. Soc. Sci.* **2022**, *92*, 102774. [CrossRef]
23. Tuballa, M.L.; Abundo, M.L. A review of the development of Smart Grid technologies. *Renew. Sustain. Energy Rev.* **2016**, *59*, 710–725. [CrossRef]

24. De Dutta, S.; Prasad, R. Digitalization of Global Cities and the Smart Grid. *Wirel. Pers. Commun.* **2020**, *113*, 1385–1395. [CrossRef]
25. Tsalikidis, N.; Mystakidis, A.; Tjortjis, C.; Koukaras, P.; Ioannidis, D. Energy load forecasting: One-step ahead hybrid model utilizing ensembling. *Computing* **2023**, *106*, 241–273. [CrossRef]
26. Wu, Y.; Wang, Z.; Huangfu, Y.; Ravey, A.; Chrenko, D.; Gao, F. Hierarchical Operation of Electric Vehicle Charging Station in Smart Grid Integration Applications—An Overview. *Int. J. Electr. Power Energy Syst.* **2022**, *139*, 108005. [CrossRef]
27. Shi, Y.; Tuan, H.D.; Savkin, A.V.; Duong, T.Q.; Poor, H.V. Model Predictive Control for Smart Grids With Multiple Electric-Vehicle Charging Stations. *IEEE Trans. Smart Grid* **2019**, *10*, 2127–2136. [CrossRef]
28. Al-Ogaili, A.S.; Tengku Hashim, T.J.; Rahmat, N.A.; Ramasamy, A.K.; Marsadek, M.B.; Faisal, M.; Hannan, M.A. Review on Scheduling, Clustering, and Forecasting Strategies for Controlling Electric Vehicle Charging: Challenges and Recommendations. *IEEE Access* **2019**, *7*, 128353–128371. [CrossRef]
29. Sumanasena, V.; Gunasekara, L.; Kahawala, S.; Mills, N.; De Silva, D.; Jalili, M.; Sierla, S.; Jennings, A. Artificial Intelligence for Electric Vehicle Infrastructure: Demand Profiling, Data Augmentation, Demand Forecasting, Demand Explainability and Charge Optimisation. *Energies* **2023**, *16*, 2245. [CrossRef]
30. Crozier, C.; Morstyn, T.; McCulloch, M. The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems. *Appl. Energy* **2020**, *268*, 114973. [CrossRef]
31. Pagani, M.; Korosec, W.; Chokani, N.; Abhari, R. User behaviour and electric vehicle charging infrastructure: An agent-based model assessment. *Appl. Energy* **2019**, *254*, 113680. [CrossRef]
32. Chung, Y.W.; Khaki, B.; Li, T.; Chu, C.; Gadh, R. Ensemble machine learning-based algorithm for electric vehicle user behavior prediction. *Appl. Energy* **2019**, *254*, 113732. [CrossRef]
33. Shahriar, S.; Al-Ali, A.R.; Osman, A.H.; Dhou, S.; Nijim, M. Machine Learning Approaches for EV Charging Behavior: A Review. *IEEE Access* **2020**, *8*, 168980–168993. [CrossRef]
34. Nimalsiri, N.I.; Mediwaththe, C.P.; Ratnam, E.L.; Shaw, M.; Smith, D.B.; Halgamuge, S.K. A Survey of Algorithms for Distributed Charging Control of Electric Vehicles in Smart Grid. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 4497–4515. [CrossRef]
35. Mohanty, S.; Panda, S.; Parida, S.M.; Rout, P.K.; Sahu, B.K.; Bajaj, M.; Zawbaa, H.M.; Kumar, N.M.; Kamel, S. Demand side management of electric vehicles in smart grids: A survey on strategies, challenges, modeling, and optimization. *Energy Rep.* **2022**, *8*, 12466–12490. [CrossRef]
36. Amara-Ouali, Y.; Goude, Y.; Massart, P.; Poggi, J.M.; Yan, H. A review of electric vehicle load open data and models. *Energies* **2021**, *14*, 2233. [CrossRef]
37. Makridakis, S.; Spiliotis, E.; Assimakopoulos, V. M5 accuracy competition: Results, findings, and conclusions. *Int. J. Forecast.* **2022**, *38*, 1346–1364. [CrossRef]
38. Ma, T.; Antoniou, C.; Toledo, T. Hybrid machine learning algorithm and statistical time series model for network-wide traffic forecast. *Transp. Res. Part C Emerg. Technol.* **2020**, *111*, 352–372. [CrossRef]
39. Kożuch, A.; Cywicka, D.; Adamowicz, K. A Comparison of Artificial Neural Network and Time Series Models for Timber Price Forecasting. *Forests* **2023**, *14*, 177. [CrossRef]
40. Helmus, J.R.; Lees, M.H.; van den Hoed, R. A data driven typology of electric vehicle user types and charging sessions. *Transp. Res. Part C Emerg. Technol.* **2020**, *115*, 102637. [CrossRef]
41. Dai, X.; Li, H.; Olanrewaju, I.; Kotter, R.; Putrus, G.; Aslam, N.; Bentley, E.; Wang, Y.; Marzband, M.; Das, R.; et al. Data-Driven EV Charging Load Forecasting and Smart Charging. *Transp. Res. Procedia* **2022**, *72*, 2832–2839. [CrossRef]
42. Kara, E.C.; Macdonald, J.S.; Black, D.; Bérges, M.; Hug, G.; Kiliccote, S. Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach. *Appl. Energy* **2015**, *155*, 515–525. [CrossRef]
43. Brady, J.; O'Mahony, M. Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data. *Sustain. Cities Soc.* **2016**, *26*, 203–216. [CrossRef]
44. Tsalikidis, N.; Koukaras, P.; Ioannidis, D.; Tzovaras, D. Hybrid CNN-LSTM Forecasting Model for Electric Vehicle Charging Demand in Smart Buildings. In Proceedings of the 2024 6th Global Power, Energy and Communication Conference (GPECOM), Budapest, Hungary, 4–7 June 2024; pp. 590–595. [CrossRef]
45. Feng, J.; Chang, X.; Fan, Y.; Luo, W. Electric Vehicle Charging Load Prediction Model Considering Traffic Conditions and Temperature. *Processes* **2023**, *11*, 2256. [CrossRef]
46. Aljohani, T.M. Multilayer Iterative Stochastic Dynamic Programming for Optimal Energy Management of Residential Loads with Electric Vehicles. *Int. J. Energy Res.* **2024**, *2024*, 6842580,
47. Abdelfattah, W.; Abdelhamid, A.S.; Hasanien, H.M.; Rashad, B.A.E. Smart vehicle-to-grid integration strategy for enhancing distribution system performance and electric vehicle profitability. *Energy* **2024**, *302*, 131807. [CrossRef]
48. Souza, G.G.d.; Santos, R.R.d.; Godoy, R.B. Optimizing power grids: A valley-filling heuristic for energy-efficient electric vehicle charging. *PLoS ONE* **2025**, *20*, e0316677. [CrossRef] [PubMed]

49. Promasa, N.; Songkoh, E.; Phonkaphon, S.; Sirichunchuen, K.; Ketkaew, C.; Unahalekhaka, P. Optimization of Sizing of Battery Energy Storage System for Residential Households by Load Forecasting with Artificial Intelligence (AI): Case of EV Charging Installation. *Energies* **2025**, *18*, 1245. [CrossRef]
50. Carvalhosa, S.; Ferreira, J.R.; Araújo, R.E. Electric Vehicle Charging Method for Existing Residential Condominiums. *IEEE Access* **2024**, *12*, 166537–166552. [CrossRef]
51. Sorensen, L.; Lindberg, K.B.; Sartori, I.; Andresen, I. Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data. *Energy Build.* **2021**, *241*, 110923. [CrossRef]
52. Norwegian Public Roads Administration. Trafikkdata. 2023. Available online: https://trafikkdata.atlas.vegvesen.no (accessed on 1 September 2023).
53. Tsalikidis, N.; Mystakidis, A.; Koukaras, P.; Ivaškevičius, M.; Morkunaite, L.; Fokaides, P.; Tjortjis, C.; Tzovaras, D. Urban Traffic Congestion Prediction: A Multi-Step Approach Utilizing Sensor Data and Weather Information. *Smart Cities* **2024**, *7*, 10. [CrossRef]
54. Norwegian Ministry of Energy. Key Facts About the Norwegian Renewable Energy Sector. 2024. Available online: https://energifaktanorge.no/en/norsk-energiforsyning/kraftproduksjon/ (accessed on 30 November 2024).
55. Statnett. Data from the Power System—Statnett. 2023. Available online: https://www.statnett.no/en/for-stakeholders-in-the-power-industry/data-from-the-power-system/#import-and-export (accessed on 1 September 2023).
56. Nord Pool. Day-Ahead Electricity Prices—Nordpool Group. 2023. Available online: https://data.nordpoolgroup.com/auction/day-ahead/prices (accessed on 30 November 2023).
57. Lee, C.H.; Lin, C.R.; Chen, M.S. Sliding-Window Filtering: An Efficient Algorithm for Incremental Mining. In Proceedings of the International Conference on Information and Knowledge Management, Atlanta, GA, USA, 5–10 October 2001; pp. 263–270. [CrossRef]