IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 18 June 2024, accepted 16 July 2024, date of publication 22 July 2024, date of current version 1 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3431992

RESEARCH ARTICLE

Optimizing Electric Vehicle Charging Considering Driver Satisfaction Through Machine Learning

SHAHAB SABZI AND LÁSZLÓ VAJTA
Budapest University of Technology and Economics, 1111 Budapest, Hungary
Corresponding author: Shahab Sabzi (sabzi@iit.bme.hu)

ABSTRACT Electric vehicles (EVs) are essential to the modernization of transportation systems. However, optimizing EV charging to align with grid stability and renewable energy availability remains a challenge. To address this challenge, this study introduces a machine learning-based framework to optimize EV charging by considering driver satisfaction—a novel approach quantifying this multidimensional construct through socio-demographic attributes, State of Charge (SoC), proximity to charging stations, and variable charging fees. *Driver satisfaction* is defined as the extent to which the EV charging experience aligns with drivers' expectations, integrating these key factors to influence decision-making and overall happiness with the charging service. Trained on a dataset from Hungarian EV users, the developed model predicts outcomes with high accuracy (87.9%), leading to an optimization algorithm that maximizes driver satisfaction while minimizing grid power purchase costs. Our results from a simulated smart grid demonstrate the model's effectiveness, achieving an average charging satisfaction score of 98.5% compared to 69.54% from a traditional method. Additionally, the proposed method maintained the SoC of the EV fleet at a stable average around 50%, optimizing energy use and grid stability. By dynamically assigning EVs to charging stations and leveraging photovoltaic sources, our solution not only boosts driver satisfaction but also aids in the sustainable growth of smart grids. This research marks a significant step forward in the smart management of EV charging by introducing a driver-centric optimization model, filling a critical gap in current literature and offering insights into its application in enhancing urban mobility solutions.

INDEX TERMS Electric vehicle, charging satisfaction, machine learning, optimization, driver behavior.

I. INTRODUCTION

Electric vehicles (EVs) are known for their dynamic interactions with smart grids, presenting unique opportunities to enhance both functionality and operational efficiency. However, integrating EVs into the grid also introduces significant challenges, particularly regarding the coordination of charging and the development of grid infrastructure. Without effective charging coordination, the electrical grid may experience severe stress, leading to instability and increased operational costs.

A proven method to prevent this issue is *smart charging*, which aims to optimize benefits for various stakeholders. Most research on EV smart charging has primarily focused on the technical parameters of grids and the financial aspects for aggregators and EVs. However, the critical element of driver satisfaction has often been overlooked. This presents a unique opportunity to propose a smart charging algorithm that places the charging satisfaction of EV drivers (EVDs) at its core. To achieve this, we investigate the human aspects of charging behavior, examining socio-demographic factors that influence charging decisions. By doing so, we aim to create a more user-centric approach to enhance the overall EV experience and promote wider EV adoption.

The associate editor coordinating the review of this manuscript and approving it for publication was Amin Zehtabian.

A. USER BEHAVIORAL RESPONSIVENESS IN ELECTRIC VEHICLE CHARGING

Our research aims to present an AI-supported smart charging solution that takes into account the charging satisfaction of users. Understanding consumer behavior within electrical systems, particularly in the context of EV charging, is crucial as it directly influences the effectiveness of grid management strategies and the adoption rate of smart charging solutions.

Studies have shown that factors such as convenience, cost, and charging time significantly impact an EVD's decision-making process regarding when and where to charge their vehicle [1]. For instance, the availability of charging infrastructure and the perceived reliability of these services are key determinants that influence consumer attitudes towards EVs and their charging habits [2]. Additionally, economic incentives, such as reduced tariffs during off-peak hours, have been effective in motivating EV owners to charge their vehicles at times that benefit grid management and energy efficiency [3]. These behavioral responses to economic incentives can be integrated into AI-driven charging systems, optimizing charging schedules based on grid load forecasts and adapting to the individual preferences and patterns of EV users.

B. SOCIO-DEMOGRAPHIC FEATURES IMPACT ON ENERGY CONSUMPTION

In our study, we consider various socio-demographic factors of EVDs and their effect on charging decisions. Understanding these variables is crucial for optimizing energy use and achieving broader environmental and economic goals.

Research shows that income and education levels significantly affect household energy consumption [4]. Electricity usage is heavily influenced by the ownership of energy-intensive appliances, which is linked to income and household composition [5].

Higher education levels, often associated with awareness and responsible consumption, do not necessarily lead to energy savings. Instead, higher education correlates with greater energy use due to higher incomes [5], [6].

Short-run demand elasticity studies show that immediate electricity demand is influenced by household appliances, with high price elasticity for energy-intensive devices like heating and air-conditioning [7]. Lower-income households are more price-sensitive, while wealthier ones show less elasticity due to owning more appliances [8]. This highlights the challenges in managing household energy use effectively.

Exploring energy consumption behaviors and social factors is crucial as global energy demand rises. Authors in [9] study socio-technical systems, emphasizing daily energy use and policy changes. Despite slow evolution in consumer habits, there is growing focus on how social norms, routines, and networks shape energy consumption [10], [11].

Energy efficiency is influenced by home attributes and resident behaviors. Newer homes, despite energy-efficient features, may not reduce overall consumption due to more appliances [7]. Larger homes require more energy for heating and cooling, using about 70% more electricity than smaller units [12], [13]. Pricing strategies show households respond to electricity price changes, with higher-income households being less sensitive [14], [15].

Interventions to enhance energy efficiency often combine financial incentives with educational measures, helping shape effective energy policies [16]. Providing consumers with adequate information significantly alters their response to electricity pricing [17], [18].

Recent studies focus on non-price factors for optimizing energy conservation without significant investments. Authors in [19] explore how informational interventions like behavioral nudges and energy-saving advice influence household energy use. This approach, particularly relevant in regions like Serbia with low electricity costs but high efficiency potential, uses Randomized Control Trials (RCT) to gain new insights into consumer energy behavior [20], [21].

C. DATA-DRIVEN ELECTRIC VEHICLE CHARGING

This study aims to incorporate socio-demographic factors into the EV charging problem, addressing it as a data-driven challenge. Integrating data-driven strategies into EV charging systems significantly advances our understanding of the practical and behavioral dynamics of EV usage. Researchers have analyzed user preferences and behaviors to optimize EV charging station placement and functionality, emphasizing strategic location choices, initial battery levels, and socio-economic factors.

For instance, user preferences for strategic locations like motorway service areas and shopping centers for fast-charging stations are emphasized by [22]. The proximity of charging stations and initial SoC significantly influence route and charging station choices for battery electric vehicles (BEVs), as discussed by [23]. Specific needs, such as battery level at the start of a journey, dictate route choices, with socio-economic factors influencing preferences for fast charging availability, as noted by [24].

In [25], a system is presented that collects in-use EV and driving data to measure and estimate energy consumption, highlighting a trade-off between minimizing travel time and optimizing energy consumption. The use of travel surveys for EV charging modeling is validated by [26], which indicates that enhanced simulation techniques can predict power demands and infrastructure requirements. Consumer charging patterns, particularly the preference for evening charging, which challenges peak grid load management, are examined by [27]. This highlights the need for effective pricing strategies.

The importance of activity-based modeling to capture detailed interactions between transportation and electricity networks is emphasized by [28]. A stochastic model to evaluate EV impacts on residential electric load profiles, considering socio-economic and behavioral factors, is developed by [29].

Machine learning (ML) methods have also been employed in various aspects of EV data analysis. For example, [30] propose a grey wolf optimizer-based ML algorithm to predict EV charging duration times, reducing inconvenience for drivers. Additionally, [31] utilize real-time data to evaluate US EV charging infrastructure performance, applying ML to user-generated content. The heterogeneity in EVDs' charging behaviors in China, highlighting user satisfaction and risk attitudes, is explored by [32].

Building on these diverse applications of ML in the EV domain, our study further explores the potential of these techniques in enhancing driver satisfaction. We extend the application of ML by focusing on the classification of EV charging satisfaction, a crucial aspect often overlooked. In the next section, we will present our method, where we employ various ML models such as Long Short-Term Memory (LSTM) ([33]), Feed-Forward Neural Network (FFNN) ([34]), Gradient Boosting (GB) ([35]), Random Forest (RF) ([36]), and Support Vector Machine (SVM) ([37]) to predict and enhance the charging satisfaction of EVDs. This approach aims to integrate technical optimization with human-centric considerations, ensuring a more holistic improvement in EV charging infrastructure.

D. CHARGING SATISFACTION

In this study, we define charging satisfaction as the degree to which EVDs are content with the charging time and location offered to them. Initially represented as a binary variable in our dataset (0 for not satisfied and 1 for satisfied), satisfaction is transformed into a continuous variable ranging from 0 to 1 through our predictive model. This continuous value represents the predicted probability of satisfaction, effectively quantifying how likely an EVD is to be satisfied with their charging experience. By translating satisfaction into this measurable quantity, our model not only facilitates the optimization of EV charging station algorithms but also introduces a novel metric within the context of EV research. This metric bridges the gap between human behavioral complexities and technical system requirements, paving the way for smarter, more user-centric EV charging solutions. Subsequently, we develop charging coordination strategies based on these insights.

In literature, satisfaction is a broad concept encompassing various dimensions depending on the context. Generally, satisfaction refers to the fulfillment of an individual's expectations, needs, or desires [38]. It measures how well a product, service, or experience meets the user-set standards. In our study, satisfaction specifically relates to the charging experience of EVDs. Charging satisfaction is influenced by factors such as the availability and convenience of charging stations location, the cost of charging, and the time required to charge their vehicles. This tailored definition allows for a precise measurement and understanding of what drives satisfaction in EV charging, thereby providing actionable insights for improving the EV charging infrastructure and enhancing user experiences. The body of literature on satisfaction with charging is not extensive, and most studies investigate satisfaction with the charging infrastructure. By introducing this continuous measure, we provide a more granular understanding of satisfaction, enabling the development of more effective and user-centric EV charging solutions.

Studies on charging infrastructure satisfaction primarily focus on key factors affecting the overall experience of EVDs. One major aspect is the availability and accessibility of charging stations. Research indicates that a significant proportion of potential EV buyers hesitate to switch from traditional internal combustion engine (ICE) vehicles to EVs due to concerns about the current availability of charging points [39]. For instance, a study found that over 80 percent of respondents considering an EV purchase believe that the existing public charging network is insufficient [40]. Similarly, another study highlighted that public charging access satisfaction has declined, with many EVDs citing poor access as a major drawback [41]. These findings underscore the critical need for expanding the charging infrastructure to match the growing number of EVs on the road [42].

Another crucial factor is the convenience and efficiency of the charging process, including the speed of charging and the cost associated with using public chargers. According to the McKinsey survey [40], 42 percent of respondents indicated that charging speed is their most important consideration when selecting a public charge point, with many expecting charging times of 30 minutes or less. Cost is also a significant factor, with drivers willing to pay more for faster, more convenient charging options. Additionally, the integration of green charging solutions, such as the use of renewable energy, is becoming increasingly important to consumers. About 70 percent of survey participants expressed willingness to pay a premium for green charging options, reflecting a growing environmental consciousness among EVDs. Addressing these factors—availability, convenience, speed, cost, and sustainability—can enhance overall EVD satisfaction and support broader adoption of electric vehicles.

In the study presented in [43], key mechanisms influencing consumer satisfaction, such as perceived control and expectation mismatch were identified. Consumers with higher perceived control over their charging experience and those whose expectations aligned more with reality reported higher satisfaction levels. These findings highlight the importance of managing consumer expectations and enhancing their perceived control over the charging process.

In this article, factors such as SoC, distance to the charging station, and charging fees are considered the most influential on satisfaction. Based on our methodology, the satisfaction of EVDs in charging will be quantified and translated into a numerical measure. This will be a key contribution of this study, proposing a charging plan that considers EVD charging satisfaction not only based on grid and technical parameters but also by incorporating the socio-demographic features of the drivers. This approach ensures that the charging infrastructure meets the diverse needs of all users, promoting a more efficient and user-centric EV charging ecosystem. Given these objectives, the major contributions of this article can be summarized as follows:

1) **Novel Satisfaction Quantification:** We propose a method to quantify and translate EVD charging

satisfaction into a numerical measure, integrating socio-demographic features.

2) **Innovative Charging Plan:** We introduce a charging plan that optimizes both grid parameters and driver satisfaction, considering technical and socio-demographic factors.
3) **Human-Centric Optimization:** Our approach ensures the charging infrastructure considering the diverse needs of users, utilizing an efficient and user-centric EV charging ecosystem.

Continuing from the discussion of our novel human-centric approach to EV charging optimization, the structure of this paper is laid out as follows: Section II investigates the development of the ML model for satisfaction classification, detailing the innovative techniques used to accurately quantify driver satisfaction. In Section III, we describe the optimization algorithm, including its formulation and implementation, and highlight how it dynamically incorporates the participation of various actors in the EV charging process. Section IV presents the results from applying our approach within a simulated smart grid environment, demonstrating the practical effectiveness and potential real-world applicability of our model. Finally, Section V concludes the paper, summarizing our key findings and offering suggestions for future research to further enhance the integration and optimization of EV charging systems.

II. DEVELOPMENT OF THE METHOD FOR CHARGING SATISFACTION CLASSIFICATION

In this section, we develop a ML algorithm for the classification of EVDs' charging satisfaction using a dataset that was prepared based on a survey of questions asked to 225 Hungarian EV users. We refer to them as EV users rather than EV owners because ownership was not a requirement; some participants regularly use EV rental systems and thus need to charge the vehicles. The dataset includes detailed socio-demographic features such as age, gender, education level, income, EV adoption year, and driving experience. It also incorporates specific EV-related attributes, including the SoC of the vehicle, the distance to the charging stations, and the charging fee. Each record in the dataset represents a unique combination of these features, with the target variable indicating the user's charging decision (1 for satisfied, 0 for not satisfied). The framework of the developed algorithm is shown in Figure 1. As illustrated, the model processes these input features to predict the likelihood of an EV user being satisfied with charging their vehicle under specific conditions, effectively classifying their charging satisfaction. The developed model will be used in a higher-level optimization model, which will be explained in detail in the next section.

In order to create the model, we defined nine parameters as inputs for the dataset. The demographic characteristics of the drivers were included in the survey in order to gain a greater understanding of their charging habits. Plus, there were three

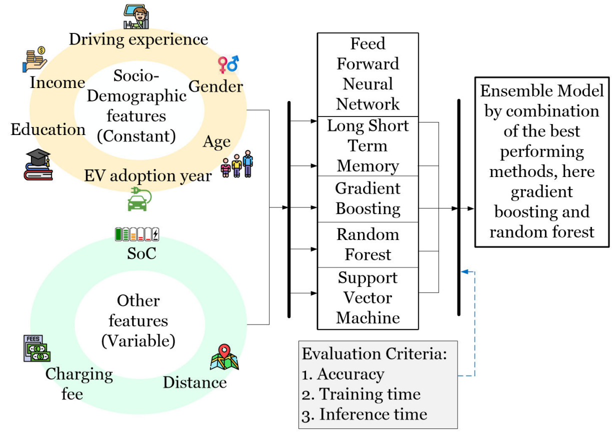


FIGURE 1. Illustration of EV charging classification method.

levels of SoC, three levels of charging fee and three levels of distances. In the survey, each driver was asked 27 questions about different scenarios built upon different SoC levels, charging fees and distances, making in total 6075 rows of data in total (225, the number of drivers time 27 questions). As the response for each question, they had to answer if they would charge their vehicle in a certain scenario or not. In our previous paper, we analyzed deeply the distribution of parameters and effects of each parameter on the charging decisions [44]. It is worth mentioning that in our dataset, out of 6075 observations, 2587 responses were labeled as 'satisfied' (coded as 1). This represents approximately 42.6% of the data, while the remaining 57.4% were labeled as 'not satisfied' (coded as 0). This class distribution highlights that the dataset is not heavily imbalanced, which is important for evaluating the model's performance.

A. IMPORTANCE OF THE FEATURES

It is crucial to know which factors influence the charging satisfaction more. Therefore, Figure 2 shows the importance of each feature based on the charging decision, calculated with a Keras-based model. Specifically, we used the Sequential model from the Keras library in Python, with a dense layer architecture suitable for classification tasks. The feature importance scores were obtained using the permutation_importance method from the sklearn.inspection module, which calculates the importance of each feature by measuring the change in the model's accuracy when the feature values are randomly shuffled. At the forefront is the SoC with a substantial importance score of 34.9%. This highlights the pivotal role played by the current battery charge level in determining whether drivers choose to charge their EVs. Following closely is the charging fee feature, with an importance score of 21.7%, indicating that the cost associated with charging also weighs heavily in the decision-making process. Additionally, the distance to be covered holds notable importance 17.8%, reflecting its impact on drivers' choices. The analysis further highlights the relevance of factors such as the EV adoption year (7.3%), income (5.9%),

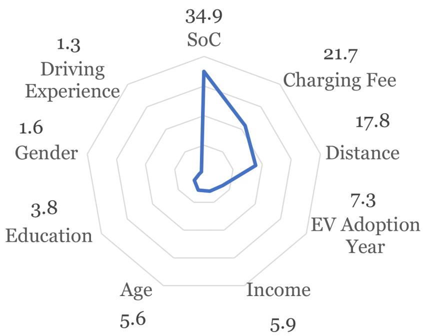


FIGURE 2. Importance of each feature based on the impact on the charging decisions.

age (5.6%), education (3.8%), gender (1.6%) and driving experience (1.3%) in influencing EV charging preferences.

B. CHARGING SATISFACTION PREDICTION METHOD

Predicting the charging satisfaction of EVDs involves complex variables that range from the technical specifications of charging infrastructure to the personal and socio-demographic characteristics of the drivers. To navigate this complexity, our study introduces an ensemble method designed to leverage the collective strengths of several ML models, thereby enhancing prediction robustness and accuracy. Initially, we explored different models, including SVM, FFNN, RF, GB, and LSTM, each chosen for its unique ability to capture different aspects of the data set.

Given the vast potential of these models, we hypothesized that an ensemble approach could offer superior predictive performance by integrating the diverse insights provided by each model. This hypothesis is grounded in the ensemble method ability to aggregate outputs from the RF and GB models, selected for their balanced efficiency in terms of training and inference times, as well as commendable accuracy, meaning the share of true responses the algorithm can predict correctly.

The foundation of our ensemble approach is the mathematical combination of probability predictions from the RF and GB models. The ensemble prediction (P_{ensemble}) is calculated using the equation:

$$P_{\text{ensemble}} = \frac{P_{\text{RF}} + P_{\text{GB}}}{2} \tag{1}$$

where P_{RF} and P_{GB} are the vectors of probability predictions for the positive class from the RF and GB models, respectively. We apply a threshold $T = 0.5$ to these averaged probabilities to classify predictions as 'satisfied' or 'not satisfied'. Key parameters for both models include `n_estimators`, set to 100 to balance model complexity and performance, and `random_state`, used to ensure reproducibility of results by controlling the random number generation process. These parameters help manage the trade-off between model accuracy and overfitting while maintaining consistency across multiple runs.

The examination of the six predictive models presented in Table 1 reveals a detailed landscape of trade-offs between accuracy, training time, inference time per sample, F1 score (the harmonic mean of the precision and recall of a classification model), and precision. SVM achieves an accuracy of 87.3%, demonstrating the model's robustness in handling complex classification tasks, but it has a relatively higher training time of 3.03 seconds. The SVM also achieved a precision of 81.9% and an F1 score of 85.7%. FFNN, while more accurate at 88.1%, has a significantly longer training duration (19.26 seconds), suggesting a computational intensity that might not be ideal for rapid deployment scenarios. It also shows a precision of 82.1% and an F1 score of 86.7%, which are comparable to the SVM.

Both RF and GB models offer a compelling balance, with quicker training times (0.88 and 0.60 seconds, respectively) and quick inference times (0.035 and 0.006 milliseconds, respectively) and competitive accuracies (87.3% and 86.0%, respectively). The RF and GB models also demonstrate the same precisions (81.9%) and F1 scores (85.7% and 83.9%). LSTM's longer inference time (0.671 milliseconds) and lower accuracy (85.3%) indicate its suitability for scenarios where temporal dynamics are critical, despite the computational overhead. Its precision and F1 score (83.4% and 82.5%) reflect its ability to capture complex temporal patterns.

Given these considerations, developing an ensemble model based on RF and GB provides a suitable balance of time and accuracy. This method also achieves a precision of 82.2% and an F1 score of 86.5%. The ensemble's operational efficiency is further highlighted by its inference time per sample of 0.037 milliseconds, showcasing its feasibility for deployment in dynamic, real-time environments. This is particularly relevant in the context of smart grids, where timely decision-making can greatly influence overall system efficiency and user satisfaction.

III. CHARGING OPTIMIZATION ALGORITHM

The ensemble prediction model developed in the previous section is used to predict the charging satisfaction of EV users if we have information such as their socio-demographics, location, SoC of their vehicle, and charging fee at the charging station. This way, we can coordinate the charging of EVs, taking into account the satisfaction of EVDs.

Figure 3 shows the participants in the algorithm and the type of data received from each one of them. There are three main actors involved in our system: EVs (and EVDs), charging station operators, and the utility company. The system is assumed to be controlled by an aggregator, whose responsibility is to coordinate all actors and bring the system to an optimized point where all actors benefit in some way, which will be investigated. As mentioned, from each actor, a set of data is received, which will be used in the optimization problem.

The information regarding the maximum allowed purchased power from the grid at each hour ($P^t_{G,\max}$), data

TABLE 1. Model performance comparison.

Method	Accuracy (%)	Training Time (s)	Inference Time per Sample (ms)	F1 Score (%)	Precision (%)	Recall (%)
SVM	87.3	3.03	0.111	85.7	81.9	89.9
FFNN	88.1	19.26	0.003	86.7	82.1	91.8
Random Forest	87.3	0.88	0.035	85.7	81.9	89.9
Gradient Boosting	86.0	0.60	0.006	83.9	81.9	86.0
LSTM	85.3	14.94	0.671	82.5	83.4	81.7
Ensemble	87.9	N/A	0.037	86.5	82.2	91.3

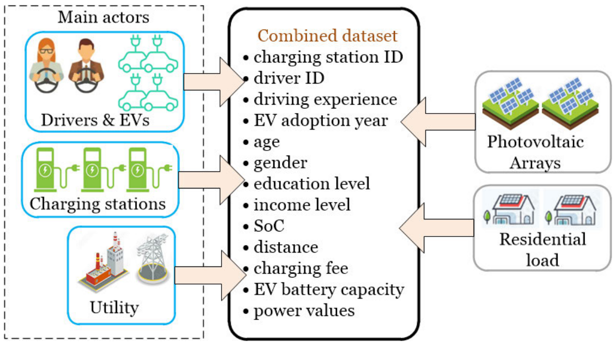


FIGURE 3. The sources of data with the dataset of all actors.

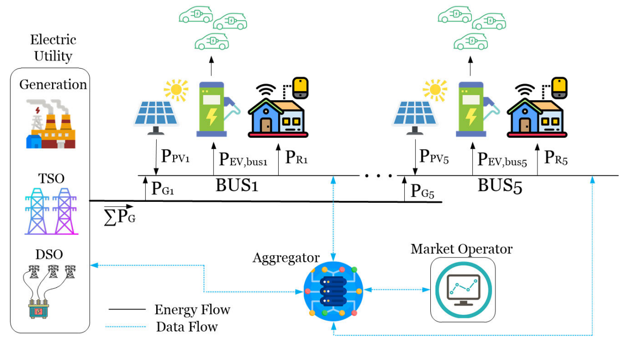


FIGURE 4. Schematic illustration of the system configuration. This schema shows the energy and data flow between various components in the smart grid.

regarding the power generated by PVs at each hour ($P^t_{PV,j}$), and predicted data regarding the residential load ($P^t_{R,j}$) are received frim the grid and residential actors. From the charging stations, information such as the location of the charging station ($L_{CS,j}$), the number of available charging points (Av^t_j), and charging price ($C^t_{ch,j}$) are received. The main actor is the EV, which gives us information regarding the driver's age, gender, driving experience, education level, EV adoption year, income level, SoC level, location ($L_{EV,i}$), and EV battery maximum capacity ($P_{EV,\text{capacity},i}$).

From all this information, a unified dataset of $I \times J$ rows is created, consisting of a combination of each EV user (indexed by i) for each charging station (indexed by j). Specifically, the letter i corresponds to individual EV users, j corresponds to charging stations, and t represents the time index. The constants I and J represent the total number of EV users and charging stations, respectively. The required features to predict whether an EV user will be satisfied with charging at a charging station are obtained here. Distance is calculated as a function of the location of the drivers and charging stations:

$$D_{i,j} = f(L_{EV,i}, L_{CS,j}) \tag{2}$$

In this equation, $D_{i,j}$ represents the shortest distance between the i-th EV and the j-th charging station. The function $f(L_{EV,i}, L_{CS,j})$ computes the road distance, which reflects the actual driving distance. This approach takes into account the practical considerations of EV users who are driving to the charging stations and represents real-world travel paths.

Then, Based on our ensemble model developed in the previous section, for all combinations of each EV user for each charging station, a satisfaction factor $S^t_{i,j} \in [0, 1]$ is determined, which shows how satisfied each EV user will be if assigned to the corresponding charging station.

A. ELECTRICAL SYSTEM CONFIGURATION

Figure 4 shows the system configuration under study. The network is considered a residential area consisting of five buses with residential loads, public charging stations, and EVs. Apart from the main actors, there are PV panels on each bus to support the grid whenever possible. The main objective is to place the EVs at charging stations while maximizing the satisfaction factor of individual drivers and minimizing the cost of power purchased from the main grid.

B. OBJECTIVE FUNCTION

The main objective is to place the EVs on charging stations while maximizing the satisfaction factor of individual drivers and minimizing the cost of power purchased from the main grid. Therefore, the objective function is defined as follows:

$$\text{Maximize} \left(\alpha \sum_{i=1}^{I} \sum_{j=1}^{J} \mathbf{X}^t_{i,j} S^t_{i,j} - \beta \sum_{j=1}^{J} P^t_{G,j} C^t_G \right) \tag{3}$$

In this equation, $\mathbf{X}^t_{i,j}$ is the binary decision variable that determines if driver i is assigned to charging station j at time t. Each $S^t_{i,j}$ represents the satisfaction factor for driver i at charging station j. The coefficients α and β are positive real numbers that serve as weights assigned to the terms of the objective function, allowing the optimization to balance between maximizing driver satisfaction and minimizing power purchase costs. The specific values of α and β can be adjusted based on the desired emphasis on either objective.

The second term of the objective function seeks to minimize the cost of purchasing electrical power from the main grid and encourages the efficient use of energy resources. In this context, $P^t_{G,j}$ denotes the power drawn from the grid to supply bus j, and C^t_G is the cost per unit of purchased power. As all buses are supplied from the same grid, this cost parameter is universal for all. By adjusting the values of α and β, the optimization algorithm can be fine-tuned to prioritize one objective over the other or to find a balanced compromise between maximizing driver satisfaction and minimizing power purchase costs.

C. CONSTRAINTS

The power balance constraint, ensuring that the total power purchased from the grid and the PV system is sufficient to meet the combined demands of residential loads and EV charging, is expressed as:

$$P^t_{G,j} + P^t_{PV,j} \geq P^t_{R,j} + \sum_{i=1}^{I} \mathbf{X}^t_{i,j} P^t_{EV,i} \quad \forall j \in \{1, \ldots, J\} \quad (4)$$

The power required by each EV, denoted as $P^t_{EV,i}$, is computed based on the SoC and battery capacity of the vehicle:

$$P^t_{EV,i} = \mathrm{SoC}^t_{EV,i} \times P_{EV,\text{capacity},i} \quad (5)$$

where $\mathrm{SoC}^t_{EV,i}$ represents the SoC of the i-th EV at time t, and $P_{EV,\text{capacity},i}$ is the maximum capacity of the i-th EV battery.

Each EV can be assigned to only one charging station at a time. This constraint ensures that no EV is assigned to more than one charging station:

$$\sum_{j=1}^{J} \mathbf{X}^t_{i,j} \leq 1 \quad \forall i \in \{1, \ldots, I\} \quad (6)$$

Additionally, the number of drivers assigned to each charging station must not exceed the number of available charging points at that station (Av^t_j):

$$\sum_{i=1}^{I} \mathbf{X}^t_{j,i} \leq \mathrm{Av}^t_j \quad \forall j \in \{1, \ldots, J\} \quad (7)$$

The total power drawn from the grid by all charging stations must not exceed the grid's maximum power capacity:

$$\sum_{j=1}^{J} P^t_{G,j} \leq P^t_{G,\max} \quad (8)$$

To ensure that drivers are assigned to charging stations where they are likely to be satisfied, a minimum satisfaction threshold must be met:

$$\mathbf{X}^t_{i,j} S^t_{i,j} \geq \mathbf{X}^t_{i,j} S^t_{i,j,\min} \quad \forall i \in \{1, \ldots, I\},\ \forall j \in \{1, \ldots, J\} \quad (9)$$

$S^t_{i,j,\min}$ is the minimum satisfaction of drivers charged, which we define as the lowest acceptable level of satisfaction that ensures the driver's experience at the charging station is positive. By setting this threshold, we aim to guarantee a certain standard of service quality and optimize the allocation process to maintain driver satisfaction. In the simulations, we set this parameter to 0.5.

The placement matrix, shown in Equation 10, represents the assignment of EVs to charging stations at time t. Each element $\mathbf{X}^t_{i,j}$ in the matrix indicates whether the i-th EV is assigned to the j-th charging station (1 if assigned, 0 otherwise). This matrix is crucial for achieving the highest value of the objective function defined earlier, with a greater weight α and a smaller weight β used in the optimization to balance between satisfaction and cost.

$$\mathbf{X}^t_{i,j} = \begin{bmatrix} x^t_{1,1} & x^t_{1,2} & \cdots & x^t_{1,J} \\ x^t_{2,1} & x^t_{2,2} & \cdots & x^t_{2,J} \\ \vdots & \vdots & \ddots & \vdots \\ x^t_{I,1} & x^t_{I,2} & \cdots & x^t_{I,J} \end{bmatrix} \quad (10)$$

Figure 5 illustrates the complete optimization algorithm, which is divided into three main phases: Classification, Optimization, and Data Update.

IV. RESULTS AND DISCUSSION

The algorithm's effectiveness was evaluated in a simulated smart grid environment, designed to mirror a small-scale urban setting. This simulated network encompasses five distinct neighborhoods, each serviced by a separate bus network as depicted in Figure 4. These buses link residential areas, PV power sources, and public EV charging stations, creating an integrated model of a smart urban grid. During a comprehensive 24-hour simulation period, we monitored a variety of data points including residential demand for each bus, PV output, charging fees for EVs at public charging stations, as illustrated in Figure 6 through Figure 8. Notably, the charging fees were set artificially to emulate a dynamic pricing environment that reflects a feasible future scenario. While these fees were crafted for the purposes of our simulation, they were designed to stay within realistic bounds, aiming to provide insights into the system's capacity to adapt to and accommodate future pricing models. This approach allows us to explore the implications of varying charging fees on EV charging behavior and grid performance, offering a glimpse into a future where dynamic pricing plays a pivotal role in optimizing smart grid operations.

The algorithm's operation throughout a 24-hour cycle dynamically assigns EVs to charging stations. Notably, the data from the first hour, as presented in Table 2, showcases high 'Charging Satisfaction' scores with an average of 98.5%, indicating the algorithm's effectiveness in aligning with driver preferences. This high level of satisfaction, achieved despite the variations in distances and fees, suggests that the model balances multiple factors to optimize the charging experience. Such a balanced approach is crucial for the successful integration of EVs into the grid and demonstrates the proposed method's superiority in accommodating drivers' needs. In contrast, we also explored a more traditional method of charging coordination for comparison, which

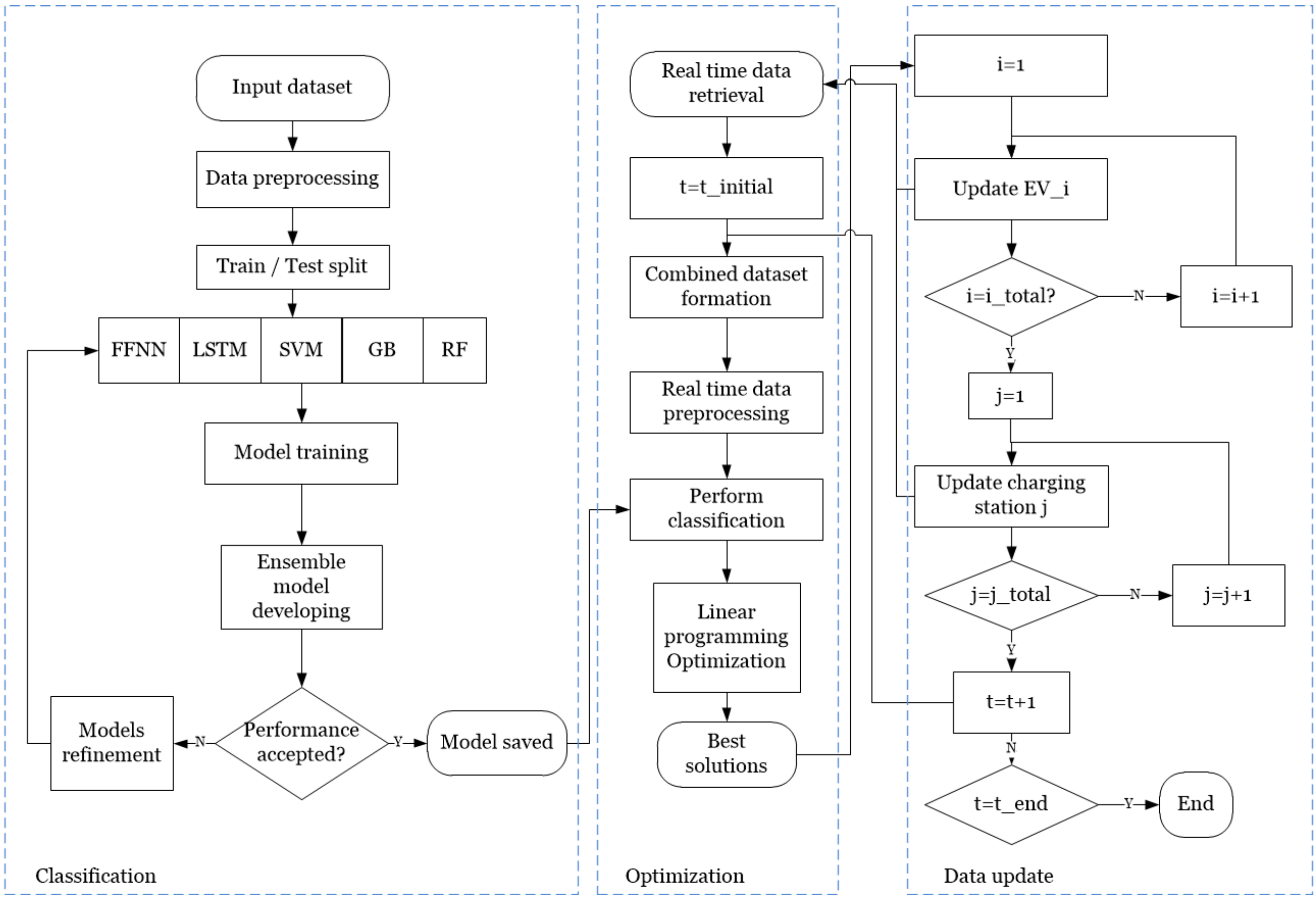


FIGURE 5. The algorithm of the proposed method, including three stages, classification, optimization and data update.

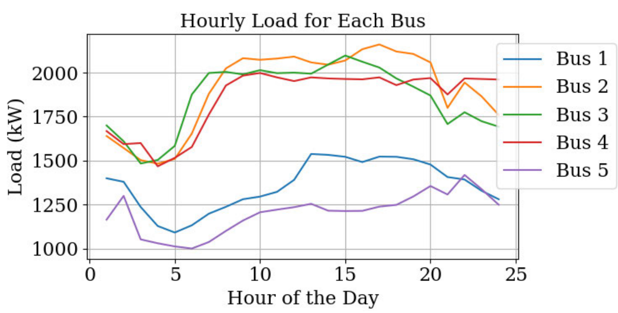


FIGURE 6. The residential load on different buses during 24 hours.

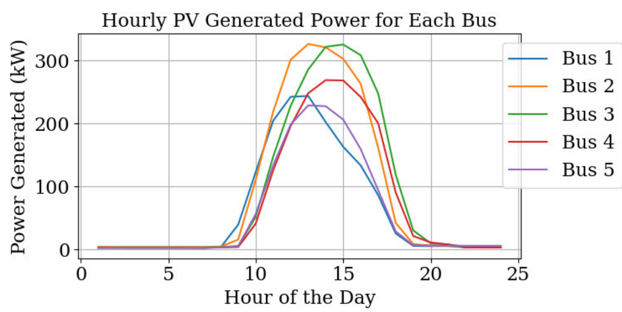


FIGURE 7. PV power on different buses during 24 hours.

prioritizes EVs based solely on their proximity to the charging station and considers vehicles with SoCs up to 50%. While this method is simpler and may be less computationally demanding, it misses the complete set of variables that can influence charging satisfaction. Consequently, this traditional approach resulted in a lower average satisfaction score of 69.5%, illustrating the potential for less reliable satisfaction outcomes. This stark difference in satisfaction scores—98.5% for the proposed method versus 69.5% for the random method—underscores the importance of employing multi-faceted decision-making frameworks in EV charging station allocation. By doing so, it is possible to satisfy more effectively the needs of EVDs and the power grid, thereby enhancing the overall charging infrastructure.

Figure 9 represents the average SoC of the EV fleet over a 24-hour simulation period. The SoC mean oscillates with minor fluctuations, maintaining a relatively stable average close to 50%, suggesting a balanced charging strategy. Starting at 49.27%, the SoC mean peaks at 51.20% towards the end of the day, indicating a gradual increase in charge levels as the algorithm adapts to the vehicles' requirements and grid conditions. This consistent SoC maintenance across the fleet signifies an efficient management of charging

TABLE 2. EV placement and charging satisfaction in the first hour.

CS ID	Proposed Method					Random Charging				
	EV ID	Fee	SoC	Dist.	Sat. (%)	EV ID	Fee	SoC	Dist.	Sat. (%)
1	121	Avg.	Low	Close	99.9%	4	Avg.	Low	Close	98.9%
1	86	Avg.	Low	Close	98.5%	20	Avg.	Med.	Close	77.4%
2	45	Avg.	Low	Close	99.9%	77	Avg.	Low	Close	96.6%
2	83	Avg.	Low	Close	98.9%	89	Avg.	Low	Close	92.5%
3	103	Avg.	Low	Close	94.6%	138	Avg.	Med.	Close	36.4%
3	104	Avg.	Low	Avg.	99.2%	40	Avg.	Med.	Close	82.9%
4	17	Blw. Avg.	Low	Close	99.4%	80	Blw. Avg.	Low	Close	93.2%
4	18	Blw. Avg.	Low	Close	99.4%	94	Blw. Avg.	Med.	Close	94.8%
5	13	Abv. Avg.	Low	Avg.	97.7%	3	Abv. Avg.	Med.	Close	17.1%
5	150	Abv. Avg.	Low	Close	98.4%	119	Abv. Avg.	Med.	Close	5.6%

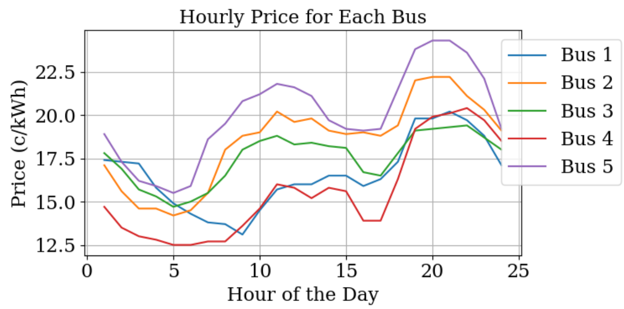


FIGURE 8. Charging fees on each bus during 24 hours.

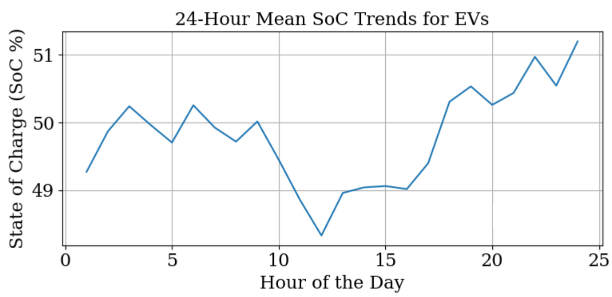


FIGURE 9. 24-Hour average SoC trends for all EVs.

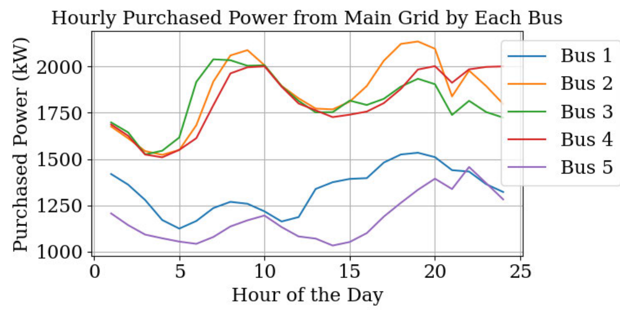


FIGURE 10. Hourly purchased power at each bus at each hour by the optimization algorithm.

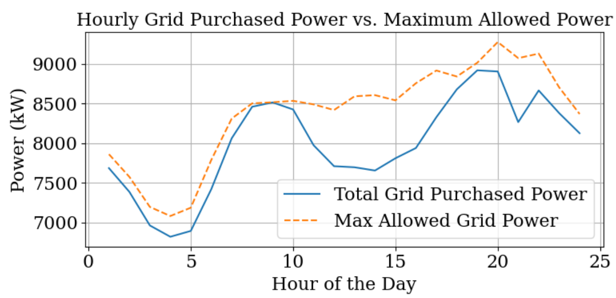


FIGURE 11. Hourly comparison of optimized purchased power sum and maximum grid capacity over a 24-hour period.

schedules, ensuring that vehicles are adequately charged while mitigating the risk of overloading the grid during peak hours, thus contributing to the overall reliability and sustainability of the smart grid system.

Figure 10 stages a power allocation across the five buses over a 24-hour period. Notably, Bus 2 consistently registered higher purchased power values, peaking at 2135 kW at 19 o's clock. Conversely, bus 5's has the lowest purchased power from the grid with a peak of 1457 kW at 22 o's clock, potentially indicating areas with lower power demands. The temporal purchased power trends align with the expected load profiles, demonstrating the algorithm's ability to adapt power distribution in real-time. This responsiveness ensures the optimization of the grid's performance, balancing the complex dynamics between EV charging demand, renewable energy input, and grid stability.

Additionally, the alignment of purchased power $P^t_{G,j}$ with the grid's maximum power capacity $P^t_{G,\max}$ is crucial for maintaining the constraint in Equation 8. Figure 11 illustrates the sum of hourly purchased power across all buses and the maximum allowed power that can be purchased from the grid. Throughout the 24-hour period, the $P^t_{G,j}$ values consistently approach but do not exceed the prescribed $P^t_{G,\max}$ thresholds, showcasing the algorithm's effectiveness in optimizing power distribution. Particularly noteworthy is the algorithm's responsiveness during peak hours (around 8 and 9 AM), where it shifts the purchased power to avoid overloading the grid, hence maintaining a stable and reliable energy supply. This balance is critical to integrating EVs into the smart grid, ensuring that the charging demand does not compromise grid integrity. Mid-day solar effects further influence this dynamic.

Figure 12 illustrates the comparison between the sum of total power purchased from the grid and power generated by photovoltaic sources ($\sum_{j=1}^{J} P^t_{G,j} + \sum_{j=1}^{J} P^t_{PV,j}$) and the total residential power consumption ($\sum_{j=1}^{J} P^t_{R,j}$) over a 24-hour period. The grey area represents the EV power consumption, which is the difference between the power injected to all

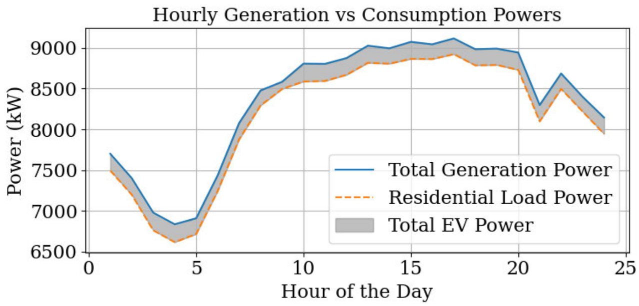


FIGURE 12. **Hourly comparison of generation and demand powers over 24 hour period.**

buses (by the grid and PVs) and the residential consumption, indicating the surplus energy available for EV charging. The figure displays the dynamics of energy production and usage, which is a key consideration in optimizing charging schedules to ensure grid stability and efficient use of renewable energy.

V. CONCLUSION

In this study, we presented a novel smart charging approach to optimize EV charging by incorporating machine learning algorithms to predict driver satisfaction and integrate these predictions into an optimization framework. Our methodology emphasizes not only the alignment of EV charging strategies with grid stability and renewable energy availability but also places a significant focus on the human aspect of EV charging —driver satisfaction. Through the development of a classification model based on driver satisfaction, we achieved a high accuracy of 87.9% in predicting charging behaviors. This high accuracy facilitated the creation of an optimization algorithm that balances energy supply, demand, and user preferences. Additionally, the ensemble method achieved an F1 score of 86.5% and a precision of 82.2%, indicating a balanced performance in precision and recall metrics.

The simulation results within a smart grid environment demonstrate the effectiveness of our approach in enhancing grid efficiency, maximizing the utilization of PV sources, and improving driver satisfaction. Key findings reveal that the SoC and charging fees are pivotal factors influencing charging decisions, with the model achieving an average charging satisfaction score of 98.5% compared to 69.5% from a traditional method. The algorithm maintained the SoC of the EV fleet at a stable average of 50.26%, optimizing energy use and grid stability.

However, it is essential to acknowledge the limitations of our study, primarily the reliance on a dataset limited to Hungarian EV users, which may affect the generalizability of the findings. Future research should aim to validate the model across different demographics and geographic regions, as well as incorporate real-time data feeds to further enhance the model's accuracy and applicability. Additionally, exploring the integration of V2G technologies and assessing the economic and environmental impacts of widespread adoption of our optimization strategy could provide valuable insights for policymakers, grid operators, and EV manufacturers.

In conclusion, this research marks a significant step forward in the smart management of EV charging, offering a scalable and adaptable solution that supports the transition towards sustainable transportation while aligning with broader goals of energy efficiency and grid stability. The broader adoption of our algorithm could have far-reaching effects on EV acceptance, traffic management, and the economic landscape of energy consumption. Future research should aim to further explore these implications, offering concrete strategies for stakeholders in the transition towards more sustainable and efficient transportation and energy systems. By bridging the gap between technical optimization and user satisfaction, we pave the way for a more integrated, responsive, and user-friendly EV charging infrastructure.

REFERENCES

[1] I. Ullah, K. Liu, S. B. Layeb, A. Severino, and A. Jamal, "Optimal deployment of electric Vehicles' fast-charging stations," *J. Adv. Transp.*, vol. 2023, pp. 1–14, Apr. 2023, doi: 10.1155/2023/6103796.

[2] P. Patil, K. Kazemzadeh, and P. Bansal, "Integration of charging behavior into infrastructure planning and management of electric vehicles: A systematic review and framework," *Sustain. Cities Soc.*, vol. 88, Jan. 2023, Art. no. 104265, doi: 10.1016/j.scs.2022.104265.

[3] G. A. Ogunkunbi, H. K. Y. Al-Zibaree, and F. Meszaros, "Modeling and evaluation of market incentives for battery electric vehicles," *Sustainability*, vol. 14, no. 7, p. 4234, Apr. 2022, doi: 10.3390/su14074234.

[4] J. Zheng, Y. Dang, and U. Assad, "Household energy consumption, energy efficiency, and household income–evidence from China," *Appl. Energy*, vol. 353, Jan. 2024, Art. no. 122074, doi: 10.1016/j.apenergy.2023.122074.

[5] A. Paul, R. Subbiah, A. Marathe, and M. Marathe, "A review of electricity consumption behavior," Consortium Building Energy Innov. (CBEI), U.S. Dept. Energy, Washington, DC, USA, Tech. Rep. DE-EE0004261, Feb. 2012.

[6] E. Leahy and S. Lyons, "Energy use and appliance ownership in Ireland," *Energy Policy*, vol. 38, no. 8, pp. 4265–4279, Aug. 2010, doi: 10.1016/j.enpol.2010.03.056.

[7] P. C. Reiss and M. W. White, "Household electricity demand, revisited," *Rev. Econ. Stud.*, vol. 72, no. 3, pp. 853–883, Jul. 2005, doi: 10.1111/0034-6527.00354.

[8] F. Zhang, "Energy price reform and household welfare: The case of Turkey," *Energy J.*, vol. 36, no. 2, pp. 71–96, Apr. 2015, doi: 10.5547/01956574.36.2.4.

[9] R. Galvin, "Economic inequality, energy justice and the meaning of life," in *Inequality and Energy*, R. Galvin, Ed., New York, NY, USA: Academic, 2020, pp. 75–96, doi: 10.1016/B978-0-12-817674-0.00004-7.

[10] M. Jürisoo, N. Serenje, F. Mwila, F. Lambe, and M. Osborne, "Old habits die hard: Using the energy cultures framework to understand drivers of household-level energy transitions in urban Zambia," *Energy Res. Social Sci.*, vol. 53, pp. 59–67, Jul. 2019, doi: 10.1016/j.erss.2019.03.001.

[11] M. Tesfamichael, C. Bastille, and M. Leach, "Eager to connect, cautious to consume: An integrated view of the drivers and motivations for electricity consumption among rural households in Kenya," *Energy Res. Social Sci.*, vol. 63, May 2020, Art. no. 101394, doi: 10.1016/j.erss.2019.101394.

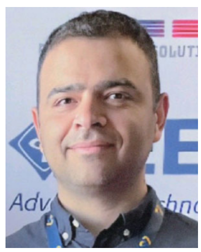
[12] D. Holloway and R. Bunker, "Planning, housing and energy use: A review: Practice reviews," *Urban Policy Res.*, vol. 24, no. 1, pp. 115–126, Mar. 2006, doi: 10.1080/08111140600591096.

[13] W. Abrahamse, "Energy conservation through behavioural change: Examining the effectiveness of a tailor-made approach," Ph.D. thesis, Univ. Groningen, Groningen, The Netherlands, 2007.

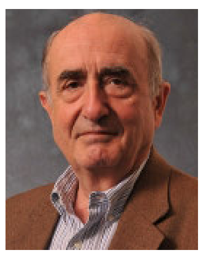
[14] D. Romero-Jordán, P. del Río, and C. Peñasco, "An analysis of the welfare and distributive implications of factors influencing household electricity consumption," *Energy Policy*, vol. 88, pp. 361–370, Jan. 2016, doi: 10.1016/j.enpol.2015.09.037.

[15] M. G. Lijesen, "The real-time price elasticity of electricity," *Energy Econ.*, vol. 29, no. 2, pp. 249–258, Mar. 2007, doi: 10.1016/j.eneco.2006.08.008.

[16] K. Gillingham, R. G. Newell, and K. Palmer, "Energy efficiency economics and policy," *Annu. Rev. Resource Econ.*, vol. 1, no. 1, pp. 597–620, Oct. 2009, doi: 10.1146/annurev.resource.102308.124234.
[17] F. A. Wolak, "Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment," *Amer. Econ. Rev.*, vol. 101, no. 3, pp. 83–87, May 2011, doi: 10.1257/aer.101.3.83.
[18] I. Kastner and P. C. Stern, "Examining the decision-making processes behind household energy investments: A review," *Energy Res. Social Sci.*, vol. 10, pp. 72–89, Nov. 2015.
[19] I. Podbregar, S. Filipović, M. Radovanović, O. M. Isaeva, and P. Šprajc, "Electricity prices and consumer behavior, case study serbia—Randomized control trials method," *Energies*, vol. 14, no. 3, p. 591, Jan. 2021, doi: 10.3390/en14030591.
[20] M. Pelenur, "Household energy use: A study investigating viewpoints towards energy efficiency technologies and behaviour," *Energy Efficiency*, vol. 11, no. 7, pp. 1825–1846, Oct. 2018, doi: 10.1007/s12053-018-9624-x.
[21] J. A. List, R. D. Metcalfe, M. K. Price, and F. Rundhammer, "Harnessing policy complementarities to conserve energy: Evidence from a natural field experiment," Working Paper Series, National Bureau of Economic Research, Apr. 2017, doi: 10.3386/w23355.
[22] R. Philipsen, T. Schmidt, and M. Ziefle, "A charging place to be–users' evaluation criteria for the positioning of fast-charging infrastructure for electro mobility," *Proc. Manuf.*, vol. 3, pp. 2792–2799, Jan. 2015, doi: 10.1016/j.promfg.2015.07.742.
[23] Y. Li, S. Su, B. Liu, K. Yamashita, Y. Li, and L. Du, "Trajectory-driven planning of electric taxi charging stations based on cumulative prospect theory," *Sustain. Cities Soc.*, vol. 86, Nov. 2022, Art. no. 104125, doi: 10.1016/j.scs.2022.104125.
[24] P. Ashkrof, G. H. de Almeida Correia, and B. van Arem, "Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in The Netherlands," *Transp. Res. D, Transp. Environ.*, vol. 78, Jan. 2020, Art. no. 102206, doi: 10.1016/j.trd.2019.102206.
[25] R. O. Kene and T. O. Olwal, "Energy management and optimization of large-scale electric vehicle charging on the grid," *World Electr. Vehicle J.*, vol. 14, no. 4, p. 95, Apr. 2023, doi: 10.3390/wevj14040095.
[26] G. Pareschi, L. Küng, G. Georges, and K. Boulouchos, "Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data," *Appl. Energy*, vol. 275, Oct. 2020, Art. no. 115318.
[27] S. Hardman, A. Jenn, G. Tal, J. Axsen, G. Beard, N. Daina, E. Figenbaum, N. Jakobsson, P. Jochem, N. Kinnear, P. Plötz, J. Pontes, N. Refa, F. Sprei, T. Turrentine, and B. Witkamp, "A review of consumer preferences of and interactions with electric vehicle charging infrastructure," *Transp. Res. D, Transp. Environ.*, vol. 62, pp. 508–523, Jul. 2018.
[28] A. Danese, B. N. Torsæter, A. Sumper, and M. Garau, "Planning of high-power charging stations for electric vehicles: A review," *Appl. Sci.*, vol. 12, no. 7, p. 3214, Mar. 2022.
[29] D. Fischer, A. Harbrecht, A. Surmann, and R. McKenna, "Electric vehicles' impacts on residential electric local profiles—A stochastic modelling approach considering socio-economic, behavioural and spatial factors," *Appl. Energy*, vols. 233–234, pp. 644–658, Jan. 2019, doi: 10.1016/j.apenergy.2018.10.010.
[30] I. Ullah, K. Liu, T. Yamamoto, M. Shafiullah, and A. Jamal, "Grey wolf optimizer-based machine learning algorithm to predict electric vehicle charging duration time," *Transp. Lett.*, vol. 15, no. 8, pp. 889–906, Sep. 2023, doi: 10.1080/19427867.2022.2111902.
[31] O. I. Asensio, K. Alvarez, A. Dror, E. Wenzel, C. Hollauer, and S. Ha, "Real-time data from mobile platforms to evaluate sustainable transportation infrastructure," *Nature Sustainability*, vol. 3, no. 6, pp. 463–471, Jun. 2020.
[32] Y. Wang, E. Yao, and L. Pan, "Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction," *J. Cleaner Prod.*, vol. 286, Mar. 2021, Art. no. 124982, doi: 10.1016/j.jclepro.2020.124982.
[33] A. Martin-Cirera, M. Nowak, T. Norton, U. Auer, and M. Oczak, "Comparison of transformers with LSTM for classification of the behavioural time budget in horses based on video data," *Biosystems Eng.*, vol. 242, pp. 154–168, Jun. 2024, doi: 10.1016/j.biosystemseng.2024.04.014.
[34] M. Ellis, A. S. Bosman, and A. P. Engelbrecht, "Regularised feed forward neural networks for streamed data classification problems," *Eng. Appl. Artif. Intell.*, vol. 133, Jul. 2024, Art. no. 108555, doi: 10.1016/j.engappai.2024.108555.
[35] S. Kiran, G. R. Reddy, S. P. Girija, S. Venkatramulu, and K. Dorthi, "A gradient boosted decision tree with binary spotted hyena optimizer for cardiovascular disease detection and classification," *Healthcare Anal.*, vol. 3, Nov. 2023, Art. no. 100173, doi: 10.1016/j.health.2023.100173.
[36] O. R. Olaniran and M. A. A. Abdullah, "Bayesian weighted random forest for classification of high-dimensional genomics data," *Kuwait J. Sci.*, vol. 50, no. 4, pp. 477–484, Oct. 2023, doi: 10.1016/j.kjs.2023.06.008.
[37] G. Wu, C. Li, L. Yin, J. Wang, and X. Zheng, "Compared between support vector machine (SVM) and deep belief network (DBN) for multi-classification of Raman spectroscopy for cervical diseases," *Photodiagnosis Photodynamic Therapy*, vol. 42, Jun. 2023, Art. no. 103340, doi: 10.1016/j.pdpdt.2023.103340.
[38] S. Sugiarto and V. Octaviana, "Service quality (SERVQUAL) dimensions on customer satisfaction: Empirical evidence from bank study," *Golden Ratio Marketing Appl. Psychol. Bus.*, vol. 1, no. 2, pp. 93–106, Jun. 2021.
[39] J. Hagman and J. J. Stier, "Selling electric vehicles: Experiences from vehicle salespeople in Sweden," *Res. Transp. Bus. Manage.*, vol. 45, Dec. 2022, Art. no. 100882, doi: 10.1016/j.rtbm.2022.100882.
[40] McKinsey and Company. (2024). *Exploring Consumer Sentiment on Electric-Vehicle Charging*. McKinsey & Company. [Online]. Available: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/exploring-consumer-sentiment-on-electric-vehicle-charging
[41] J. D. Power. (2024). *Electric Vehicle Experience (EVX) Ownership Study*. Driven by PlugShare. [Online]. Available: https://www.jdpower.com/business/press-releases/2023-us-electric-vehicle-experience-evx-ownership-study
[42] M. Fischer, W. Michalk, C. Hardt, and K. Bogenberger, "Bill it right: Evaluating public charging station usage behavior under the presence of different pricing policies," *World Electr. Vehicle J.*, vol. 15, no. 4, p. 175, Apr. 2024, doi: 10.3390/wevj15040175.
[43] B. Lin and M. Yang, "Changes in consumer satisfaction with electric vehicle charging infrastructure: Evidence from two cross-sectional surveys in 2019 and 2023," *Energy Policy*, vol. 185, Feb. 2024, Art. no. 113924, doi: 10.1016/j.enpol.2023.113924.
[44] S. Sabzi and L. Vajta, "Machine learning based electric vehicle drivers charging satisfaction analysis and prediction," in *Proc. IEEE Conf. Technol. Sustainability (SusTech)*, Apr. 2024.



SHAHAB SABZI received the master's degree in electrical engineering from the Arak University of Technology, with a focus on development of power electronics units and controllers along with energy management system for EV applications. He is currently pursuing the Ph.D. degree with Budapest University of Technology and Economics. His research interests include e-mobility energy optimization focusing on the application of machine learning methods in power systems optimization and control.



LÁSZLÓ VAJTA received the Master of Electrical Engineering degree in BME, in 1975, the Ph.D. degree, in 1981, the M.B.A. degree, in 2000, and the Ph.D. degree in picture processing, in 2005. He was a Research and Development Expert Engineer, in 1980. He was the Deputy Dean for Economic Affairs, from 2005 to 2008, and the Dean of the Faculty of Electrical Engineering and Informatics, from 2008 to 2016. He was the Vice-Rector for innovation and company relations at Budapest University of Technology and Economics, from 2008 to 2012. He worked at many companies in the frame of co-operation participating in numerous industrial projects. Since 1989, he has been the CEO of Telekodex Ltd. He is currently an Associate Professor with the Department of Control Engineering and Information Technology. He leads numerous research projects financed by national and EU grants. He has over 200 publications, mostly in international journals and conference proceedings. He owns eight patents. His research interests include control engineering, computerized image processing, robotics, industrial, and energy informatics.