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RESEARCH ARTICLE

A Comprehensive Data Analysis of Electric Vehicle User Behaviors Toward Unlocking Vehicle-to-Grid Potential

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ABSTRACT Electric vehicles (EVs) improve the power grid by increasing intermittent renewable energy consumption and providing financial support to EV users via vehicle-to-grid (V2G) integration. While estimating these advantages, a number of studies have neglected to consider the effect of driving and charging behavior patterns on their results. This article provides a framework that systematically evaluates EV driving and charging behaviors to improve charge management in the light of recent standards and advancements. In addition, the collected data on driving habits are analyzed in order to provide a consistent and usable dataset. By evaluating the individual and simultaneous charging demand characteristics, the V2G potential is further explored. Moreover, managerial recommendations for EV charging management are offered by improving the time step using the Bootstrap approach for more precise results than lower resolution. It is also addressed that the simultaneous use of a limited number of EVs required minimum time. According to the findings of this study, daily travel habits have a crucial influence in defining seasonal and individual charging demands. In order to continue with EV charging-related assessments with a confidence interval of more than 95%, the findings suggest that time steps of lower than ten minutes must be used. In addition, the purpose of this study is to assist researchers from academia and business with further information as they build initiatives linked to EV charging infrastructure and real-time charging management standards that account environmental aspects.

INDEX TERMS Bootstrap, charging behavior, distributed network, driving data, electric vehicle.

I. INTRODUCTION

Electric vehicles (EVs) have been introduced as a prominent solution for reducing carbon emissions and improving air quality since transportation is one of the biggest global energy consumers, mainly supplied by conventional energy sources. The transportation sector is responsible for approximately 62.3% of the world's fuel consumption [1], [2]. Tighter sanctions have been introduced for high-emission vehicles in line with energy deficit and climate change problems, green growth, and sustainable development goals (European Parliament and Council, 2012) [1]. With the initiation of the Paris Agreement in 2015 under the United Nations Framework Convention on Climate Change (UNFCCC), air pollution control policies and technologies have been promoted to improve fuel economy and vehicle emissions worldwide. For example, California will not allow internal combustion engine vehicles to enter its cities after 2025. Although many developed countries are stepping to expand the EV industry in terms of the economy by developing policies such as tax exemption, purchase subsidies, and emission restrictions [3], EV integration still faces many technical and economic constraints [4]. The challenges and barriers, such as technological, financial, infrastructural, etc., are presented in Figure 2. Much effort should be made to make the benefits of EV integration quantitative by designing sustainable business models for vehicle-to-grid (V2G) technologies [5]. V2G could empower EVs to improve grid performance and profitability,

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adapt renewable energy sources, and reduce emissions and costs. It is assumed that V2G will not increase EV adoption but will have a small economic benefit. Namely, if the EV driving and charging behaviors excludes from the V2G impact analysis, it exaggerates the value of V2G [6]. For example, instead of a 100 MW gas turbine unit, it will require approximately 30,000 vehicles capable of providing 6.6 kW, assuming 50% V2G availability [7].

An interesting and potential research area for V2G is to move toward behavioral challenges, including notions of inconvenience, confusion, and range anxiety. The conducted overview on V2G reveals that few studies simultaneously investigate the V2G impact analysis at behavioral and technical aspects. The most common V2G analyses are based on surveys, assumptions, and generalizations. The applicability and technical-economic benefits of the V2G option have been evaluated in many studies to reduce uncertainties and increase highly-populated EVs' benefits [8], [9]. Furthermore, the V2G impacts on distribution grid operations have been investigated in terms of stability, reliability [10], and technical flexibility [11], [12]. For example, distribution network management was performed using an algorithm capable of valley filling, peak load shaving, and priority charging in three modes [13]. Moreover, few studies explicitly evaluate V2G potential using real driving data explaining socially, economically, and environmentally affected behaviors. For instance, driving data shows that EVs with larger batteries are not regularly plugged-in daily [14]. The Electric Nation project has shown that the charging times of users with large batteries are irregular, and the plug-in frequency is two to three times per week [15]. The random plug-in behavior will decrease the number of simultaneous plugged-in EVs, and hence user participation in incentive packages will decrease. Making V2G participation popular via increasing the number of plug-ins and predictability should be ensured to minimize the negative effects of uncontrolled EV charging on the grid. Otherwise, assuming systematic plug-in behavior may overstate the benefits of smart charging and V2G options [16]. The non-systematic charging demands will be combined with increasing instability in the networks with large penetrations of renewable energy source (RES), causing considerable managerial challenges. The centralized and decentralized methodologies have been developed to overcome these issues utilizing V2G [17]. The system optimization aims to develop methods to address these issues by considering the interaction of charging power, V2G availability, and grid parameters. Therefore, there are many unrealistic assumptions, like systematic plug-in acceptance, disregarding free charging incentives and long-range vehicle behavior, survey-based management methods, generalization of regional socio-economic dynamics, and data problems related to the development of infrastructure and management algorithms considering local dynamics [18], [19].

Vehicle-grid integration can be unidirectional (V1G) under uncontrolled charging, smart charging, and controlled charging or bidirectional like V2G, which makes it possible for many ancillary applications easy [20]. Ancillary services are mandatory for ensuring grid reliability and balancing supply-demand. They are priced separately, like regulation services balance between power generation and demand, regarding keeping the voltage and the frequency stable. Also, customer reactive power needs should be met in real-time to manage customer impact on system voltage, frequency, and system losses, ensuring power quality. These services require capacity more than demand. Peak shaving is required during high levels of demand, especially large demands on hot summer days or in the evening. Gas turbine-based power plants can generate power during peak demand thanks to the quick activation. However, it is a relatively inefficient investment because these plants are only utilized for peak time and are idle approximately 90% of the year. Spinning reserve power contributes to grid stability to synchronize with the grid frequency if another generator is suddenly breakdown or unavailable. Again, the gas turbines quickly generate capacity for only spinning reserves, not for demand power. Therefore, the capacity essentially required for the spinning reserve seems like an underutilized investment. Load shifting may significantly reduce the impact of an EV fleet on the grid. Furthermore, peak loading caused by the increased popularity of EVs and uncontrolled charging loads may prioritize system replacement/investment costs [21], [22]. The development of smart-charging control strategies could reduce peak load and shift energy demand by discharging during daily peaks and charging during low demand (overnight, off-peak hours). Otherwise, much new energy generators would be required if all EVs are charged in the overnight peak. A larger group of aggregated EVs are more desirable load for the grid. When the renewable power supply is too high, the power plants must reduce production, or DG units must be curtailed to maintain the balance. The V2G implementation can balance for the intermittent RES uncertainties. EVs can be charged with excess renewable energy and discharge the stored energy for driving and supporting the power grid when necessary. Thus, V2G utilize RES more flexibly for the grid. Most ancillary services can be provided by the V2G thanks to the bi-directional power flow, including regulation for frequency and voltage, load leveling, peak power reduction, and spinning reserves [23].

Studies focusing on EV charging and travel behaviors are summarized in Table 1. The effects of the behaviors were examined from environmental, financial, and technical aspects at the same time, while some examined the results from only one aspect. Some studies determine EV usage pattern collecting real mobility EV data or using publicly available EV data. Other studies generate the EV charge and usage behavior based on survey data. Furthermore, most studies analyze V2G impact on power grid using hour-based data or hourly average data from minute-based recordings.

This study addresses EV driving behaviors, such as charging location, time, level, and duration, which affect

TABLE 1. Studies related to EV usage patterns.

Year	E	T	F	- Main outputs of studies: How to obtain EV behaviors (Data source) - Time resolution	Ref.
2016	-	-	-	- a deep examination of 72 different EV usage patterns (charge and trip) using 15 BEV with leasing between 2011-2014 in Ireland - min-based measured mobility data (Green eMotion)	[24]
2019	+	-	+	- investigating the flexibility potential of EV using the charging data of EV charging stations from 2450 users between 2015-2018 (mySMARTLife) in Finland, also in Germany and France - 15 min- based analysis	[25]
2020	-	+	-	- EV charging demand prediction through stochastic and probabilistic methods using the survey data (NHTS) - hourly-based analysis	[26]
2020	-	+	-	- driving and charging habits of 7979 EVs (PHEV and BEV) investigating different 7-day long CVRP data between 2016-2017 in California - frequency based analyses	[27]
2020	-	+	-	- technical prosperity of controlled over random charging strategies of EVs using generated charging and driving habits based on measured one-year-long mobility data of 1000 BEV in China - 30 min data resolution	[28]
2020	-	+	-	- V1G and V2G effects on power grid investigating behaviors generated using NHTS and projected number of EVs and RES share for 2040 in the US - 5 min to one hour analysis	[29]
2021	-	-	+	- optimal economic planning of charging stations along German motorways using the real traffic flow data corresponding to MILES - hourly resolution of data	[30]
2021	+	-	+	- evaluation of emission reduction potential via V1G and V2G using generated EV mobility behavior based on 100 randomly sampled survey data (SHTS) - 15-minute resolution of data	[31]
2021	-	+	-	- revealing non-systematic plug-in and charging behaviors of 265 EVs having large or small size batteries using large data of the Electric Nation project between 2016-2018 in the UK - hour based analysis	[16]
2021	-	+	-	- investigates the large penetration EV impacts on low voltage distribution, considering the generated charging time, method, and characteristics - hourly base analysis	[32]
2022	+	+	+	- exploring grid flexibility potential of EVs satisfying daily mobility need using several manipulated EV driving patterns in Italian - 30 min data resolution	[33]
2022	-	-	+	- EV travel analysis of different patterns (charging and travel) using the collected large mobility data of 26,606 BEVs (taxi and private EVs) in 2018 in China - hour based analysis	[34]
2022	+	+	+	- travel and charging behavior analyses of about 5 thousand PEV owners in California - repeat surveys data (CVRP, eVMT) 2015-2019	[35]
2022	+	+	+	- benefits of V2G via behavioral modeling of households with EV/EVs and not EV making survey - hour based analysis	[36]
2022	+	+	+	- evaluating the flexible V2G integration via 120 EV usage patterns generated using NHTS in China - hour based analysis	[37]
2022	+	+	+	- impacts of high penetration of EV and RES on power systems investigating EV trip behaviors generated using the survey of 20,178 French households' travel habits - hourly time resolution	[38]

E: Environmental, T: Technical, F: Financial, MILES: Model of International Energy Systems (a Pan-European project), NHTS: National Household Travel Survey, SHTS: Swiss Household Travel Survey, eVMT: electric vehicle miles traveled, CVRP: California Vehicle Rebate Project

the relationship between the distribution network and charging station (CS) in the scope of recent requirements of EV and CS. In addition, comprehensive data analysis was performed to empower the charging management, optimizing the simulation time interval to maximize the consistency of the results. The original contributions of this study are as follows:

- Exploration of the additional advantages and potentials of V2G operations for EV charging management through the conceptualization that systematically evaluates pertinent input data of EV user behaviors.
- Evaluating actual electro-mobility data, such as charging location, duration, levels, and timings, to develop a framework for generating a consistent dataset for more realistic EV charging management systems.
- The simultaneous and separated individual charging demand are evaluated toward the expanding EV population focusing on the exact V2G events.
- Determination of an improved time interval for more accurate EV charging management simulations using the Bootstrap method.
- Proposing managerial suggestions to increase the performance of EV real-time charging management and alternative paths to achieve zero-emission targets.

This paper is organized as follows. Section II explains EV behaviors' impacts, potentials, and limitations directly affecting the charging management framework. The methodological evaluation of driving and charging is presented in Section III. Time step verification using Bootstrap is analyzed in Section IV. The results and discussion are included in Section V. Section VI concludes the study.

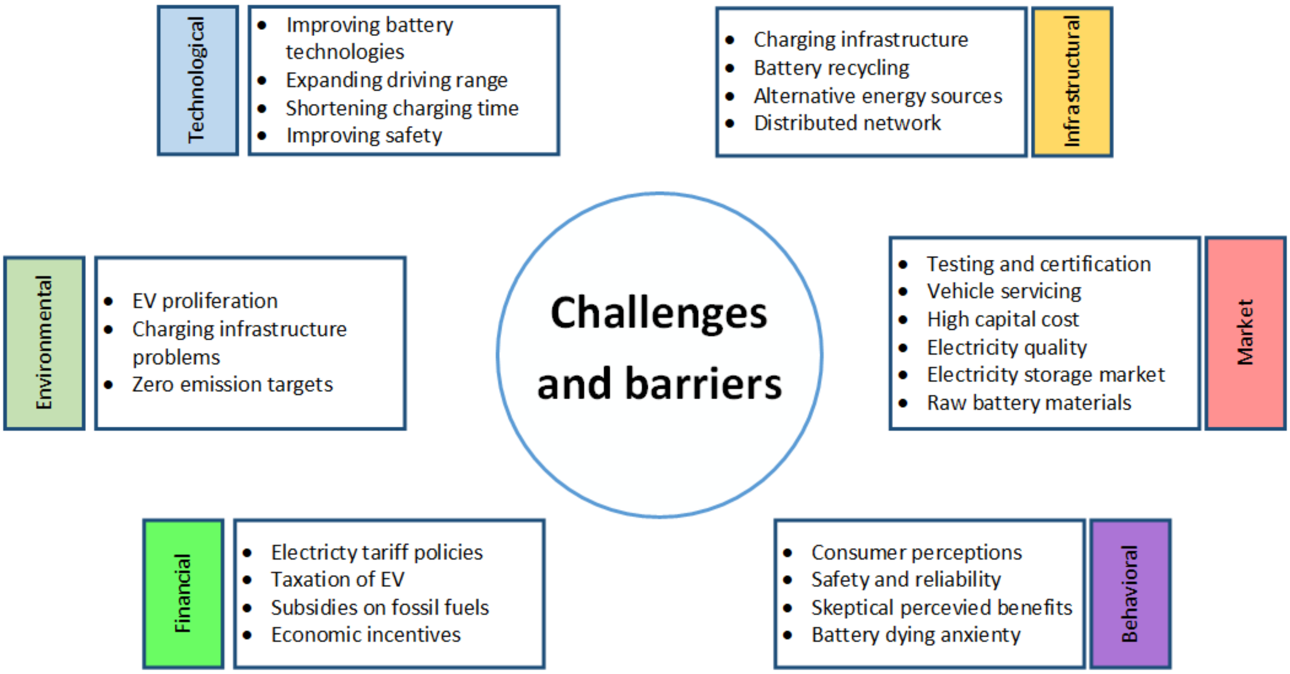

FIGURE 1. Challenges and barriers that EV faces.

II. THE IMPACTS, POTENTIALS, AND LIMITATIONS OF EV BEHAVIORS ON CHARGING MANAGEMENT

EVs can be charged with cables at a home charger or public CS, known as conductive charging. Residential or public CSs can transfer power unidirectional or bidirectional to empower V2G. Generally, the conductive chargers are Level 1, Level 2, and Level 3 according to power level. Level 1 is AC charging at low power levels, around 1.6 kW. Level 2 charges at higher levels between 3.6–22 kW AC power. Level 3 is DC fast charging at higher power levels of up to 50 kW. Also, developments of charging technology to increase charging level to about 400 kW can limit the charging time to about 15 min even for large battery EVs [39]. However, the importance of controlled charging or V2G is inevitable if the power level of chargers increases since higher power charging loads make gird peaks additionally higher than normal charging loads.

Moreover, wireless charging, known as inductive charging, is a developing technology that significantly affects the behavior of EVs [40]. Wireless power transfer can be static or dynamic, adding wireless charging lanes to motorways. Since static wireless charging can only remove the cable connection, dynamic wireless charging or roadway charging has been developed to transfer electrical power at high voltage and current levels when the EV is entirely moving with certain speeds. Thus, the EV downtime to charge is reduced to zero. The first demonstrated dynamic wireless roadway charging has transferred 60 kW with an efficiency of 72% in 2009. Then, this system was successfully installed to charge electric buses with an 83% efficiency and trams with a three-phase power of 250 kW. Since, the realization of dynamic wireless charging is costly due to requirements of land, a protection system, a vehicle alignment controller, and electromagnetic equipment, the optimal allocation of dynamic wireless charging can reduce the size of the EV battery, which is a significant part of the EV total cost and increases the driving range, and maximizes traffic flow. Moreover, significant research on the commercialization of dynamic wireless charging has recently shown that the range anxiety and the total EV cost can be reduced and consequently the EV adaptation increases. Dynamic wireless roadway charging with bidirectional ability can be used widely and commercially in future EVs and V2G [41], [42].

Accordingly, increased EV penetration and uncontrolled charging may cause overloading of grid elements, more voltage deviations, and extra power losses [26], [43]. Many charge control methods have been developed to increase economic and technical benefits by examining the relationship and interaction between CS and microgrid [44], [45], [46] and optimizing the charger level, location, and charging time [47], [48]. Additionally, energy efficiency, power system quality, grid renewal costs, and local constraints (geographic, regulation, etc.) are taken into account in the design and construction of CS [49], [50], [51]. Due to regional EV usage differences, the siting and sizing of CS are some of the main topics of smart city control and management [52]. This coordination will contribute to green energy targets by eliminating the main barriers to increasing renewable energy sources (RES) penetration [53].

Charging management can be carried out with centralized or decentralized controllers [54]. EV usage patterns are collected in a virtual data center in both control methods to optimize the solutions with the objective functions that support sustainable environment and energy targets. Although the decentralized V2G management technique can suppress network peaks, the grid side's expected technical and economic benefits are not maximized since deficits of long-term plans and adequate information share [55]. Charging demands, network information, and other critical parameters can be used in centralized methods by archiving for optimal V2G timing and power detection. Therefore, decentralized programs come to the forefront where travel behaviors are kept locally without being shared with others [55]. However, the slower decision-making rate in centralized systems, in which the participants do not get involved due to privacy concerns, limits the optimal solutions for peak shaving and power regulation. Therefore, temporary fluctuations of load and power can be balanced in central control methods using 5-10 minutes or longer time-step [54].

Limited or no sharing of EV travel information with grid operators may limit EVs' CO2 emissions reduction potential. The timing mismatch between RES generation and charging demand can be resolved with grid-connected energy storage system (ESS) or EV by storing energy to mitigate the challenges associated with RES. However, trying to reach the zero-emission targets with 100% penetration of RES for charging demands may enlarge the ESS costs. Intelligent charging management can achieve optimal charging management by replacing the charging power from high to low emission times with RES. Therefore, if participation in smart charging programs can be increased, the economic value of flexible charging can be embodied by reducing the size of ESS required to achieve zero-emission targets.

On the other hand, it is likely to have a negative impact on the program participation rate as the gains due to increased participation in smart charging programs and reduced ESS costs will be divided into more vehicles. A survey on willingness to participate in smart charging determined that participation in grid-controlled charging was 49-78%, emphasizing privacy and loss of control concerns, and V2G program participation decreased by 7-12% for every 20% decrease in the reliable driving range [56]. The state of charge (SOC) at the plug-in time is important for the grid supply-demand balance in terms of its impact on the number of participants in the smart charging program. Namely, users who join V2G earlier meet a more significant portion of their energy storage needs per vehicle. On the other hand, a higher level of V2G participation will lower the energy storage capacity more than smart charging, thus reducing the benefits per vehicle. V2G allows discharge from the EV to the grid controlling the recorded or planned daytime travel behavior and energy demand. If 50-60% of the stored energy is discharged from the EV to the grid, the battery cycle is approximately doubled. V2G requires more battery cycles resulting in battery degradation and greater power losses during AC-DC conversion. Therefore, battery degradation worries EV owners. Also, EV owners may suffer from charge anxiety refers to the stress of reaching destinations if participating in V2G functions [57]. The full participation of the EV fleet in controlled charging and V2G integration allows for supplying the system load of 4% and 11.1% from zero-emission sources, respectively [58].

III. METHODOLOGICAL EVALUATION OF DRIVING CONSUMPTION AND CHARGING BEHAVIOR

The framework of the study is shown in Figure 3. This framework appeared due to the need for challenges and assumptions of V2G studies and consists of charging and driving analysis empowered with Bootstrap distribution giving suggestions for further analysis. Furthermore, the framework has faced challenges and barriers such as technological, financial, infrastructural, etc. The findings of the framework may enlighten potential applications of EV charging management optimization models. The growing popularity of EVs has led to the need for CS in public parking lots, shopping malls, workplaces, and university campuses [59]. However, increasing EV penetrations have created many technical and economic uncertainties regarding power generation, distribution, and consumption. It has been emphasized in many studies that charging demands can vary significantly based on EV users' preferences [60]. Travel behaviors and EV range differentiate where, when, and how much to charge. Easy access, flexible charging time, and charging incentives affect charging time and location [61], [62]. Studies investigating the temporal trend of charging behaviors show that nighttime charging at home is the most frequent simultaneous charging [56], [63]. For example, the energy tariff is cheaper during the nighttime, encouraging overnight charging effectively for domestic EV users [15], [64]. However, daily driving ranges and cheaper or free-charge opportunities nearby workplaces can change charging time [27]. EV charging management methodologies should evaluate possible locations for CS and the energy pricing policies of that locations together rather than individually. Thus, the My Electric Avenue project (MEAP) created a dataset by monitoring EV behaviors for two years in 12 regions with 256 different users in the South Gosforth region fed from the Northern PowerGrid feeder [65], [66].

Figure 3 shows the average daily energy consumption in seasons within the scope of MEAP. Here, it is apparent that the average energy consumption of EVs in the spring, summer, and autumn are approximately the same. Also, the winter demand is significantly lower than in other seasons. Seasonal average consumption in Figure 3 cannot provide the desired sensitive data to the algorithms for promising vehicle-grid integration, especially within the scope of smart city applications. In this respect, seasonal, daily, hourly, and even minute-based individual consumption data is needed for real-time system management. Furthermore, as seen in Figure 5, EV behaviors can have very different characteristics for the same season. For example, while the daily average energy consumption is similar for the same season, the energy consumption amounts vary.

Figure 4 shows the total energy consumption in the critical hours. A day is divided into critical hours according to energy

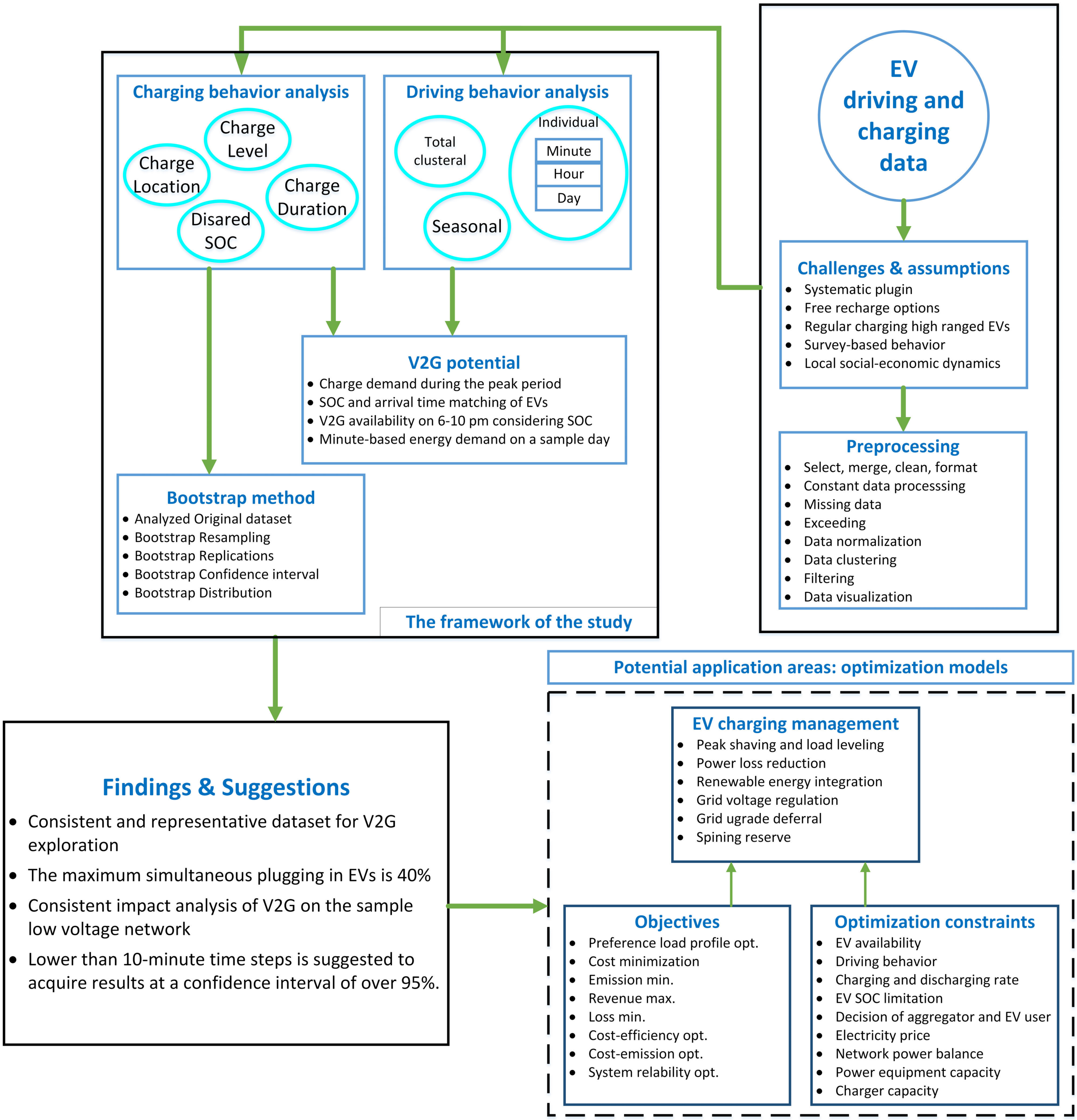

FIGURE 2. The framework of the study.

consumption. Accordingly, the EV energy consumption ratio between 7 am and 6 pm is 76%, between 6 and 10 pm is 18.54%, and between 10 pm and 7 am is 5%. Therefore, it is observed that a large proportion of energy consumption occurs during working hours.

Figure 6 presents the energy consumption during the critical hours and the average travel distances. The travel distances and durations of EVs during critical hours are very different. For example, the energy consumption of the EV01 was 69% during working hours, but it is not consumed as much after 10 pm. On the other hand, an average of 36% of EV09 daily travel distance occurred after 10 pm. In addition, it has been observed that 70% of the relevant vehicles travel between 24-32 km in the evening hours, which is critical for energy management and control. These findings provide valuable information on how many EVs are suitable for V2G, especially during the evening peak.

The seasonal active and passive days are displayed in Figure 7. Namely, if an EV is active, it travels and is charged. If EV is passive, it does not travel and is charged on that

FIGURE 3. Seasonal energy consumption distribution.

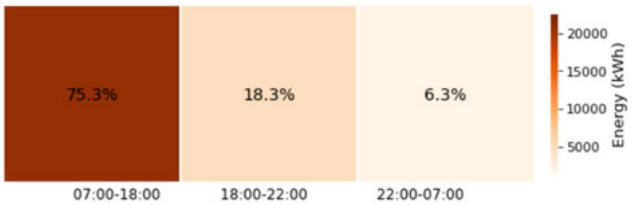

FIGURE 4. Total energy consumption.

day. Some EV users (EV 02–06–07–09) seem to drive regularly throughout the year. However, some EVs like EV08 are passive most of the year, while EVs like EV09 are active throughout the year.

Figure 8 reveals the total EV charging demand distribution during the daily critical hours. The total charging demands were 58.63%, 29.1%, and 12.28% during working hours, the evening, and the night, respectively. According to Figure 4, the hours of consumption and charging do not fully overlap. Therefore, the charging demand between 6 and 10 pm is more than twice that of after 10 pm. It has been determined that 77% of the energy consumed during working hours is met again in the same period. Also, in Figure 4, only 6.3% of energy consumption occurs after 10 pm due to the short amount of travel. Figure 9 shows that the charging demand between 6 and 10 pm is approximately evenly distributed. Additionally, the proportion of charging demand during the evening peak was 82%.

Figure 10 shows EVs' arrival times and SOC at the specified hours. For example, 35.6% of the home arrivals of EV01 occur between 6-7 pm, with a 32.2% probability of a SOC less than 5, a 45.2% probability of between 5-8, and a 22.6% probability of greater than 8. Most EV plug-ins were around 6-8 pm with a ratio of 60%. However, EV10 plug-ins with a ratio of 52%, while EV03 plug-ins only with a ratio of 15.8% between 6-7 pm. So, this reflects the behavioral differences of EV users. Furthermore, the SOC of EV04 EV at plug-in during 6-8 pm was mostly less than 5, while the SOC of the EV07 EV in the same period was greater than 8. However, EV08 EV arrives home between 9-10 pm with a ratio of 25.9%, and the SOC at the time of plug-in is less than 5 with a probability of 85.7%. It has been indicated that a small number of EVs are connected to the charging between 9-10 pm with a SOC of less than 5. Depending on the user travel behaviors in Figure 6, it has been determined that there are suitable users for V2G programs with full or partial participation, as well as incompatible users with the proposed algorithms for minimizing the effects of EVs on the grid. For example, EV06 and EV07 have an average travel range of 28.17 km and 36.22 km between 6-10 pm, respectively, while their SOCs are greater than 8 between 6-7 pm with a ratio of 68.6% and 54.5%, respectively. However, this is not compatible with V2G programs, given that the SOC of the EV04 is less than 5 with a 75.7% probability between 6-7 pm, and it travels an average of 71 km between 6-10 pm.

Figure 11 shows the minute distribution of the total charging demand for one day. The maximum charging demand intensifies in the evening. It is apparent that the evenly distributed charging demand after 6 pm in Figure 9 fluctuates for the minute-based periods of the relevant hours. For example, although there is a maximum charging demand between 13-32 minutes during the 8 pm period, the charging demand decreases by approximately 85% after the 45th minute of that hour. It is observed that charging demand increases at working hours, before noon, and at the end of the working hours.

According to MEAP, four of the ten EVs made a minute-based simultaneous charge request 446 times on 14 different days throughout the year. It is evident in Figure 12 that EVs (07-10) have no plug-in for the selected day. EV06 has been separated from the system after a very short charge request. EV01 and EV02 are important in terms of the V2G option, wherein the SOCs at the plug-in are greater than 6, and the average travel range in the evening is 22 and 38 km, respectively. However, it is observed in Figure 12 that the SOC of EV04 at the plug-in time is smaller than 4, and the average travel of 60 km is not available for V2G. On the other hand, EV03 and EV05 are considered appropriate candidates for V2G because their SOC at the plug-in is 10 and more, and their evening travels are only around 30 km.

IV. TIME STEP VERIFICATION USING BOOTSTRAP

The Bootstrap method is a resampling technique used to estimate distributions of statistics based on independent observations by resampling the original dataset to create datasets. The Bootstrap method has been successfully used in many engineering fields, especially mathematics, physics, and statistics. This method can obtain the standard error estimate, confidence interval, and statistic distributions [67]. The original sample is resampled in this method by replacing it with a Bootstrap sample. The resulting Bootstrap sample is treated as a real population. This process is repeated many times to generate an experimental distribution for the estimator. Population parameters are estimated by minimizing the standard error [68]. Estimates from Bootstrap-generated samples represent the likely range of the estimate in the population. This method makes it easy to obtain the standard deviations and confidence intervals (CI) of parameters with complex distributions. Bootstrap is a systematic method of calculating

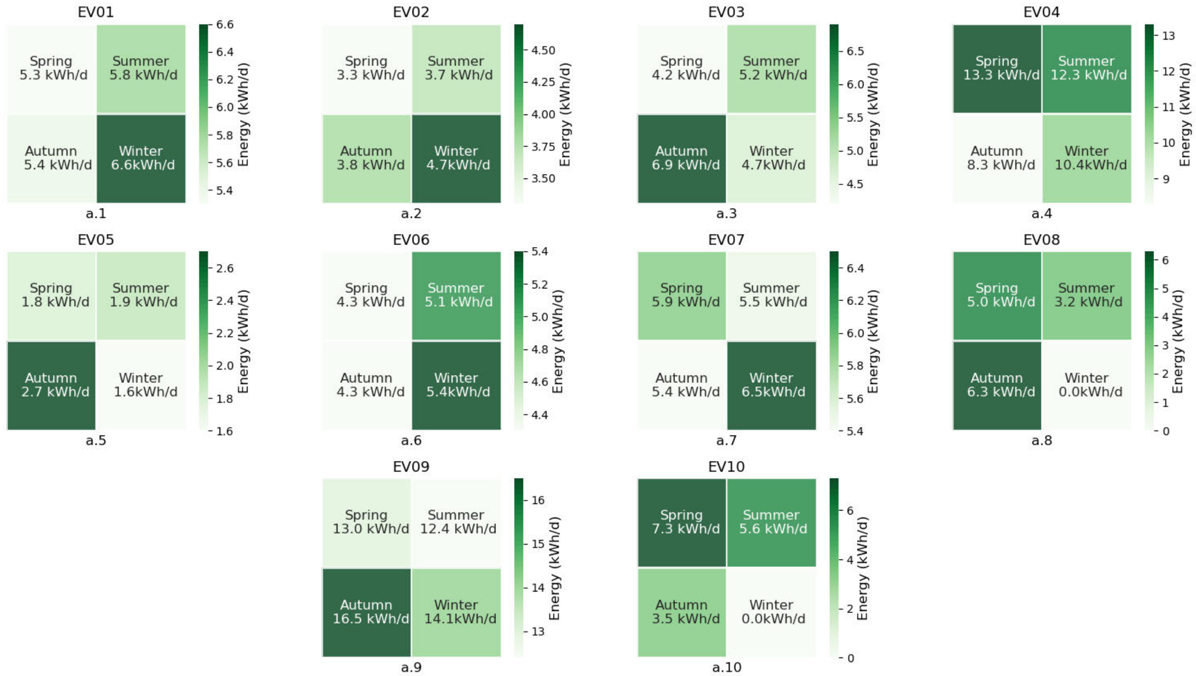

FIGURE 5. Individual energy consumption of EV users.

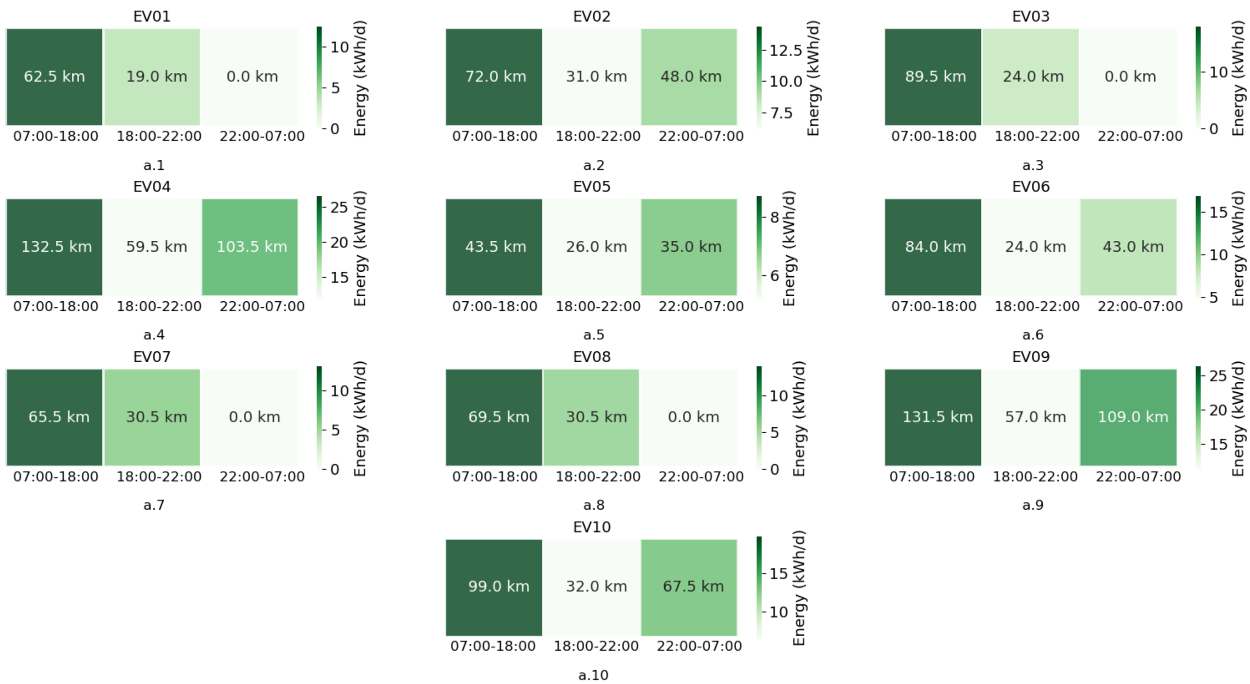

FIGURE 6. Average energy consumption and distances of individual EVs.

CI. There are many different methods for estimating CI using Bootstrap distribution. The five most used methods are normal Interval, Percentile Interval, Basic Interval, Studentized Interval, and Bias-Corrected & Accelerated Interval. The Percentile Interval method was used in this study since it is the easiest method to implement and comprehend. The literature emphasizes that increasing the number of samples while performing Bootstrap resampling improves the estimation accuracy and has a minor disadvantage in terms of processing time [69], [70]. Figure 13 shows the Bootstrap

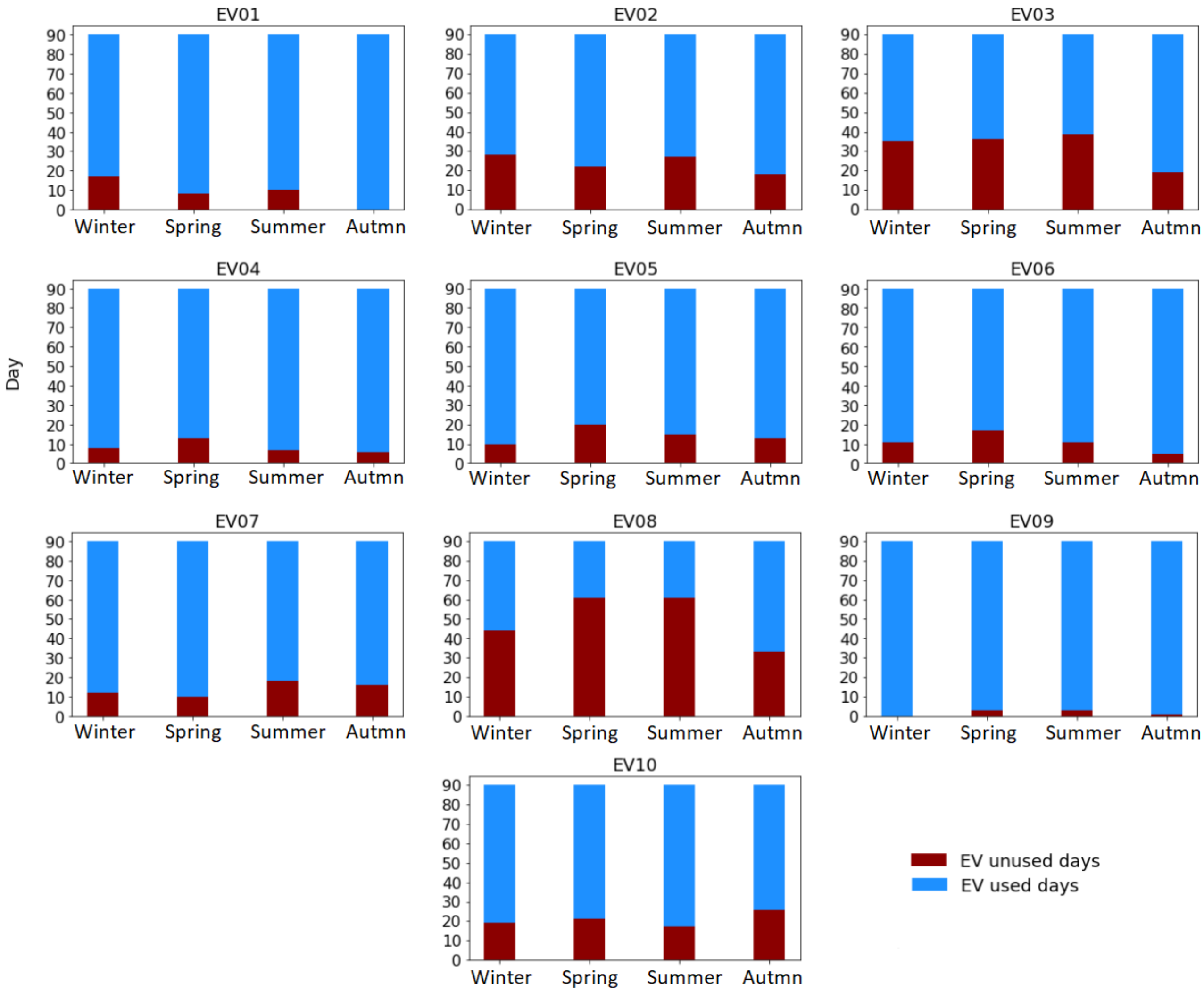

FIGURE 7. Seasonal EV usage.

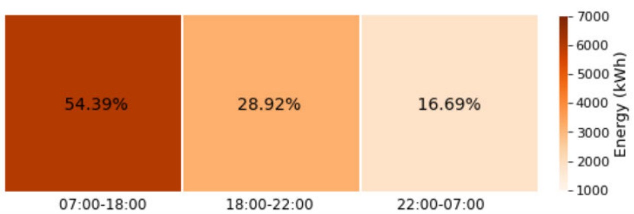

FIGURE 8. Total EV charging demand.

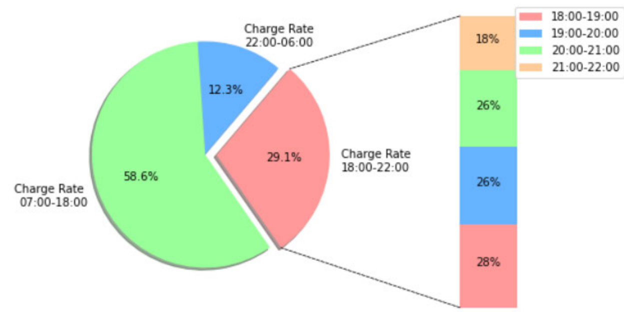

FIGURE 9. Distribution of charging demand over the hours of the day.

stages in creating the dataset. In our study, CI was calculated by resampling 1,000 times Bootstrap. It showed in Figure 14 that 95% CI was obtained within the time interval of between 9.92 and 11.37 minutes. The results show that the analysis of EVs with an average resolution of 10 minutes and below will yield high accuracy in new study proposals investigating the effects of EVs on the grid.

In the Bootstrap method, B Bootstrap samples $x_1^*, x_2^*, \ldots, x_B^*$ are created by selecting the standard error estimation $\hat{\theta}$ from the n-dimensional sampling dataset $x = (x_1, x_2, \ldots, x_{n-1})$. An asterisk indicates that it was obtained from among the actual values determined in the sampling method. For θ, $\hat{\theta}^*$ is estimated by repeating B times within the Bootstrap samples $x_1^*, x_2^*, \ldots, x_B^*$. Estimates of $\hat{\theta}^{*1}$, $\hat{\theta}^{*2}$, $\ldots$, $\hat{\theta}^{*B}$ are obtained after B iterations. $\overline{\hat{\theta}^*}$ is the mean of $\hat{\theta}^*$

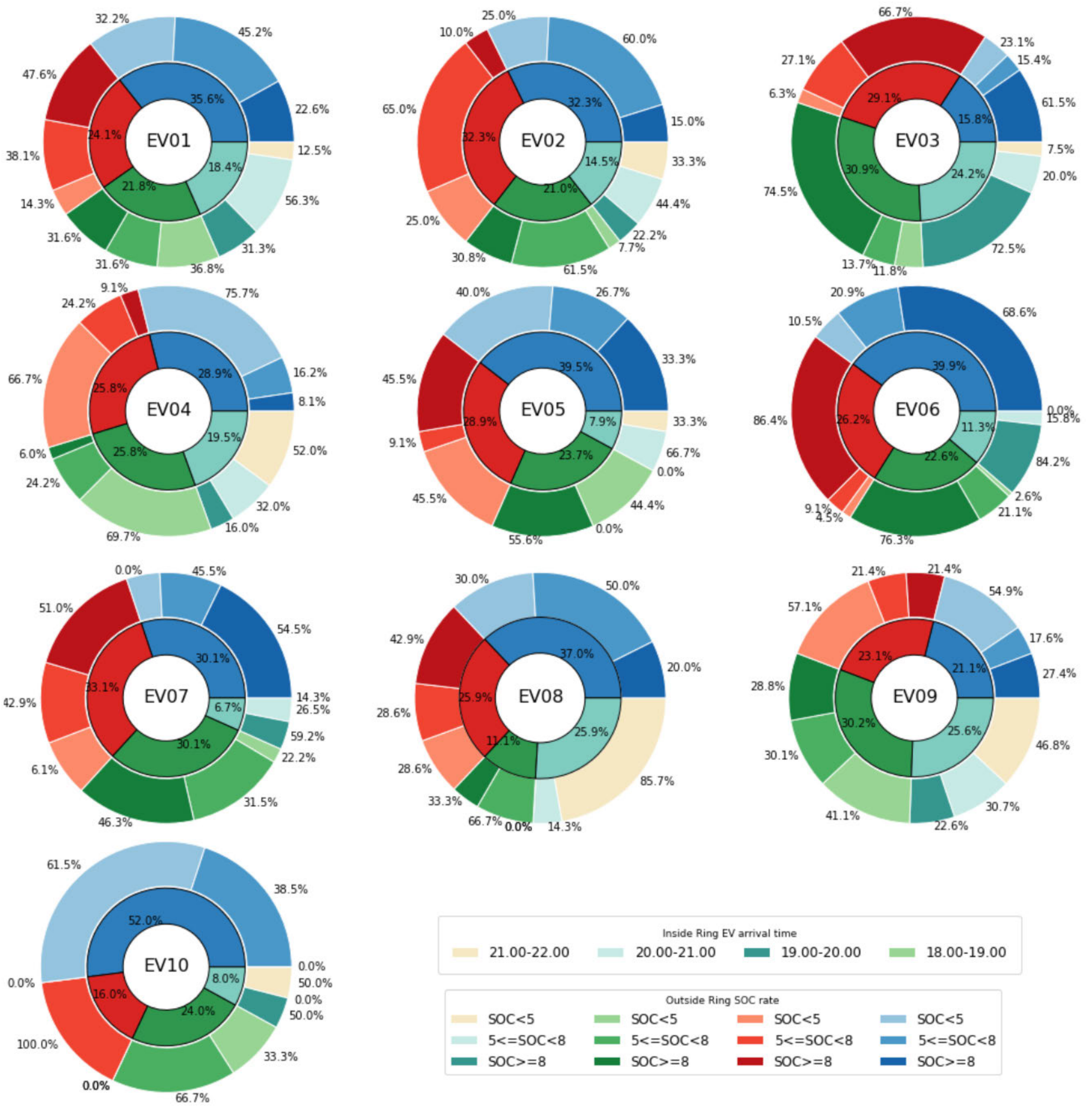

FIGURE 10. The SOC distribution between 6-10 pm.

as given in Equation (1). The square root of $s^2_{\hat{\theta},boot}$ is defined as the standard error of the prediction for Bootstrap samples in Equation (2).

$$\overline{\hat{\theta}*} = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}^{*b} \tag{1}$$

$$s^2_{\hat{\theta},boot} = \frac{1}{B-1}\sum_{b=1}^{B}\left(\hat{\theta}^{*b} - \overline{\hat{\theta}*}\right)^2 \tag{2}$$

IEEE European low voltage test feeders represent a radial distribution network suitable for simulating the dynamic behavior of distributed power sources, voltage/reactive power controls, and ESS with various time steps. The test network consists of 906 buses and 55 single-phase residential loads. The substation connects a medium voltage at 11 kV with an 800 kVA delta-wye transformer to the low voltage at 416 V shown in Figure 15. This section examines voltage sag and swells problems that may occur in future scenarios where the number of EVs increases and the accuracy of the active power flow analysis on the IEEE European low voltage test feeder. The results of power flow analysis carried out in 1-min, 5-min, 10-min, 30-min, and 60-min intervals are shown in Figure 16. Line loading, losses, and minimum voltage level differ by 15%, 3%, and 3.5%, respectively, in the analyses with 1-min and 60-min. On the other hand, it has been

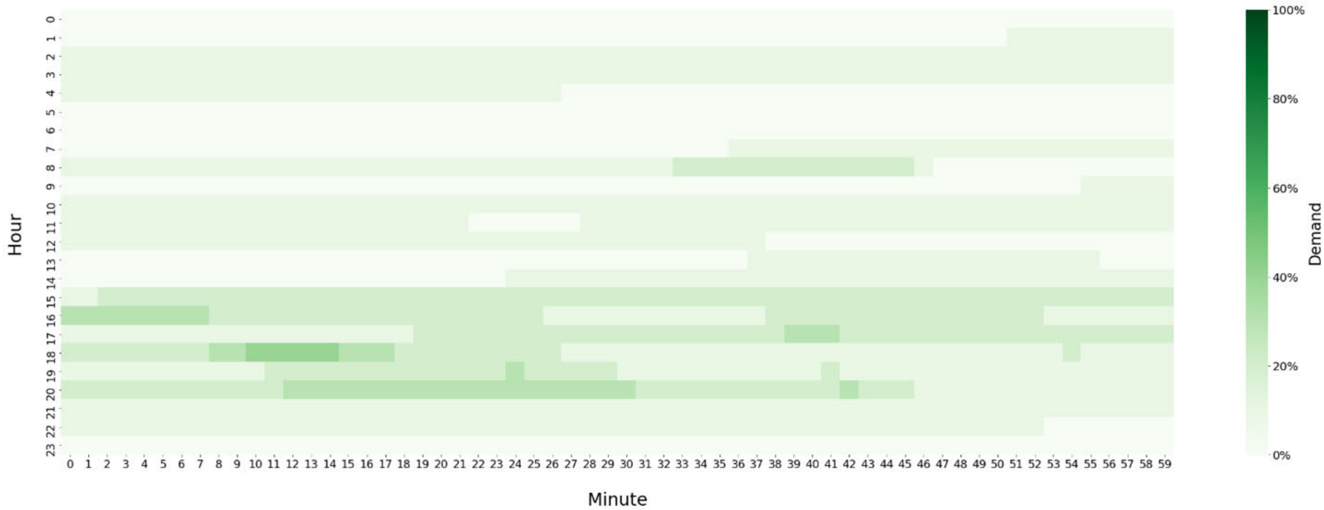

FIGURE 11. Daily total EV demand charging power.

determined that EV penetration increases maximum line loading and energy losses by up to 15% and 24%, respectively. Three-phase AC power flow analyses are carried out according to Equations (3)-(7), including an energy storage system (ESS).

$$P_{G_{i,t}} - P_{D_{i,t}} = \sum_{j=1}^{N} V_{i,t} \cdot V_{j,t} \cdot Y_{ij} \cdot \cos\left(\theta_{ij} + \delta_{j,t} - \delta_{i,t}\right), \quad \forall i, j, t \tag{3}$$

$$Q_{G_{i,t}} - Q_{D_{i,t}} = \sum_{j=1}^{N} V_{i,t} \cdot V_{j,t} \cdot Y_{ij} \cdot \sin\left(\theta_{ij} + \delta_{j,t} - \delta_{i,t}\right), \quad \forall i, j, t \tag{4}$$

$$I_{ij,t} = \left|Y_{ij}\right| \cdot \left[V_{i,t}^2 + V_{j,t}^2 - 2 \cdot V_{i,t} \cdot V_{j,t} \cdot \cos\left(\delta_{j,t} - \delta_{i,t}\right)\right]^{1/2}, \forall i, j, t \tag{5}$$

$$P_{loss} = \sum_{i=1}^{M} I_{i,j}^2 \cdot r_{ij}, \forall i, j \tag{6}$$

$$V_{\min} \leq V_{i,t} \leq V_{\max}, \forall i, t \tag{7}$$

Equation (3) determines active power flow where $P_{G_{i,t}}$ and $P_{D_{i,t}}$ are generated and demand active power at bus i, at time t, respectively. Equation (4) defines the reactive power balance where $Q_{G_{i,t}}$ and $Q_{D_{i,t}}$ are generated and desired reactive power generated at bus i, at time t. Equation (5) defines the line current from bus i to bus j through lines where $V_{i,t}$ and $\delta_{i,t}$ are the magnitude and angle of the voltage of bus i at time t. Y_{ij} and θ_{ij} are the magnitude and angle of the admittance of the bus between i and j. Equation (6) calculates the total active power losses in all lines. Equation (7) is the voltage constraint widely used in DN stability. Slack bus voltage and angle are equal to $V_{i,t} = 1$, $\delta_{i,t} = 0°$.

To predict EV charging demands with an accuracy of over 95%, the 10-min time interval determined by Bootstrap analyses agree with the results of different analyses in the study. The analysis results show that maximum line loading, total line losses, and minimum voltage fluctuations can be determined with an error of less than 0.5% in power flow analysis of 5 minutes or less, compared to 1-min analysis.

The comprehensive quantitative comparison of time intervals in terms of the maximum line loading, the total energy losses, and the minimum voltage level are given in Table 2.

V. RESULTS AND DISCUSSION

Specific dynamics affecting EV charging behaviors are increasing battery costs, expanding driving range, and shortening charging time due to battery-related technological developments. For example, traveling less than 30 km/day, having a second internal combustion engine vehicle, or the increased range of up to 300-400 km with large batteries causes the EV to be charged every two to three days instead of regular daily charging. In addition, expanding CS infrastructures, policies related to taxation and subsidies on EVs, and the limitations due to zero-emission targets change EV behaviors. EV charging behavior research has some scientific challenges since it is relatively new [2]. First, many scientists find it difficult to reliably simulate the impacts of EV charging on the power grid and society. Second, most EV charging behavior data is provided by charging companies or several projects since collecting the data is difficult and needs a long time, like several years. Privacy concerns in the charging data collection make the process slower. Thus, behavioral studies are in the development stages. Therefore, the need for measured EV driving data arises to represent the EV behavioral trends accurately. Several project-based studies have been performed to obtain driving data [71]. However, they mostly assume periodic EV plug-ins, disregard

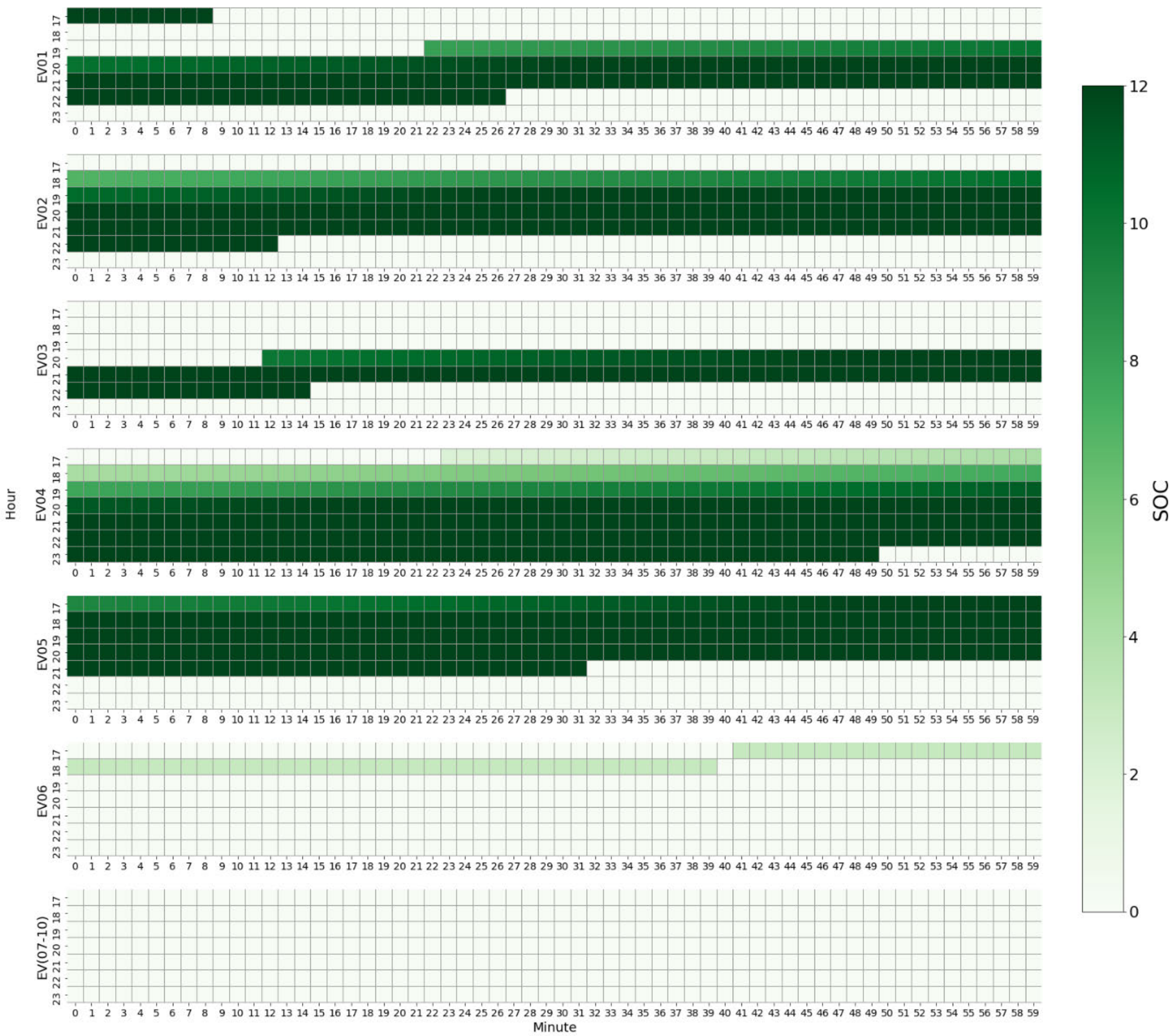

FIGURE 12. The SOC distribution between 5-12 pm.

free charging options and incentives, and generalize regional socio-economic dynamics. Consequently, the impact analysis of EVs on the distribution network may reflect some inconsistent results.

Moreover, the findings are valuable in terms of the effects of EVs on the grid. For example, a considerable proportion of charging demand between 6 and 9 pm during the evening peak can be supplied when energy costs and grid usable capacity are more feasible at night. In this respect, it is possible to meet these charging demands using green energy resources with active control and management because the hours of consumption and charging do not fully overlap. Thus, V2G options are promising alternative solutions here. Many studies focus on the impact analysis of distributed networks based on a systematic plug-in that exaggerates the benefits of V2G [18], [19]. The minute-based analysis has revealed that only 40% of the EVs were plugged in simultaneously, according to the studied projects. Around half seem suitable for V2G, depending on SOC and travel. Therefore, a sufficient number of EVs and the significant energy production from RES in the future will make V2G exciting and more helpful for the grid and EV owners [31].

Furthermore, most recent studies focusing on the grid impact analysis of EVs conduct hour-based simulations regardless of the validation of time steps. The technical, economic, and environmental results of these studies differ significantly. For example, in the 15-minute time step analysis results of the distribution network with uncontrolled EV charge loads of 10% penetration, the total system cost varies up to 7% compared to the hourly analysis, depending on the RES penetration. A lower time step gives a higher cost, which creates higher ramping for the higher RES. Also, 15-minute

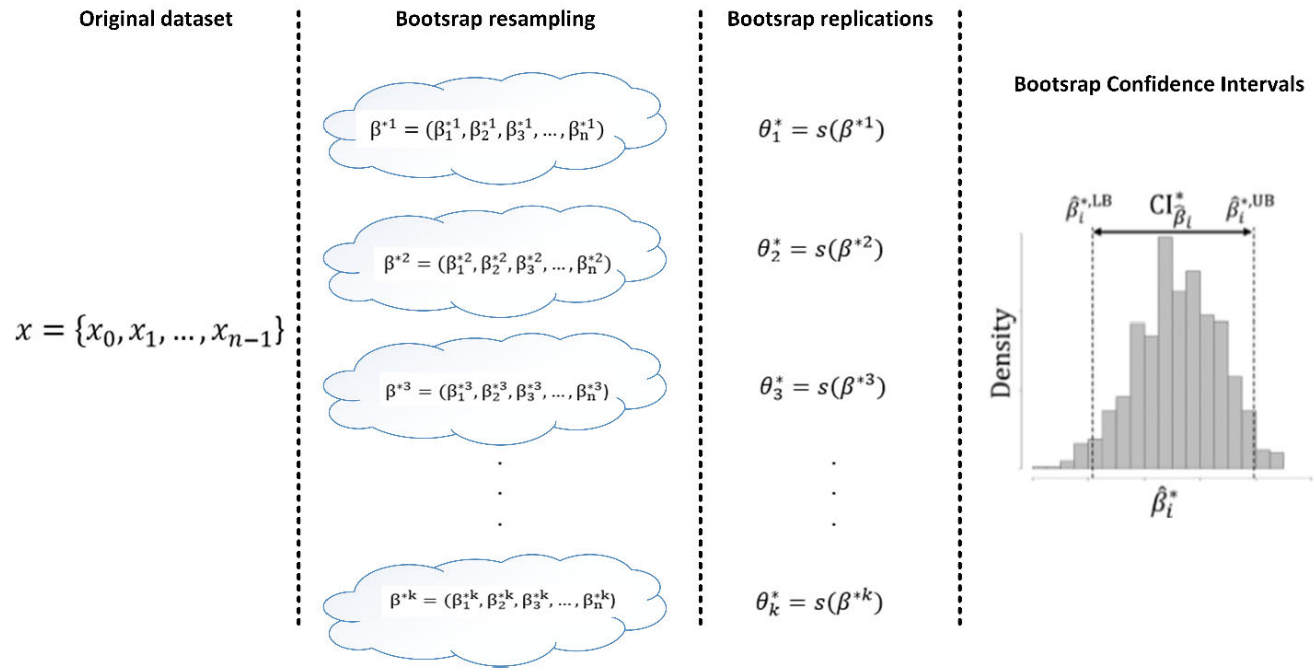

FIGURE 13. General Bootstrap method.

TABLE 2. The effects of time intervals on the results.

Time interval (min)	Max. Line Loading (%)	Energy Losses (kWh)	Min. Voltage (pu)
1	114.18	172.92	0.940
5	113.98	172.17	0.941
10	102.12	171.78	0.966
30	102.12	169.53	0.966
60	100.44	167.30	0.974

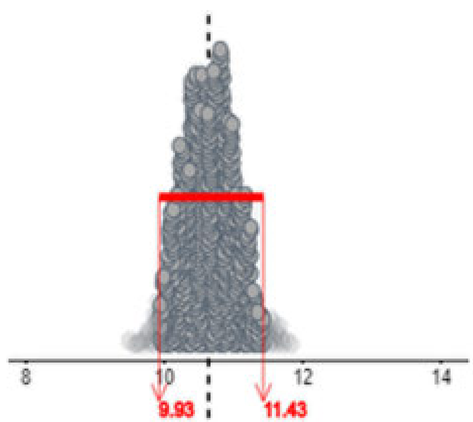

FIGURE 14. Bootstrap distribution function with 95% confidence interval for EV charging behavior.

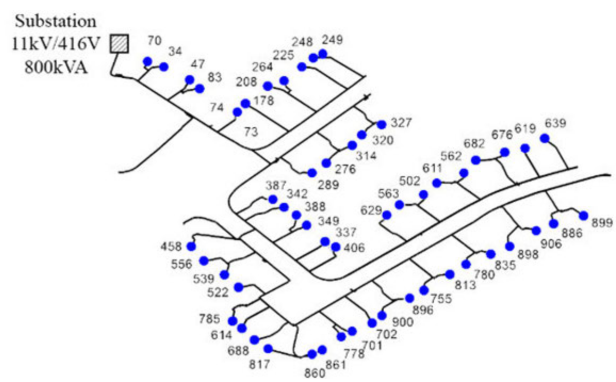

FIGURE 15. IEEE European low voltage test feeder.

analyzes cost less, as higher time resolution results in lower peak demand for uncontrolled charging. In other words, the hourly results are more optimistic [72]. Thus, the time interval for the EV simulations should be determined by an advanced analysis framework using real driving data. The impacts of V2G on the power grid can give significantly better results in terms of technical, economic and environmental if real EV behavior-based time interval is used [73]. We have compared the technical result of commonly used time intervals in V2G impact analyses. Line loading and losses were reduced by 15% and 3% when the time interval was changed from 1-min

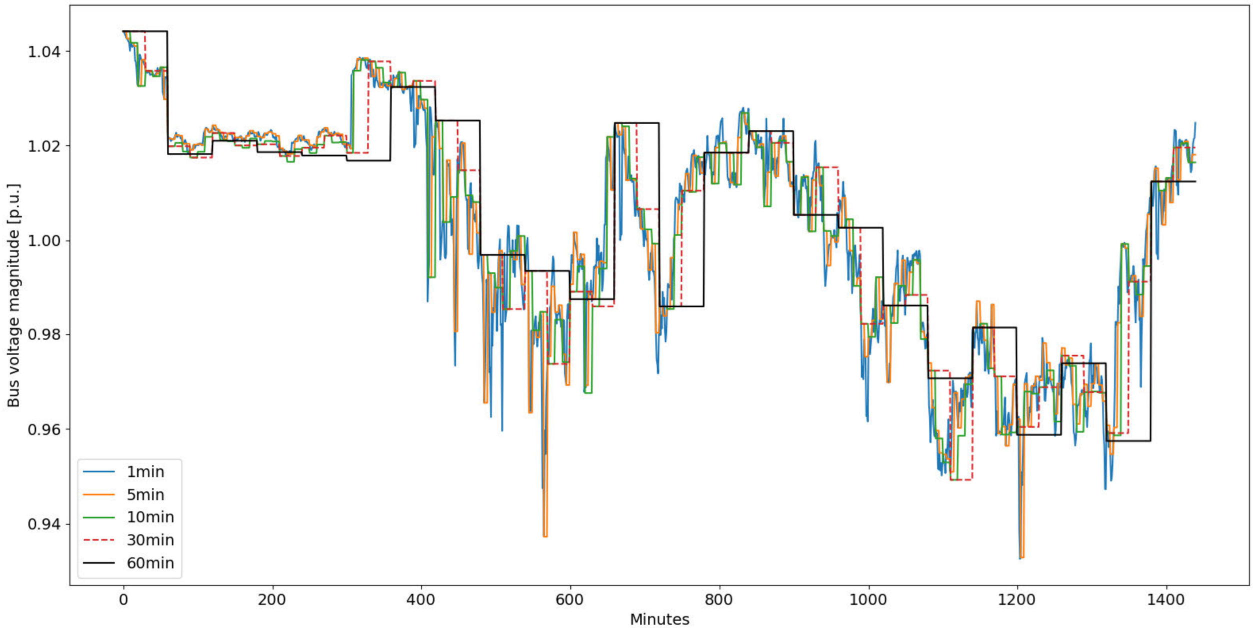

FIGURE 16. **Voltage fluctuation at the bus 906.**

to 60-min, whereas the maximum voltage drop decreased by 3.5

VI. CONCLUSION

Electric vehicles benefit the power grid, improving intermittent renewable energy use and supporting EV owners financially through the integration of V2G. A comprehensive literature review confirms that numerous studies have missed focusing on how driving behaviors may influence the real V2G potential. Existing research captures mobility data or use publicly accessible real data to estimate EV usage patterns. In contrast, some research uses only survey data to generate EV charging and usage behavior patterns. Furthermore, most research examines the influence of V2G on the electrical grid utilizing hour-based or minute-based data. The technical outcomes of commonly used time periods in V2G impact assessments are studied in this research. Therefore, the line loading and losses were decreased by 15% and 3%, respectively, and the maximum voltage drop was reduced by 3.5%, when the time step was changed from 1-min to 60-min. Thus, the outcomes in this scenario are more optimistic than they are. In order to generate more realistic results, this study proposes a framework that methodically processes EV driving and charging behaviors for EV charging management operations, given the implications of the recent requirements and enhancements. Additionally, real driving data has been investigated to reflect the new behavioral trends of EV users considering recent advancements and real electro-mobility data. EV driving and charging behaviors have been evaluated to create a consistent dataset that includes charging location, duration, levels, and times. Joint V2G potential analysis was focused on the simultaneous and individual charging demand toward the growing EV population. Moreover, a time interval has been suggested to increase the accuracy of EV benefit analyses using the Bootstrap method. The studied project revealed that only 40% of the EVs were plugged in simultaneously. Around half seem suitable for V2G, depending on SOC and travel habit. The results indicate that using around 10-minute time steps is significant to acquire results at a confidence interval of over 95%. This work also examines the benefits of the various options that have been explored in terms of energy losses and maximum line loading. This work can help develop projects related to infrastructure and real-time charging management of EVs considering environmental impacts. Therefore, infrastructure and management algorithms should be developed that account for the effects of EVs on electricity grids, local and regional consumer behaviors, and needs. Policymakers should develop infrastructure, control, and protection methods considering stakeholders' demands and process flows. Future studies may aim to investigate the impacts of EVs and V2G that employ dynamic wireless roadway charging with bidirectional capability on the power systems and EV user behavior.

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