Assessing Electric Vehicles Behavior in Power Networks: A Non-Stationary Discrete Markov Chain Approach

Mohammad Hassan Bahmani[a], Mostafa Esmaeili Shayan*[b], Davide Fioriti[c]

[a] *Department of Electrical & Computer Engineering, Tarbiat Modares University, Tehran, Iran.*
[b] *Department of Mechanical, Chemical and Materials Engineering, University of Cagliari, Via Marengo, 2, 09123 Cagliari, Italy*
[c] *Department of Energy, Systems, Territory and Constructions Engineering, University of Pisa, L.go Lucio Lazzarino 1, Pisa, 56122, Italy.*
*Corresponding Author: mostafa.esmaeili@unica.it

Abstract

Since the inception of the idea to utilize electrically driven vehicles on the power grid, numerous valuable investigations have been carried out to showcase the advantageous capabilities of such technologies. However, there are still uncertainties surrounding the integration of electric vehicles into the power grid. These uncertainties encompass the number of electric vehicles that will be linked to the grid at any given time, the quantity of energy stored in their batteries during both daytime and nighttime, and the impact of their charging patterns on the overall power grid load. Moreover, there are numerous other unanswered queries that demand attention. This study presents a unique model that effectively addresses these uncertainties by utilizing a non-stationary Markov chain. The utilization of a non-stationary discrete Markov model in this study provides a precise and valuable understanding of the constantly evolving and time-dependent nature of electric vehicle behavior in the power network. Through a comprehensive case study, the outputs of the model offer intriguing insights into the number of electric vehicles connected to the grid and the energy they reserve over a 24-hour period. Furthermore, this study assesses the model's accuracy in representing the load modeling of electric vehicle charging.

Keywords: **Electric Vehicles, Load Modeling, Markov Chain, Power Grid, Vehicle-To-Grid.**

1. Introduction

With the increasing frequency of natural disasters caused by climate change and growing concerns about the depletion of traditional energy sources, it is not difficult to understand why there is a significant shift towards electrically-driven vehicles [1]. Electric vehicles (EVs) are becoming increasingly popular as a sustainable alternative to traditional gasoline-powered cars. As the number of EVs on the roads continues to rise, it is important to understand their behavior in the power grid and their impact on electricity consumption. One key aspect of studying EV behavior is analyzing their load profile, which refers to the pattern of electricity consumption by EVs over a given period [2]. This understanding is crucial for grid operators and policymakers to effectively manage the integration of EVs into the existing power infrastructure. V2G technology plays a significant role in enabling bidirectional energy flow between EVs and the power grid [3]. It allows EVs not only to consume electricity from the grid but also to feed excess energy back into the grid when needed. V2G technology has the potential to balance power supply and demand, optimize grid stability, and integrate renewable energy sources. By utilizing V2G capabilities, EVs can act as mobile energy storage units, providing valuable flexibility to the power grid. This technology opens up opportunities for various applications, such as demand response programs, peak shaving, and frequency regulation. Understanding the behavior of EVs in the context of V2G is crucial for unlocking the full potential of this technology [4].

Analyzing EV behavior using Markov Chains offers a powerful tool for modeling and understanding the behavior of complex systems with probabilistic transitions. In the context of EV behavior, Markov Chains can be employed to predict the charging and discharging patterns based on historical data. This analysis provides valuable insights into the future behavior of EVs and helps optimize their integration into the power grid. By capturing the probabilistic nature of transitions, we can accurately model and predict the load profile of EVs over time, considering factors such as charging infrastructure availability, user preferences, and external conditions. While Markov Chain models have been widely used in various fields;

- Our study specifically focuses on the non-stationary nature of the system, which is a unique aspect that has not been extensively explored in the existing literature.
- By incorporating this non-stationary aspect, our model provides a more accurate representation of real-world scenarios and offers insights into the dynamic behavior of EV charging load profiles.
- This novel approach adds significant value to the existing body of knowledge in the field of energy management and electric vehicle charging, as it addresses the limitations of stationary Markov Chain models and provides a framework for modeling and predicting the behavior of EV charging load profiles in a non-stationary environment.
- We have also presented an innovative method for calculating the grid load caused by electric vehicle charging. This new model serves as a valuable framework to assist experts in analyzing the behavior of a group of vehicles in a given area.

The ultimate objective of this research is to address the current challenge of the lack of interactivity between the power grid and electric vehicles in terms of their placement when connected to the grid. The results of this model offer crucial information for the management and control of electric vehicles within a specific region's power grid.

Such a model to understand the behavior of a fleet of EVs from the power grid's perspective and gaining insights into the EVs' load profile brings significant benefits to various entities within the power grid ecosystem. Power system managers and policy makers can make informed decisions regarding grid planning, infrastructure development, and policy formulation related to EV integration. Independent Power System Operators (ISOs) can accurately forecast EV charging demand and effectively manage the grid's supply-demand balance, reducing the risk of grid instability. Transmission System Operators (TSOs) can assess the impact on transmission infrastructure, ensuring reliable power delivery. Distribution System Operators (DSOs) can plan and upgrade the distribution network to accommodate increased EV charging demand.

Aggregators and retailers can optimize charging strategies, pricing schemes, and energy procurement, offering innovative services. EV owners can optimize their charging patterns, maximizing range and cost savings. Other power grid customers can anticipate and manage potential impacts on their operations, optimizing energy usage. Overall, this model can provide valuable insights for efficient grid operation, enhanced customer satisfaction, and optimized resource allocation within the power grid ecosystem.

After a brief review of the literature in the section 2, in section 3 of the current paper, the fundamentals of the presented Markov chain model are delved into. The section begins by introducing and discussing the set of state space utilized in this paper. Additionally, the variable components of the transition probabilities associated with the presented Markov model are explained. The non-stationary elements of these transition probabilities are also highlighted and discussed. To provide a visual representation, the state transition diagram of the Markov model is presented. Furthermore, in this section, the process of defining the initial states of the presented Markov model is thoroughly examined. The section concludes by outlining the proposed assumptions of the Markov model.

Moving on to section 4, a case study is presented to demonstrate the capability of the presented model in a real-world scenario. Specifically, the effectiveness of the model in exploring the behavior of a fleet of electric vehicles is showcased. Additionally, the model's utilization in diagnosing the load profile associated with the charging of these electric vehicles is demonstrated. Section 5 is dedicated to discussing the results of the paper and comparing them with the findings of current relevant research studies. This allows for a comprehensive evaluation of the model's performance. Finally, in section 6, the paper concludes by summarizing the key findings and implications. Potential topics for future studies are also suggested, highlighting areas that warrant further exploration.

2. A BRIEF LITERATURE REVIEW

In recent years, there has been a significant focus on the emergence and integration of electric vehicles, leading to a wealth of valuable studies in this field. The increasing prominence of electric vehicles has sparked widespread interest and research efforts, as they represent a crucial component of the evolving transportation landscape. These studies have sought to explore various aspects of electric vehicles, including their impact on the environment, the process of their integration in power networks and their role in the future power systems. In this regard, reference [5] provides an overview of the current status of electric vehicles and discusses future expectations for their growth and impact, [6] analyzes the long-term outlook for electric vehicles and discuss the potential impact on the electric grid. [7] assesses the factors that influence the penetration of electric vehicles in the European Union by 2030 using a model-based policy assessment. [8] evaluates various policy interventions aimed at stimulating the transition to electric vehicle technology in the European Union. Beside all these driving forces, many tempting advantages are widely discussed for these technologies under the name of vehicle-to-grid (V2G) applications, in this regard, [9] presents a bidirectional grid-connected AC/DC converter for V2G applications. [10] provide a comprehensive review of V2G concepts, interface topologies, marketing strategies, and future prospects. [11] presents a comprehensive review and performance evaluation of bidirectional charger topologies for V2G and grid-to-vehicle (G2V) operations in electric vehicle applications. Such advantages could be mentioned from the ultimate goal of stabilizing the intermittent sustainable resources to provision of power system ancillary services such as frequency regulation[12-14]. where [15] discusses the upgrading of conventional power systems to accommodate electric vehicles through demand-side management and V2G concepts. [16] presents an optimal allocation strategy for V2G stations in a microgrid environment with a focus on demand response, [12] and [13] explore the use of optimal control strategies for V2G in frequency regulation, with the former using deep reinforcement learning. [14] propose a power imbalance-based droop control for V2G in primary frequency regulation. In this regard, the technical aspects of V2G integration have been widely investigated and discussed in a variety of valuable scientific articles and literature. These include the impacts of EV presence on the stability and reliability of power grids, optimal charging and discharging strategies in V2G-enabled power networks, the bidirectional interrelations of smart grids and V2G concepts [17, 18], the economic and environmental potentials of V2G implementation, V2G's dedication to providing resource flexibility for grid management, and the regulatory and policy frameworks necessary to facilitate widespread adoption of V2G. where [19] and [20] discuss the benefits and technical feasibility of smart EV charging and V2G technologies, with the latter focusing on renewable power integration. [21] and [22] review the progress and impact of V2G technologies on the power grid and battery simultaneously. The reference [23] and [24] examine the impact of EVs on power grid operation and the strategies for charging-dispatch and V2G technologies in distribution networks, respectively also reference [25] review the challenges and impacts of V2G integration. The references [26], [27] and [28] conduct cost-benefit analyses of V2G implementation and optimal charging strategies for EVs. [29] propose a green smart grid predictive analysis to integrate sustainable energy of emerging V2G in smart city technologies. [30], [31] and [32] provide comprehensive reviews on the incorporation of EVs and renewable energy distributed generation to smart grid, smart energy systems management in a smart grid environment, and multi-agent reinforcement learning for intelligent V2G integration, respectively. The references [33], [34], and [35] discuss the business models, innovation activity systems, and economic challenges for V2G technology. [36], [37] and [38] explore the value of V2G in a decarbonizing grid, techno-economic analysis of V2G integration, and economic and environmental impact of V2G integration, respectively. The references [39], [40], and [41] propose coordinated EV management systems for grid-support services, optimal energy management of cooperative energy communities, and driver plug-in patterns for V2G, respectively. [42] and [43] present new models for a smart grid considering joint power and reserve scheduling, V2G, and demand response, and barriers and frameworks for flexibility services, respectively.

The references [44] and [45] discuss the regulatory and political challenges to V2G and the final hurdles to large-scale V2G deployment. [46] review the assessment of charging technologies, infrastructure, and charging station recommendation schemes of EVs. Although some good efforts have been made to highlight the advantages of using electric vehicles from both a network and customer perspective [46-50], like [48], [49] and [50] review the optimal charging strategy for EVs under dynamic pricing schemes, Chinese consumers' preferences for EVs, and the business of EVs from a PowerGrid perspective, respectively. [51], [52] and [53] discuss various aspects of EVs and V2G, including load modeling techniques, state space model, large-scale provision of frequency control, transactive energy, distributed coordination, and learning EV driver range anxiety. [54] present a comprehensive review of the current state of EV charging services, infrastructure provision, players, and policies. The research highlights the challenges and opportunities in the EV charging market, discussing the roles of various stakeholders, including governments, utilities, and private companies. [55] focuses on the trends and developments in EV charging technologies, discussing advancements in charging station hardware, communication protocols, and charging strategies. In the reference [56] reviews the optimal location of EV charging stations and their impact on the distribution network. The paper discusses the challenges associated with charging station placement, such as load balancing, network capacity, and cost optimization. [57] compares the performance of lithium-ion batteries and nickel-metal hydride batteries in EVs, analyzing factors such as energy density, cost, and environmental impact. The reference [58] presents a review of the future challenges of extending the range of EVs. The paper discusses advancements in battery technology, charging infrastructure, and range extension strategies, highlighting the need for continued research and development in this area. The reference [59] proposes a multi-type EV load prediction model based on Monte Carlo simulation, which takes into account various factors such as vehicle types, charging patterns, and user behavior. The reference [60] proposes a combined online and offline prediction framework for estimating the remaining discharge energy of EVs. The paper discusses the importance of accurate load prediction for effective grid management and propose a method to improve the accuracy of load forecasting. The reference [61] provides an overview of EV behavior modeling and its applications in vehicle-grid integration. The paper discusses various modeling approaches, including stochastic and deterministic methods, and highlights the potential benefits of EV participation in grid services. The reference[62] reviews the modeling of EV charging patterns, focusing on the prediction of charging demand and the impact of various factors such as user behavior, infrastructure availability, and pricing schemes. They discuss the importance of accurate charging pattern modeling for grid planning and optimization. Also in [63] proposes a probabilistic method to model plug-in hybrid electric vehicles (PHEVs) for participation in the electricity market. The authors discuss the challenges of incorporating PHEVs into the market and propose a method to estimate the probability of PHEV participation. The reference [64] investigates the potential of domestic EVs to contribute to power system operation through vehicle-to-grid (V2G) technology. The authors discuss the benefits of V2G, including energy storage and frequency regulation, and present simulation results to demonstrate the feasibility of using EVs for grid support. [65] introduces a new concept for utilizing plug-in EVs in frequency regulation services. The authors propose a control strategy that enables EVs to provide regulation services while considering the battery state of charge and user preferences. [66] proposes a stochastic distributed protocol for EV charging, which allows EVs to adjust their charging rates based on real-time information. The paper discusses the benefits of distributed charging, such as load balancing and peak shaving, and presents simulation results to evaluate the performance of the proposed protocol. [67] presents the results of a test of V2G technology for energy storage and frequency regulation in the PJM system. The authors discuss the technical and economic feasibility of V2G and highlight the potential benefits of using EVs for grid support and [68] discusses the driving range of EVs and presents strategies to extend the range, such as battery improvements, charging infrastructure expansion, and vehicle-to-vehicle energy transfer. The author emphasizes the importance of range anxiety reduction for widespread EV adoption.

The reviewed research generally follows a statistical and engineering perspective on electric vehicles. As a result, there is still a lack of a formulated and definitive approach to evaluate the various aspects of the widespread integration of electric vehicles into the power grids of a country or region.

The need to develop a model to investigate the behavior of the fleet of EVs from the power system's perspective arises from the increasing integration of EVs into the grid and the associated challenges it presents. As EV adoption continues to rise, it becomes crucial for power system operators, managers, and policymakers to understand the impact of EV charging on the grid. A comprehensive model can provide valuable insights into the charging patterns, load profiles, and overall behavior of the EV fleet, enabling stakeholders to anticipate and address potential issues related to grid stability, reliability, and congestion. Moreover, such a model can assist in optimizing the utilization of renewable energy sources, managing supply-demand imbalances, and planning for the necessary infrastructure upgrades to support the growing EV market. In this regard, the purpose of this research is to present a new method based on a non-stationary discrete Markov chain to track changes in the amount of reserved energy and the number of vehicles in different modes of vehicle usage during the day and night in the regional power network.

3. Model Introduction

A. Markov chain basics:

A Markov chain is a random process with the property that given the values of the process from time zero up through the current time, the conditional probability of the value of the process at any future time depends only on its value at the current time [69-71].

$$P(X_{n+1} = i_{n+1} | X_n = i_n, \ldots, X_0 = i_0) = P(X_{n+1} = i_{n+1} | X_n = i_n) \quad [69] \qquad (1)$$

a. State space:

The set of possible values that the random variable X_n can take is called the state space of the chain [72].

While the V2G application is not being considered in this paper, the potential state space sets for the proposed model are being examined. It is important to note that while a vehicle is in idle mode, its state of charge (SOC) remains stable. However, the opposite conclusion may not always be true. There are other states in which the vehicle's SOC remains unchanged, but the vehicle is not in idle mode. For example, when the vehicle is plugged into the grid and its SOC has reached the upper limit, or when the vehicle has reached its lower limit of charge (depletion mode) while in the state of discharging [73]. The EV states in this paper are described as follows:

- Plugged: This state represents the situation in which the vehicle is connected to the power grid to be charged. The vehicle's state of charge may either be increasing or have reached its upper limit of charging. However, in either situation, being connected to the grid is common.
- Discharging: In this state, the vehicle is being used and its initial state of charge is decreasing. It is worth noting that this paper does not consider V2G applications. Therefore, there will be no decrease in the vehicle's SOC due to power injection into the grid.
- Idle: In this state, the vehicle is neither being used nor plugged into the grid, so its SOC remains unchanged.

It is worth to mention that while in our assessments the V2G application is not being considered but this model has the capability to be inserted with such applications and it would be represented in the authors' further works.

b. *Transition probabilities*

The conditional probabilities P ($X_{n+1} = j \mid X_n = i$) are called transition probabilities [71, 72].
In regard of the time dependency of transition probabilities, the model utilized in this paper is called a "non-stationary Markov chain"[74, 75].
The $P_{ij}(t)$ = P (X_{n+1}= j | X_n= i) are called one-step transition probabilities [72], because they are the probabilities of moving from state i to state j in one time step. The transition probabilities in this model consist of two separate parts: The first part emphasize on time variant parameters, and is derived from the diagram of vehicle usage probability. Of this diagram, the probability of vehicles being used (P_u) in a specific region is extracted during the 24 hours of weekdays. While having P_u, logically the probability of vehicle being unused (P_{uu}) in every moment is calculated from (2):

$$P_{uu}(t) = 1 - P_u(t) \qquad [69] \tag{2}$$

It is very difficult to model and predict the behavior of every single vehicle because it encounters many unexpected events[5, 51, 52, 76], hence it is not far from reality to admit that modeling the behavior of a single vehicle is almost as hard as modeling white noise in communication systems. However, as soon as changing the viewpoint from a single vehicle to the bulk of available vehicles in a region, their aggregated behavior would be much predictable and the results of modeling will be far more reliable[52, 77-79]. This is why; we can insist that the applied diagram of vehicle usage probability is highly reliable. Table I, shows the time variant parameters.

TABLE 1. TIME VARIANT PARAMETERS.

j	Plugged	Idle	Discharge

i			
Plugged	$P_{uu}(t)$	$P_{uu}(t)$	$P_{u}(t)$
Idle	$P_{uu}(t)$	$P_{uu}(t)$	$P_{u}(t)$
Discharge	$P_{uu}(t)$	$P_{uu}(t)$	$P_{u}(t)$

The second part of the proposed transition probability, is its logical part, which indicates the logical possibilities of transition from one state to another. The model has also the flexibility to specifically define these logical parameters to simulate the actual human behavior of vehicle owners in any region. As it can be seen from table II, the logical parameters of transitioning between plugged and idle states have been manually put to zero. It is because in this paper we have simplified our assumptions, that "the vehicle owner has rationally decided either states of charging(plugging) the vehicle or not, after a period of driving", so there would not be any considerably amount of probability, of changing his/her mind before the next period of vehicle usage.

In table II, the term BF stands for "Behavioral Function" that describes the vehicle owner's decision to choose between either plugging his vehicle or, letting it stay unplugged after a period of driving. Normally without considering the persuasive signals from the contracted aggregator, and punitive signals from hourly electricity cost pattern, this parameter should be a function of vehicles battery SOC. Which would dedicate more probability of plugging vehicle while it has lower states of charge and higher probability of letting the vehicle stay unplugged (Idle state) while it has higher states of charge. For simplicity, a linear function of SOC has been used in the study case of this paper.

One of the most common ways to specify the transition probabilities is using "state transition diagram"[72] as shown in Fig. 1.

TABLE 2. LOGICAL PARAMETERS.

j / i	Plugged	Idle	Discharge
Plugged	1	0	1
Idle	0	1	1
Discharge	BF	1-BF	1

TABLE 3. TRANSITION TABLE.

j / i	Plugged	Idle	Discharge	Summation
Plugged	$P_{uu}(t)$	0	$P_{u}(t)$	1
Idle	0	$P_{uu}(t)$	$P_{u}(t)$	1
Discharge	BF*($P_{uu}(t)$)	(1-BF)*($P_{uu}(t)$)	$P_{u}(t)$	1

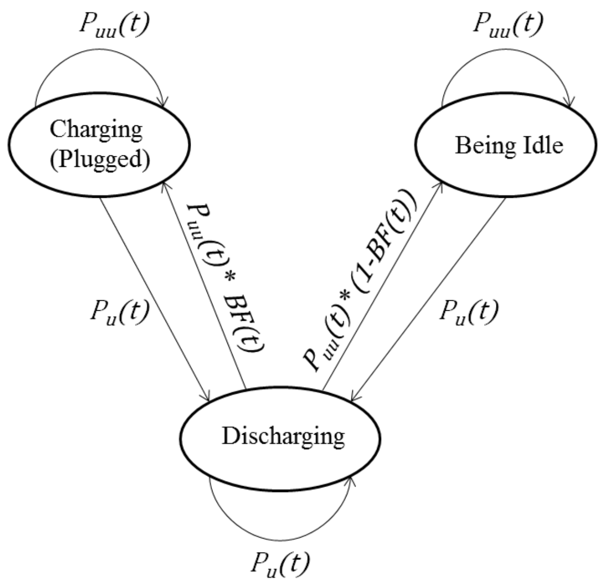

Fig. 1. State transition diagram

c. Initial states:

One of the major questions dealing with Markov chains is the determination of starting states[53, 72]. Coping with this issue, we have applied a heuristic method in this model. Starting states determine where the Markov chain starts from and, indicates the number of vehicles in each introduced state and their relative SOC in the beginning of a typical day in this model. To solving this problem, we have applied an auto amendment method. The model starts in a definite start point that may or may not be the absolute correct point, but by proceeding the model to the final hours of the first day, there would be three stationary distribution for both the expected rates of presence possibility in each introduced states[69, 71, 72], and the available SOC in each one. These data would be the initial start trio for the next run of the model. This procedure would be repeated until reaching that final trio that clearly supports its applied initial starting data. In this way the cycling assumption for the Overall SOC (OSOC) trend would be confirmed[71, 72]. This process is represented in fig. 3. In this regard the initial start state for the Markov model is considered as:

- A hundred percent of the vehicles are in the charging state with their relative SOC being fixed on $\mathrm{SOC}_{\max}$

And also, we have supposed a similar daily probability of use for all days of a week so the cycling period has been reduced to one day. If different daily probabilities of use for a week are considered, the cycling period would change to a week and thus similarly as mentioned different starting states for each days of week should be evaluated.

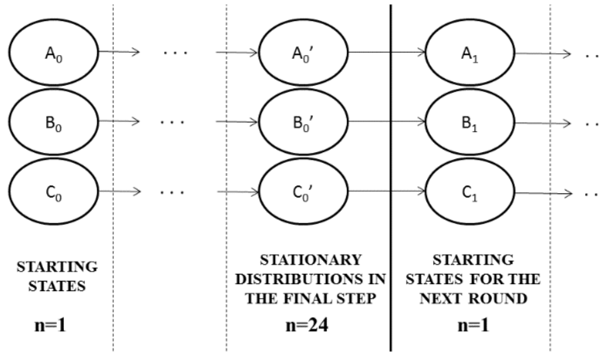

Fig. 2. This process is repeated until the desired conditions of $\mathbf{A'_n} \cong \mathbf{A_n}$, $\mathbf{B'_n} \cong \mathbf{B_n}$ and $\mathbf{C'_n} \cong \mathbf{C_n}$ are satisfied

d. *Model assumptions:*

- Charging rate:

The charging rates of electric vehicles can vary depending on factors such as the vehicle model and the level of charging stations employed [48-50]. Defining a single average value for the charging rate may not fully capture the complexity introduced by these factors. Therefore, it is crucial to consider the range of factors that can influence the charging rate.

In addition to the vehicle model and charging station level, other factors that can impact the charging rate include weather conditions, calendar indicators, grid congestion, and charging infrastructure availability. These factors play a significant role in shaping the charging behavior of electric vehicles and can have implications for the overall load profile of the power network.

However for the sake of simplicity we have utilized an average value for the charging rate in this stydy, but to address the variety of factors affecting the charging rate, a suggestion is to incorporate a function for the charging rate instead of using a single average value. This would allow for the consideration and simulation of different parameters, resulting in a more accurate representation of the charging rate dynamics.

It is worth mentioning that the represented model in this paper has the capability to handle a function for the charging rate. Although, for the purpose of this study, we have utilized a single average value as a representative charging rate, we acknowledge the potential benefits of incorporating a function to account for the variability introduced by different factors.

- Discharge rate:

Discharge rates can also vary in different types of vehicles regarding their type of use[57, 58]. Nevertheless, an average rate for this rate would be applied in this paper.

In fig. 3, the Markov chain proceeding graph is represented. This graph explains the formation of Markov chain. As it can be seen in this figure, the Markov starts from a single presumed state and according to the proposed transition probabilities for the corresponding stage, the consecutive three states are generated in the proceeding time-step.

These new states have their respective state-presence probability, which is calculated as below:

$$for\ X_i \longrightarrow X_j$$

$$P(X_j) = P_{ij}(t) \times P(X_i) \quad [71] \tag{3}$$

In which the $P(X)$, is the probability of state X occurrence, and $P_{ij}(t)$ is the Markov transition probability from state X_i to the X_j [71, 72].

And, relative state of charge which is calculated as in (4):

$$SOC(X_j) = SOC(X_i) + \Delta SOC_{ij} \tag{4}$$

Where SOC is bound as follows:

$$SOC_{min} \leq SOC(X_j) \leq SOC_{max}$$

Regarding to the states X_i and $X_j$the noted ΔSOC_{ij} is driven from table IV. ACR and ADR are the considered average rates for charging and discharging during *i* and *j* intervals.

TABLE 4. ΔSOC_{ij}

i \ *j*	Plugged	Idle	Discharge
Plugged	+ACR	0	-ADR
Idle	+ACR	0	-ADR
Discharge	+ACR	0	-ADR

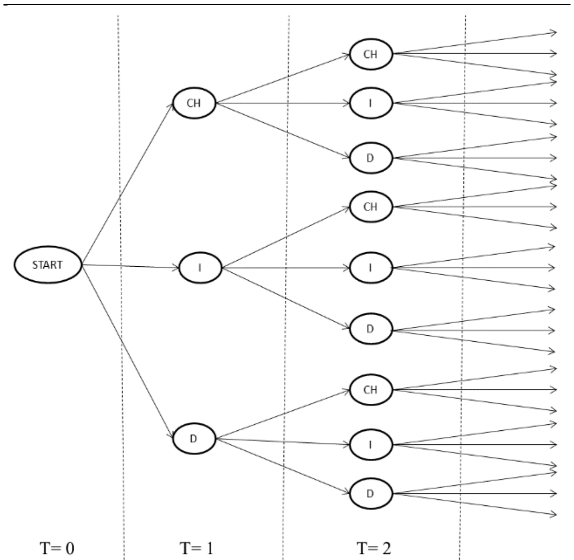

Fig. 3. Programming procedure diagram, CH, I and D stand for Charging, Idle and Discharging states respectively.

B. Markov memoryless-ness:

One of the most important features of a Markov model is its memory less behaviors. This property insists that the future value of states in the Markov process only depends on the value of the state in the current time regardless of its behavior in the past. As it can be seen in equations, 5 and 6 this constraint is observed in the model. In these equations *i* shows the current state while *j* represents the future state and $P_{ij}(t)$, ΔSOC_{ij} are the introduced transition probability and SOC variation, during *i* and *j* transition.

$$P\left(X_j\right) = P_{ij}(t) \times P(X_i) \tag{5}$$

$$SOC\left(X_j\right) = SOC(X_i) + \Delta SOC_{ij} \tag{6}$$

C. Daily expected OSOC changes diagram:

Proceeding from the initial start point, according to previously defined transition probabilities, the next scenarios would be generated. Thus in each stage there would be 3^{n} scenarios of different size of SOC and their respective probability. SOC variations are bound to be between SOC_{max} and SOC_{min}. Calculating the expected value for SOC in each step as in (7), the Daily OSOC trend would be generated. Some applications of this output are discussed during the case study in this paper.

$$\text{For step: n}$$

$$\text{Expected\_OSOC(n)} = \sum_{n=1}^{3^n} P(X_n) \times SOC(X_n) \tag{7}$$

D. Daily load profile due to vehicles charging

From the perspective of power system operators, one of the primary concerns when dealing with electric vehicles is their lack of awareness about the impact, they have on the power grid's load [53-57]. In this paper, we present a novel method, utilizing the proposed model, to calculate the daily load profile specifically related to the charging of electric vehicles.

To achieve this, we compare the calculated OSOC trend with the same output obtained when the average charging rate is manually set to zero. This comparison allows us to isolate and analyze the contribution of electric vehicle charging to the overall load profile.

By employing data mining, we can leverage the available data to develop a more accurate estimation of the hourly load imposed by the charging of electric vehicles. This estimation is formulated through equation (8), which captures the relationship between the charging behavior of electric vehicles and the resulting load on the power grid. This enhanced analysis provides valuable insights for power system operators, enabling them to effectively manage and plan for the integration of electric vehicles into the grid.

$$load(n) = \left(OSOC_0(n) - OSOC_0(n+1)\right) - \left(OSOC_{ACR}(n) - OSOC_{ACR}(n+1)\right) \tag{8}$$

Where:

$load(n)$: Power system, imposed load due to vehicles charging in the n^{th} hour
$OSOC_0(n)$: Overall state of charge in the n^{th} hour while the average charging rate is set to zero in the model
$OSOC_{ACR}(n)$: Overall state of charge in the n^{th} hour

More discussions are performed during the study case.

4. CASE STUDY

In this section, the model has been applied for a scenario of vehicle electrification of a specific region [63-65]. A scenario of 10000 electric vehicles has been considered for a region with the daily vehicle-usage probability pattern of fig. 4 [64, 65]. For the sake of simplicity, a linear function of SOC has been used as the proposed BF function for this region.

We have assumed an average size of 15 kWh for the battery size of vehicles and have set the average rates for charging and discharging (ACR & ADR) of the electric vehicles %11.1 and %18 for the typical daily usage in the supposed region [65, 66]. These data are being represented in table 5. As it can be seen in Fig. 5, the usage pattern shows two separate peaks of vehicle usage probability in a daylong. The first peak shows the time while vehicle owners are driving to work and the second peak indicates the time of returning to home from work. Employing the proposed model, some outputs are discussed for this region.

TABLE 5. MODEL CONSUMPTIONS FOR THE STUDY REGION

Number of electric vehicles	10000
Average size of EV batteries	15 KWh
Total size of available capacity	150 MWh
Average Rate of Charging (ACR)	11.1%
Average Rate of Discharging (ADR)	18%
Maximum acceptable value for SOC ($\boldsymbol{SOC_{max}}$)	95%
Minimum acceptable value for SOC ($\boldsymbol{SOC_{min}}$)	0%
Applied Behavioral Function (BF)	Linear function of vehicles SOC

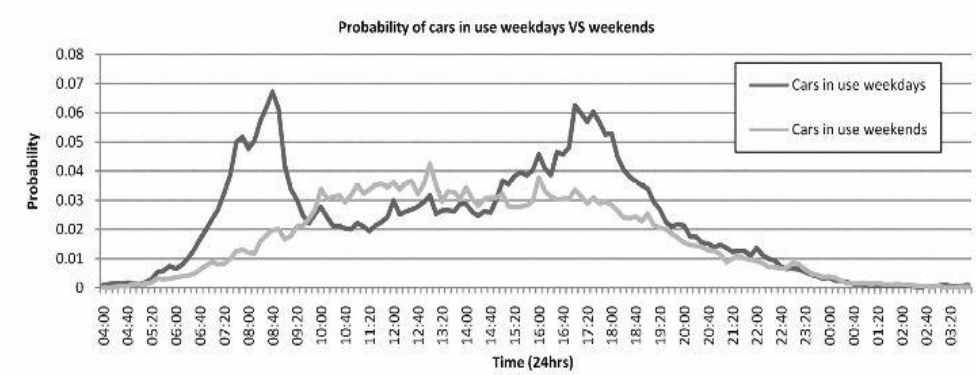

Fig. 4. Probability of cars being driven during weekdays and weekends

A. Daily expected OSOC trend for the study region:

The OSOC trend, as it was discussed in previous sections is plotted in Fig. 7. As it can be seen, two drastic falls are obvious in this Fig around 8 o'clock in the morning and 6 o'clock in the evening. These declines are the results of those discussed peaks in vehicle-usage probability pattern for this region. This diagram is plotted for the first run of the model while initial start states are not defined yet. As the day starts in this region, a steep declining occurs in the Overall SOC as the result of vehicle-usage probability peak of traveling to work. After this period the trend reaches a plateau that is the result of two reasons, decreasing in vehicles usage probability and charging of a portion of previously used vehicles at the parking lots. This trend continues until the time when the second peak in vehicle usage probability happens as the result of turning home from work. In this period, another drastic drop occurs in the region OSOC. As the vehicle-usage probability decreases in the final hours of the day, OSOC starts a steady increase in result of vehicles charging in the parking of homes.

While a daily cycling period for OSOC trend has been supposed for the sake of simplicity in this region (instead of a weekly one) a foible is obvious in Fig. 5. The OSOC trend starts from SOC_{max} but never reaches the same value at the end of the day, this is because the initial starting state has been set to 100% of vehicles being in the plugged state with their SOC at the maximum. This is however in contradiction with the assumption of daily cycling period. Solving this confliction needs the modification of the model initial start states, which has been assessed in the next section.

B. Initial starting states evaluation:

Using the proposed auto amendment method discussed in part c of the model introduction in section 2, the idle starting states for the model in this study case is being obtained after the 16^{th} run of the model. In each one of these runs, the obtained expected values of presence probability and SOC of each state in the final hour of the day is applied as the initial start values for the next run until the satisfaction of the desired conditions (as proposed in Fig. 3) in the 16^{th} run. The OSOC trend with the modified starting states is being represented in Fig. 8. As it can be seen in this Fig the OSOC in the final hour of the day reaches the assumed value in the starting hour which confirms the presumption for daily cycling period of the model.

For this case study the initial states to comply with the presumptions are obtained as follows:

- 55% of vehicles in the plugged state with their SOC at the maximum
- 45% of vehicles in the Idle state with the relative SOC of 52%
- 0% of vehicles in the discharging state

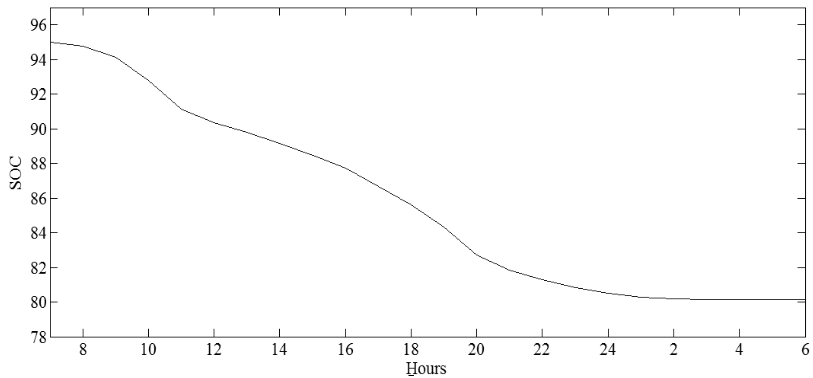

Fig. 5. Normalized overall SOC change of the group of vehicles in a sample weekday

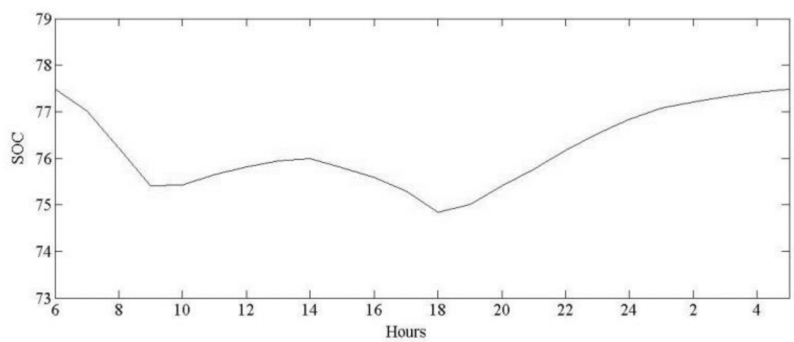

Fig. 6. Amended normalized overall SOC change of the group of vehicles in a sample weekday

C. Separate daily OSOC trend for each state:

Fig. 8 shows the obtained OSOC trend while the expected values of SOC are calculated separately for each state in each hour of the day ($OSOC_{Charging}$, $OSOC_{Idle}$, $OSOC_{Discharging}$). This trend reveals important information about the variation of reserved energy in different states of electric vehicles during a daylong, which would be highly useful in V2G application assessments. In Fig. 9, the fluctuation of presence probability ($P_{Charging}$, P_{Idle}, $P_{Discharging}$) in each introduced state is being plotted for 24 hours. If these presence probabilities were multiplied by the number of electric vehicles in this region (10000 for this study case), the expected number of vehicles in each state would be obtained. Obviously, for these expected rates of presence-probability and SOC, the following equations are true at any time:

$$P_{Charging}(t) + P_{Idle}(t) + P_{Discharging}(t) = 1 \tag{9}$$

$$OSOC(t) = OSOC_{Charging}(t) + OSOC_{Idle}(t) + OSOC_{Discharging}(t) \tag{10}$$

As it is being unveiled for the study case in this paper, if just the charging concerns are taken into consideration from the vehicle owners, there would not be much more than a half of electric vehicles plugged to the grid in any specific time of a typical day. That normally leads to the accessibility of almost half of the total existent reserve capacity of these vehicles.

As it can be seen in Fig. 7, a considerable amount of energy is reserved in the battery of idle vehicles, which is normally not accessible for vehicle to grid applications. By making the right decisions, the custodians can convert this significant potential amount of energy to V2G operational reserve.

Many useful assessments could be performed using the first time, revealed information in Fig. 7 & 8. As an example, suppose a constraint of minimum 50 percent in vehicles battery state of charge as the accepted V2G protocol (MAL).

This statement means, every single electric vehicle is allowed to be participated in vehicle to grid applications only while it has a SOC more than half. Considering this assumption, the net size of energy, available for V2G applications without violating the acceptance criteria of vehicle owners would be calculated as in (11), and is represented for this case study in Table 6.

$$NE_{V2G}(t) = OSOC_{Plugged}(t) - (P_{Plugged} \times MAL) \quad (11)$$

Where,

$NE_{V2G}(t)$: Normalized Net Available Energy for V2G applications in t.

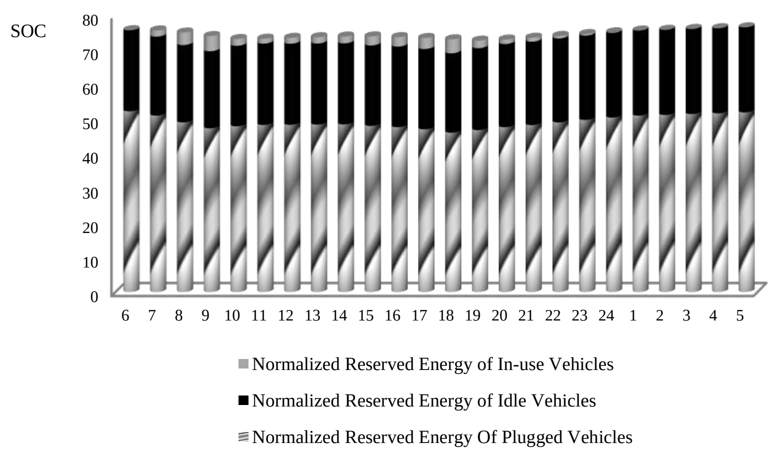

Fig. 7 the variation of reserved energy in the battery of vehicles, in the introduced states during 24 Hours

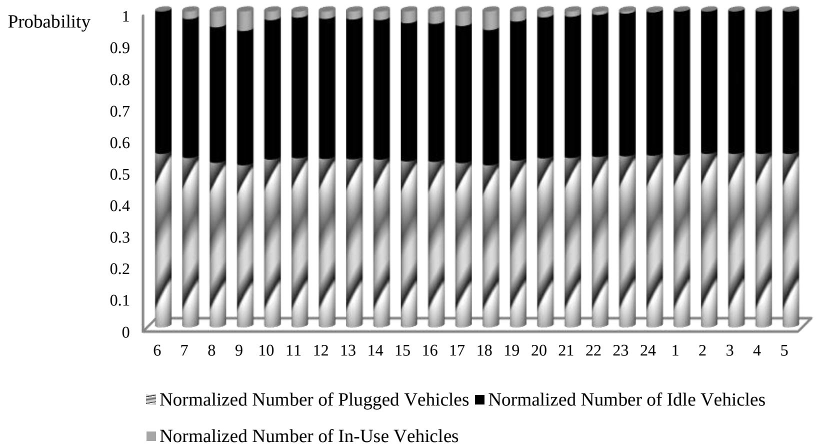

Fig. 8 the variation of presence probability in each introduced state during 24 Hours

TABLE 6. Normalized for the study case.

Hour	$OSOC_{Plugged}$	$P_{Plugged}$	NE_{V2G}
H6	55.00	52.25	28.875
H7	53.68	50.99	28.185
H8	52.18	49.03	27.665
H9	51.40	47.33	27.735
H10	53.19	47.91	29.235
H11	53.63	48.29	29.485
H12	53.41	48.33	29.245
H13	53.30	48.39	29.105
H14	53.18	48.45	28.955
H15	52.62	48.01	28.615
H16	52.49	47.66	28.66
H17	52.09	47.05	28.565
H18	51.37	46.05	28.345
H19	52.85	46.80	29.45
H20	53.58	47.65	29.755
H21	53.70	48.26	29.57
H22	54.02	49.02	29.51
H23	54.23	49.74	29.36
H24	54.44	50.42	29.23
H1	54.60	50.98	29.11
H2	54.72	51.22	29.11

Hour	$\boldsymbol{OSOC_{Plugged}}$	$\boldsymbol{P_{Plugged}}$	$\boldsymbol{NE_{V2G}}$
H3	54.84	51.68	29
H4	54.90	52.02	28.89
H5	55.01	52.23	28.895

D. OSOC trend application in electric vehicles daily charging load profile estimation:

As it is already mentioned in previous sections, a novel method has been introduced to make a description of electric vehicles charging load profile in this paper. This method is based on the comparison of $OSOC_0$ and $OSOC_{ACR}$ (the former represents the OSOC trend while the average charging rate is manually set to zero and the latter indicates the calculated OSOC trend with the average charging rate of ACR). The $OSOC_0$ trend for this study case is plotted in Fig. 9. Using the equation (8), the electric vehicles daily charging profile for this case study is represented in Fig. 10. Although the ACR is a unique value for every region (according to the type of electric vehicles and charging stations in that area) but the daily EV charging profile for a different ACR (ACR=18%) is represented in Fig. 11. By comprising these two loading profiles in Fig. 10 & 11, a general overview can be obtained about the effects of changing ACR on the power grids imposed load due to charging of electric vehicles. This alteration could be the result of a load-managing program in the smart future power grids.

As it can be concluded, the total areas below the represented load profiles are the same in both Fig. 10 and 11, and are equal to the sum of the total energy consumed in transportation systems for this region.

The daily load profile due to the charging of electric vehicles is represented in Fig. 12 (data in Fig. 10 is multiplied by the reference value to show the system load in Mega Watts). This load profile shows two peaks happening a few minutes after the two discussed peaks in vehicle-usage probability. This is a normal result of an aggregation in previously used vehicles in plugged (charging) state. As it was mentioned before, if just the charging concerns are taken into consideration by the vehicle owners, then the annoying peaks of EVs charging loads in power systems critical peak hours would be irresistible.

Although handling this conclusion for daily charging load patterns of electric vehicles, rings an alarming signal for system operators and investigators to be prepared of coping with, these new highly distributed loads, but it is not absolutely rational to consider the behavior of vehicle owners affectless of high cost of electricity in peak hours. In reality, the behavior of vehicle owners in charging their vehicles affects from hourly cost of electricity and the implementation of the introduced model to be sensitive of this concern is in the favor of Part II of this paper. In the second part of this paper, the Markov model has been modified to be able of handling electricity costs in modeling the electric vehicles behavior.

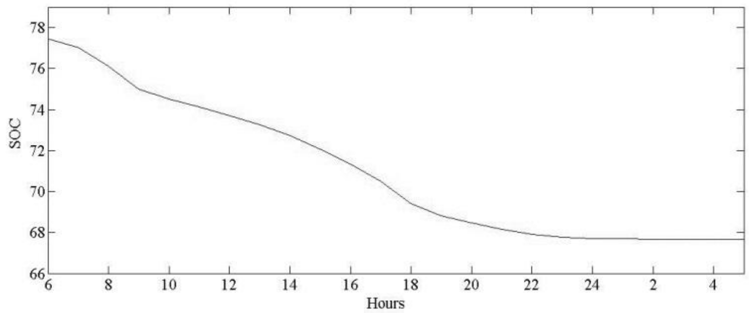

Fig. 9. Amended normalized overall SOC trend of the group of vehicles in a sample weekday while charging rate is being set to zero

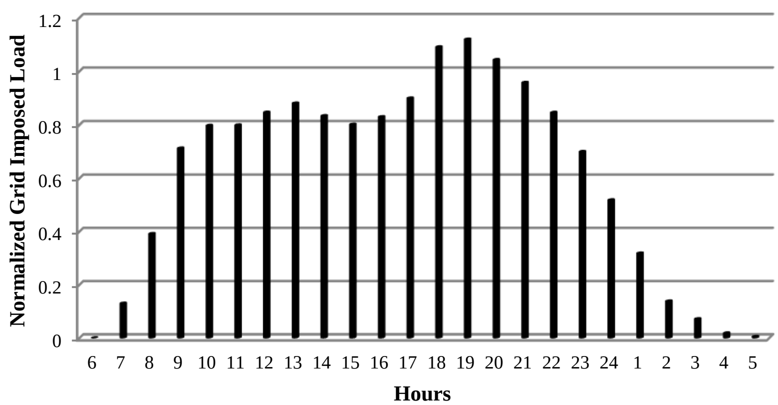

Fig. 10. Normalized Grid Imposed Load Due to Vehicles Charging With ACR=11.1%

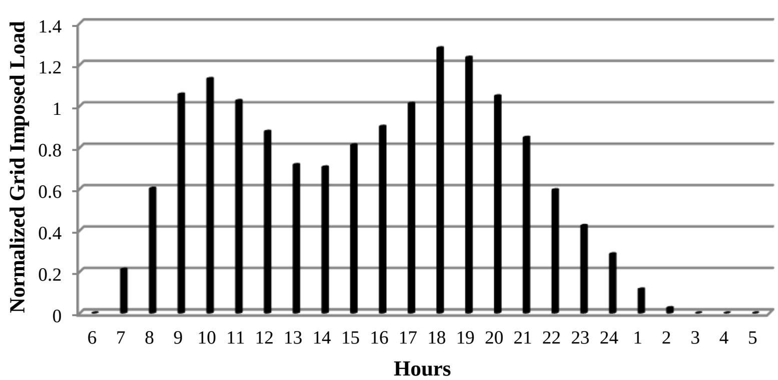

Fig. 11. Normalized Grid Imposed Load Due to Vehicles Charging with ACR=18%

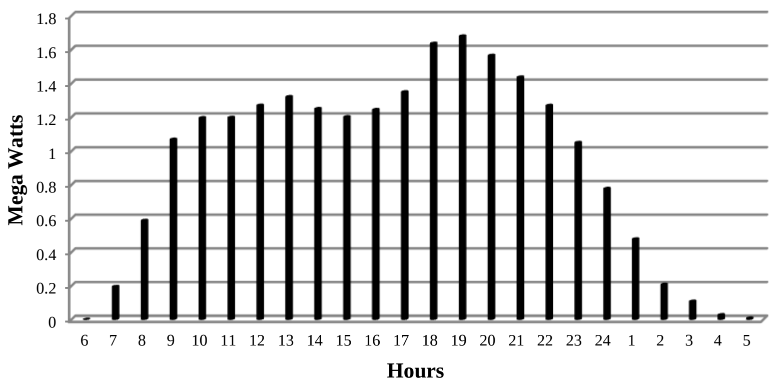

Fig. 12. Grid Imposed Load Due to Vehicles Charging With ACR=11.1% in Mega Watts

E. A simple conformation calculation:

As it can be calculated from Fig. 12 model output, shows a total sum of 29.4 MWh of energy consumption in transportation system of this studied region and also, of the usage probability diagram for the specific region can be concluded that vehicles are used for about an average of 34 minutes per day in the studied region. If an average speed of 30 km/h were considered for the supposed region [64, 67] then the total traveled path of 10000 vehicles in that region for the sample day would be calculated as:

$$\left(\frac{34}{60}\right)(h) \times 30\left(\frac{km}{h}\right) \times 10000 = 170000(km)$$

In addition, if in another consumption an electric vehicle is assumed to be able of traveling 6 km per one kWh of reserved energy in its battery [68], then the model output shows the total traveled path in the studied region as follow:

$$(6 \times 1000)\left(\frac{km}{MWh}\right) \times 29.4\ (MWh) = 176400(km)$$

Comparison of these results can be a simple method to confirm the accuracy of the proposed model.

5. DISCUSSING THE RESULTS

The rapid growth of EVs has led to the need for evaluating their behavior in power grids. Recent studies have employed various methods to assess EV behavior, these methods include:

- Data-driven approaches, where large-scale data sets collected from EVs, charging stations, and smart grids are utilized to analyze charging patterns and EVs driving behavior [80, 81]. Machine learning algorithms and statistical models are applied to identify trends, predict future behavior, and optimize charging strategies.
- Conducting surveys and questionnaires to gather information directly from EV owners [82, 83]. These methods provide insights into charging preferences, driving distances, and user experiences, helping to understand the behavior of EV users.

- Simulation models where advanced simulation models are employed to replicate real-world scenarios and assess the behavior of EVs in power grids [84, 85]. These models consider factors such as charging infrastructure, grid capacity, and user behavior to predict the impact of EVs on the grid. Various types of simulation models are introduced in research articles, including:
    - Discrete Event Simulation (DES): DES models simulate the behavior of individual electric vehicles and their interactions with the power grid [86]. They consider discrete events and actions, such as vehicle charging and discharging, and can provide detailed insights into the behavior of electric vehicles at a granular level.
    - Agent-Based Models (ABM): ABM models represent electric vehicles as autonomous agents with individual characteristics and decision-making capabilities [87, 88]. These models simulate the interactions between multiple agents and can capture the dynamics of electric vehicle behavior in a more realistic manner.
    - Stochastic Models: Stochastic models incorporate randomness and uncertainty into the simulation [89, 90]. They can capture the variability in electric vehicle charging patterns and other factors that affect load profiles, such as driver behavior and charging infrastructure availability [91].
    - Optimization Models: Optimization models aim to find the optimal charging strategies for electric vehicles based on certain objectives, such as minimizing grid stress or maximizing renewable energy utilization [92]. These models consider various constraints and optimization algorithms to determine the most efficient charging schedules.

The Non-stationary Discrete Markov approach presented in this paper offers several advantages when evaluating the behavior of electric vehicles in the power grid, firstly, a non-stationary discrete Markov approach allows for the modeling of time-varying behavior of EVs. EV charging patterns and driving habits can change over time due to factors such as technological advancements, changes in user preferences, and evolving infrastructure. By incorporating this non-stationarity into the model, a non-stationary discrete Markov approach can capture the dynamic nature of EV behavior more accurately. This is in contrast to data-driven approaches or surveys, which may provide insights based on static or limited timeframes.

Secondly, a non-stationary discrete Markov approach can account for the dependencies and correlations between different states or actions in EV behavior. EV charging and driving behavior are influenced by various factors, such as battery level, available charging infrastructure, and user preferences. A Markov approach considers the probabilistic transitions between different states or actions, allowing for a more realistic representation of how these factors interact and impact EV behavior. This is in contrast to simulation models or optimization models, which may not explicitly capture the dependencies between different variables.

Thirdly, a non-stationary discrete Markov approach can provide valuable insights into the impact of EVs on the power grid at a granular level. By modeling multiple groups of EVs as discrete entities with distinct behaviors, a Markov approach can analyze the behavior of variant EV types and their interactions with the power grid. This level of granularity allows for a more detailed understanding of the potential challenges and opportunities posed by EVs in terms of grid stability, load management, and infrastructure requirements. Other methods, such as optimization models or simulation models, may fail to capture the behaviors of different types or fleets of EVs in a study.

Additionally, a non-stationary discrete Markov approach can facilitate scenario analysis and sensitivity testing. By manipulating the transition probabilities or states in the Markov model, further studies can explore different scenarios and assess the impact of various factors on EV behavior and grid performance. This flexibility allows for a comprehensive evaluation of different policy interventions, infrastructure investments, or behavioral changes.

6. CONCLUSION

In this paper, a non-stationary discrete Markov chain model is presented to determine the stochastic behavior of electric vehicles from the system operator point of view. The study's model effectively addresses the uncertainties surrounding the integration of electric vehicles into power networks by utilizing the non-stationary nature of a Markov chain. By employing the presented model, this study offers a precise and valuable understanding of the ever-changing and time-dependent behavior of EVs within the power network.

Using this model, according to the vehicle usage probability for a region, variation in overall SOC of the fleet of electric vehicles in a sample weekday is determined. Applying data mining methods to the outputs of the model, some interesting, grid view, information are obtained. Such information includes; vehicles daily charging load profile, variations of reserved energy in different states of vehicles, and also, a view of the corresponding variation of the number of vehicles in the introduced states, during a sample 24 hours. Considering the trends of daily EV use at the community level, the study suggests that instead of solely focusing on the impact of EV load on the power grid the attention should be redirected towards the concept of the lost opportunity associated with these emerging technologies as without proper planning and understanding, the immense capacities of EVs as dispersed energy storage resources may fail to achieve desired outcomes.

As The article emphasizes, effective utilization of EVs' significant capacity in enhancing the performance indices of the power network, provision of ancillary services like frequency control, development of flexible resources for network management, and improving power system capacities to accommodate intermittent generations could only be fully realized via the promotion of mutual recognition between the power grid and EVs.

This recognition establishes a vital communication and coordination framework that enables efficient and optimized utilization of resources. By mutually recognizing each other's presence and capabilities, the power grid operator gains valuable insights into the behavior and charging patterns of EVs. This knowledge allows for better prediction and management of electricity demand, ensuring grid stability and reliability. Additionally, mutual recognition facilitates the integration of renewable energy sources, as EVs can serve as mobile energy storage units, providing flexibility to the grid. Ultimately, this collaboration between the power grid operator and EVs results in a more sustainable and resilient power network, benefiting both the environment and the overall efficiency of the grid system. This recognition involves addressing the various dimensions of the impact of EVs presence. By doing so, it fosters a better understanding of EV behavior and its impact on the power grid. This understanding is crucial as it enables network operators to make more informed decisions and effectively anticipate and manage the increased demand from EVs. Furthermore, it helps in identifying potential challenges and developing strategies to optimize power grid performance and reliability. Additionally, it aids in more effective planning of charging infrastructure and network expansion. By comprehending the load profile associated with EVs, policymakers and planners can strategically determine the placement and capacity of charging stations. This ensures that the power grid can accommodate the growing number of EVs without compromising system stability or overloading specific network areas.

In this study, the authors have focused on incorporating non-stationary transition probabilities of the Markov model to capture human behavioral functions and represent customer preferences in EV charging. However, the authors are currently conducting further research to enhance this model by incorporating the concept of EV owners' demand elasticity to energy prices. This additional research aims to improve the accuracy of the model, making it more representative of real-world scenarios. By considering the impact of demand elasticity, the model will provide a more comprehensive simulation of EV charging behavior and its response to varying energy prices

7. REFERENCES

1. Yagcitekin, B., M. Uzunoglu, A. Karakas, and O. Erdinc, *Assessment of electrically-driven vehicles in terms of emission impacts and energy requirements: a case study for Istanbul, Turkey.* Journal of Cleaner Production, 2015. **96**: p. 486-492.
2. Dogan, A., et al. *Impact of EV charging strategies on peak demand reduction and load factor improvement*. in *2015 9th International Conference on Electrical and Electronics Engineering (ELECO)*. 2015. IEEE.
3. Noel, L., et al., *History, definition, and status of V2G.* Vehicle-to-Grid: A Sociotechnical Transition Beyond Electric Mobility, 2019: p. 1-31.
4. Raustad, R.A., *The role of V2G in the smart grid of the future.* The Electrochemical Society Interface, 2015. **24**(1): p. 53.
5. Muratori, M., et al., *The rise of electric vehicles—2020 status and future expectations.* Progress in Energy, 2021. **3**(2): p. 022002.
6. Kapustin, N.O. and D.A. Grushevenko, *Long-term electric vehicles outlook and their potential impact on electric grid.* Energy Policy, 2020. **137**: p. 111103.
7. Statharas, S., et al., *Factors influencing electric vehicle penetration in the EU by 2030: A model-based policy assessment.* Energies, 2019. **12**(14): p. 2739.
8. Martins, H., et al., *Assessing policy interventions to stimulate the transition of electric vehicle technology in the European Union.* Socio-Economic Planning Sciences, 2023. **87**: p. 101505.
9. Han, J., X. Zhou, S. Lu, and P. Zhao, *A three-phase bidirectional grid-connected AC/DC converter for V2G applications.* Journal of Control Science and Engineering, 2020. **2020**: p. 1-12.
10. Inci, M., M.M. Savrun, and Ö. Çelik, *Integrating electric vehicles as virtual power plants: A comprehensive review on vehicle-to-grid (V2G) concepts, interface topologies, marketing and future prospects.* Journal of Energy Storage, 2022. **55**: p. 105579.
11. Upputuri, R.P. and B. Subudhi, *A Comprehensive Review and Performance Evaluation of Bidirectional Charger Topologies for V2G/G2V Operations in EV Applications.* IEEE Transactions on Transportation Electrification, 2023.
12. Alfaverh, F., M. Denaï, and Y. Sun, *Optimal vehicle-to-grid control for supplementary frequency regulation using deep reinforcement learning.* Electric Power Systems Research, 2023. **214**: p. 108949.
13. El-Hendawi, M., Z. Wang, and X. Liu, *Centralized and Distributed Optimization for Vehicle-to-Grid Applications in Frequency Regulation.* Energies, 2022. **15**(12): p. 4446.
14. Suh, J., S. Song, and G. Jang, *Power imbalance-based droop control for vehicle to grid in primary frequency regulation.* IET Generation, Transmission & Distribution, 2022. **16**(17): p. 3374-3383.
15. Alotaibi, M.A. and A.M. Eltamaly, *upgrading conventional power system for accommodating electric vehicle through demand side management and V2G concepts.* Energies, 2022. **15**(18): p. 6541.
16. Kirmani, S., et al. *Optimal Allocation of V2G Stations in a Microgrid Environment: Demand Response*. in *2023 International Conference on Power, Instrumentation, Energy and Control (PIECON)*. 2023. IEEE.

17. Ghasempour, A. and J. Lou, *Advanced metering infrastructure in smart grid: Requirements challenges architectures technologies and optimizations.* Smart Grids: Emerging Technologies, Challenges and Future Directions, 2017. **1**: p. 77-127.
18. Ghasempour, A., *Internet of things in smart grid: Architecture, applications, services, key technologies, and challenges.* Inventions, 2019. **4**(1): p. 22.
19. Tirunagari, S., M. Gu, and L. Meegahapola, *Reaping the benefits of smart electric vehicle charging and vehicle-to-grid technologies: Regulatory, policy and technical aspects.* IEEE Access, 2022.
20. Rather, Z.H., S. Safiullah, A. Rahman, and S.A. Lone, *Technical Feasibility of EV Infrastructure with Renewable Power Integration: A Case Study at NIT Srinagar*, in *Intelligent Manufacturing and Energy Sustainability: Proceedings of ICIMES 2022*. 2023, Springer. p. 441-449.
21. Ravi, S. and M. Aziz, *Utilization of Electric Vehicles for Vehicle-to-Grid Services: Progress and Perspectives. Energies 2022, 15, 589*. 2022, s Note: MDPI stays neutral with regard to jurisdictional claims in published ….
22. Mojumder, M.R.H., et al., *Electric vehicle-to-grid (V2G) technologies: Impact on the power grid and battery.* Sustainability, 2022. **14**(21): p. 13856.
23. Sayed, M.A., R. Atallah, C. Assi, and M. Debbabi, *Electric vehicle attack impact on power grid operation.* International Journal of Electrical Power & Energy Systems, 2022. **137**: p. 107784.
24. Mastoi, M.S., et al., *A study of charging-dispatch strategies and vehicle-to-grid technologies for electric vehicles in distribution networks.* Energy Reports, 2023. **9**: p. 1777-1806.
25. Kuruvilla, V., P.V. Kumar, and A.I. Selvakumar. *Challenges And Impacts of V2g Integration-A Review*. in *2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS)*. 2022. IEEE.
26. Singh, J. and R. Tiwari, *Cost benefit analysis for V2G implementation of electric vehicles in distribution system.* IEEE Transactions on Industry Applications, 2020. **56**(5): p. 5963-5973.
27. Fan, J. and Z. Chen. *Cost-benefit analysis of optimal charging strategy for electric vehicle with V2G*. in *2019 North American Power Symposium (NAPS)*. 2019. IEEE.
28. Hao, X., et al., *A V2G-oriented reinforcement learning framework and empirical study for heterogeneous electric vehicle charging management.* Sustainable Cities and Society, 2023. **89**: p. 104345.
29. Oad, A., et al., *Green smart grid predictive analysis to integrate sustainable energy of emerging V2G in smart city technologies.* Optik, 2023. **272**: p. 170146.
30. Ntombela, M. and K. Musasa, *A Comprehensive Review for Incorporation of Electric Vehicles and Renewable Energy Distributed Generation to Smart Grid.* 2023.
31. Muqeet, H.A., R. Liaqat, M. Jamil, and A.A. Khan, *A State-of-the-Art Review of Smart Energy Systems and Their Management in a Smart Grid Environment.* Energies, 2023. **16**(1): p. 472.
32. Dong, J., A. Yassine, A. Armitage, and M.S. Hossain, *Multi-Agent Reinforcement Learning for Intelligent V2G Integration in Future Transportation Systems.* IEEE Transactions on Intelligent Transportation Systems, 2023.
33. Sami, I., et al. *A bidirectional interactive electric vehicles operation modes: Vehicle-to-grid (V2G) and grid-to-vehicle (G2V) variations within smart grid*. in *2019 international conference on engineering and emerging technologies (ICEET)*. 2019. IEEE.
34. Sovacool, B.K., J. Kester, L. Noel, and G.Z. de Rubens, *Actors, business models, and innovation activity systems for vehicle-to-grid (V2G) technology: A comprehensive review.* Renewable and Sustainable Energy Reviews, 2020. **131**: p. 109963.
35. Noel, L., et al., *The Economic and Business Challenges to V2G.* Vehicle-to-Grid: A Sociotechnical Transition Beyond Electric Mobility, 2019: p. 91-116.
36. Wang, M. and M.T. Craig, *The value of vehicle-to-grid in a decarbonizing California grid.* Journal of Power Sources, 2021. **513**: p. 230472.
37. Huda, M., T. Koji, and M. Aziz, *Techno economic analysis of vehicle to grid (V2G) integration as distributed energy resources in Indonesia power system.* Energies, 2020. **13**(5): p. 1162.
38. Ali, H., et al. *Economic and Environmental Impact of Vehicle-to-Grid (V2G) Integration in an Intermittent Utility Grid*. in *2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES)*. 2020. IEEE.

39. Nizami, M.S.H., M. Hossain, and K. Mahmud, *A coordinated electric vehicle management system for grid-support services in residential networks.* IEEE Systems Journal, 2020. **15**(2): p. 2066-2077.
40. Tostado-Véliz, M., et al., *Optimal energy management of cooperative energy communities considering flexible demand, storage and vehicle-to-grid under uncertainties.* Sustainable Cities and Society, 2022. **84**: p. 104019.
41. Dixon, J., W. Bukhsh, K. Bell, and C. Brand, *Vehicle to grid: driver plug-in patterns, their impact on the cost and carbon of charging, and implications for system flexibility.* Etransportation, 2022. **13**: p. 100180.
42. Alirezazadeh, A., M. Rashidinejad, P. Afzali, and A. Bakhshai, *A new flexible and resilient model for a smart grid considering joint power and reserve scheduling, vehicle-to-grid and demand response.* Sustainable Energy Technologies and Assessments, 2021. **43**: p. 100926.
43. Venegas, F.G., M. Petit, and Y. Perez, *Active integration of electric vehicles into distribution grids: Barriers and frameworks for flexibility services.* Renewable and Sustainable Energy Reviews, 2021. **145**: p. 111060.
44. Noel, L., et al., *The Regulatory and Political Challenges to V2G.* Vehicle-to-Grid: A Sociotechnical Transition Beyond Electric Mobility, 2019: p. 117-139.
45. Beil, I., L. Whittemore, and A. Shrestha. *Utility Experience with Vehicle-to-Grid Regulatory and Technology Challenges, and the Final Hurdles to Large-Scale V2G Deployment*. in *2022 IEEE Power & Energy Society General Meeting (PESGM)*. 2022. IEEE.
46. Savari, G.F., et al., *Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: A review.* Ain Shams Engineering Journal, 2022: p. 101938.
47. Ravi, S.S. and M. Aziz, *Utilization of electric vehicles for vehicle-to-grid services: Progress and perspectives.* Energies, 2022. **15**(2): p. 589.
48. Amin, A., et al., *A review of optimal charging strategy for electric vehicles under dynamic pricing schemes in the distribution charging network.* Sustainability, 2020. **12**(23): p. 10160.
49. Ma, S.-C., et al., *Analysing online behaviour to determine Chinese consumers' preferences for electric vehicles.* Journal of Cleaner Production, 2019. **229**: p. 244-255.
50. Boehm, J., H.K. Bhargava, and G.G. Parker, *The business of electric vehicles: a platform perspective.* Foundations and Trends® in Technology, Information and Operations Management, 2020. **14**(3): p. 203-323.
51. Ahmadian, A., B. Mohammadi-Ivatloo, and A. Elkamel, *A review on plug-in electric vehicles: Introduction, current status, and load modeling techniques.* Journal of Modern Power Systems and Clean Energy, 2020. **8**(3): p. 412-425.
52. Wang, M., et al., *State space model of aggregated electric vehicles for frequency regulation.* IEEE Transactions on Smart Grid, 2019. **11**(2): p. 981-994.
53. Song, Y. and X. Hu, *Learning electric vehicle driver range anxiety with an initial state of charge-oriented gradient boosting approach.* Journal of Intelligent Transportation Systems, 2023. **27**(2): p. 238-256.
54. LaMonaca, S. and L. Ryan, *The state of play in electric vehicle charging services–A review of infrastructure provision, players, and policies.* Renewable and sustainable energy reviews, 2022. **154**: p. 111733.
55. Hemavathi, S. and A. Shinisha, *A study on trends and developments in electric vehicle charging technologies.* Journal of energy storage, 2022. **52**: p. 105013.
56. Ahmad, F., A. Iqbal, I. Ashraf, and M. Marzband, *Optimal location of electric vehicle charging station and its impact on distribution network: A review.* Energy Reports, 2022. **8**: p. 2314-2333.
57. Arun, V., et al., *Review on li-ion battery vs nickel metal hydride battery in EV.* Advances in Materials Science and Engineering, 2022. **2022**.
58. Ramya, P. and M. Ajaikrishnan, *A Review on Future Challenges Of Ev Range Extension.* 2022.
59. Xing, Y., et al., *Multi-type electric vehicle load prediction based on Monte Carlo simulation.* Energy Reports, 2022. **8**: p. 966-972.

60. Hatherall, O., J. Marco, A. Barari, and M.F. Niri. *Load prediction based remaining discharge energy estimation using a combined online and offline prediction framework*. in *2022 IEEE Conference on Control Technology and Applications (CCTA)*. 2022. IEEE.
61. Li, X., et al., *Electric vehicle behavior modeling and applications in vehicle-grid integration: An overview*. Energy, 2023: p. 126647.
62. Lauvergne, R., Y. Perez, and A. Tejeda, *Modeling electric vehicle charging patterns: A review*. Revue d'économie industrielle, 2023: p. 247-286.
63. Abolfazli, M., M.H. Bahmani, S. Afsharnia, and M.S. Ghazizadeh. *A probabilistic method to model PHEV for participation in electricity market*. in *2011 19th Iranian Conference on Electrical Engineering*. 2011. IEEE.
64. Huang, S. and D. Infield. *The potential of domestic electric vehicles to contribute to power system operation through vehicle to grid technology*. in *2009 44th International Universities Power Engineering Conference (UPEC)*. 2009. IEEE.
65. Bahmani, M.H., M. Abolfazli, S. Afsharnia, and M.S. Ghazizadeh. *Introducing a new concept to utilize plug-in electric vehicles in frequency regulation service*. in *The 2nd International Conference on Control, Instrumentation and Automation*. 2011. IEEE.
66. Gan, L., U. Topcu, and S.H. Low. *Stochastic distributed protocol for electric vehicle charging with discrete charging rate*. in *2012 IEEE Power and Energy Society General Meeting*. 2012. IEEE.
67. Kempton, W., et al., *A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system.* Results from an Industry-University Research Partnership, 2008. **32**: p. 1-32.
68. Kempton, W., *Electric vehicles: Driving range.* Nature Energy, 2016. **1**(9): p. 1-2.
69. Norris, J.R., *Markov chains*. 1998: Cambridge university press.
70. Chung, K.L., *Markov chains.* Springer-Verlag, New York, 1967.
71. Revuz, D., *Markov chains*. 2008: Elsevier.
72. Douc, R., E. Moulines, P. Priouret, and P. Soulier, *Markov chains*. 2018: Springer.
73. Quirós-Tortós, J., L.F. Ochoa, and B. Lees. *A statistical analysis of EV charging behavior in the UK*. in *2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM)*. 2015. IEEE.
74. Bertuccelli, L.F. and J.P. How. *Estimation of non-stationary Markov chain transition models*. in *2008 47th IEEE Conference on Decision and Control*. 2008. IEEE.
75. Salzenstein, F., C. Collet, S. Lecam, and M. Hatt, *Non-stationary fuzzy Markov chain.* Pattern Recognition Letters, 2007. **28**(16): p. 2201-2208.
76. Li, B., et al., *Modeling the impact of EVs in the Chinese power system: Pathways for implementing emissions reduction commitments in the power and transportation sectors.* Energy Policy, 2021. **149**: p. 111962.
77. Zecchino, A., A.M. Prostejovsky, C. Ziras, and M. Marinelli, *Large-scale provision of frequency control via V2G: The Bornholm power system case.* Electric power systems research, 2019. **170**: p. 25-34.
78. Masood, A., et al., *Transactive energy for aggregated electric vehicles to reduce system peak load considering network constraints.* Ieee Access, 2020. **8**: p. 31519-31529.
79. Yan, D., C. Ma, and Y. Chen, *Distributed coordination of charging stations considering aggregate EV power flexibility.* IEEE Transactions on Sustainable Energy, 2022. **14**(1): p. 356-370.
80. Pan, Z., et al., *Data-driven EV load profiles generation using a variational auto-encoder.* Energies, 2019. **12**(5): p. 849.
81. Dang, Q. and Y. Huo. *Modeling ev fleet load in distribution grids: a data-driven approach*. in *2018 IEEE Transportation Electrification Conference and Expo (ITEC)*. 2018. IEEE.
82. Kurani, K.S., T. Turrentine, and D. Sperling, *Testing electric vehicle demand in 'hybrid households' using a reflexive survey.* Transportation Research Part D: Transport and Environment, 1996. **1**(2): p. 131-150.
83. Yilmaz, S., P. Cuony, and C. Chanez, *Prioritize your heat pump or electric vehicle? Analysing design preferences for Direct Load Control programmes in Swiss households.* Energy Research & Social Science, 2021. **82**: p. 102319.
84. Schäuble, J., et al., *Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany.* Journal of Cleaner Production, 2017. **150**: p. 253-266.

85. Qian, K., C. Zhou, M. Allan, and Y. Yuan, *Modeling of load demand due to EV battery charging in distribution systems.* IEEE transactions on power systems, 2010. **26**(2): p. 802-810.
86. Lopez, N.S., A. Allana, and J.B.M. Biona, *Modeling electric vehicle charging demand with the effect of increasing EVSEs: A discrete event simulation-based model.* Energies, 2021. **14**(13): p. 3734.
87. Chaudhari, K., et al., *Agent-based aggregated behavior modeling for electric vehicle charging load.* IEEE Transactions on Industrial Informatics, 2018. **15**(2): p. 856-868.
88. Olivella-Rosell, P., R. Villafafila-Robles, A. Sumper, and J. Bergas-Jané, *Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks.* Energies, 2015. **8**(5): p. 4160-4187.
89. Bina, V.T. and D. Ahmadi, *Stochastic modeling for scheduling the charging demand of EV in distribution systems using copulas.* International Journal of Electrical Power & Energy Systems, 2015. **71**: p. 15-25.
90. Scharrenberg, R., B. Vonk, and P.H. Nguyen. *EV stochastic modelling and its impacts on the Dutch distribution network*. in *2014 international conference on probabilistic methods applied to power systems (PMAPS)*. 2014. IEEE.
91. Dai, Q., T. Cai, S. Duan, and F. Zhao, *Stochastic modeling and forecasting of load demand for electric bus battery-swap station.* IEEE Transactions on Power Delivery, 2014. **29**(4): p. 1909-1917.
92. Erdinç, O., et al., *Comprehensive optimization model for sizing and siting of DG units, EV charging stations, and energy storage systems.* IEEE Transactions on Smart Grid, 2017. **9**(4): p. 3871-3882.