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Research paper

Strategic participation of electric vehicles in vehicle-to-grid within a microgrid system: A decentralized optimization approach

Ayoub Zerka *, Mohammed Ouassaid [1], Mohamed Maaroufi [1]

Engineering for Smart and Sustainable Systems Research, Mohammadia School of Engineers, Mohammed V University in Rabat, Ibn Sina, Rabat, 10000, Morocco

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ABSTRACT

In the context of developing modern smart energy systems, integrating Vehicle-to-Grid (V2G) technology within microgrids offers valuable prospects for advancing energy efficiency and sustainability. In this perspective, motivation for the present work mainly stems from the rising need for intelligent and innovative grid management strategies that are capable of balancing energy demand and supply, sustaining economic viability, securing system stability as well as accommodating the growing penetration of Electric Vehicles (EVs). However, strategically managing the dynamic interaction between EVs participating in V2G operations and the microgrid can become complex due to various shifting factors. These include different charging/discharging preferences, EVs flexibility constraints as well as stochastic V2G variables. Thereby, a robust and comprehensive framework is needed to optimize EV-microgrid interactions. In response to this challenge, this study investigates a non-cooperative game approach for decentralized optimization of V2G operations within a microgrid environment. A case study with 5 EVs then with a fleet of 100 EVs is developed and analyzed to showcase the suggested approach. Numerical results show that with 5 EVs, the contribution to the microgrid's daily energy demand is about 5.5%, which increases to 35.37% with 100 EVs. These results highlight the effectiveness of the proposed framework and provide valuable insights for enhancing microgrid sustainability and smart grid management.

Nomenclature

π_{EV_i}	Payoff function of EV i
$\pi_M O$	Payoff function of the MO
A_i	Availability function for EV i
C_i	Battery capacity for EV i (KWh)
$d_{c,i}$	Duration of charging for EV i
$d_{d,i}$	Duration of discharging for EV i
$D^e_M(t)$	Expected energy requirement for the microgrid (kWh)
D_M	Microgrid's energy demand (kWh)
$E_{c,i}$	Desired energy for charging for EV i (%)
$E_{d,i}$	Desired energy for discharging for EV i (%)
f	Probability density function for a continuous random variable
F_i	Flexibility profile of EV i
G_M	Microgrid's generation (kWh)
L_M	Microgrid's load (kWh)
$n^e(t)$	Expected number of V2G participants at time slot t
p	Probability of the a discreet random variable
$P^e_c(t)$	Expected price of charging energy to EVs at time slot t ($/kWh)
$P^e_d(t)$	Expected price of discharging energy from EVs at time slot t ($/kWh)
P_{bG}	Price of buying energy from the main grid ($/kWh)
P_c	Price of charging energy to EVs ($/kWh)
P_d	Price of discharging energy from EVs ($/kWh)
P_{sG}	Price of selling energy to the main grid ($/kWh)
$q^*_{c/d,i}$	Maximum energy EV i is capable to trade
$q_{c,i}$	Charged energy amount to EV i (kWh)
$q_{d,i}$	Discharged energy amount from EV i (kWh)
$R_{c,i}$	Allowed charging rate for EV i (KW)
$R_{d,i}$	Allowed discharging rate for EV i (KW)
SOC_i	State of charge of EV i (%)
x	Random variable
AI	Artificial Intelligence
B2V	Building-to-Vehicle
DES	Distributed Energy Systems

* Corresponding author.
E-mail addresses: zerka.ayoub@gmail.com (A. Zerka), ouassaid@emi.ac.ma (M. Ouassaid), maaroufi@emi.ac.ma (M. Maaroufi).
[1] These authors contributed equally to this work.

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DQN	Deep Q-Network
ECP	Expected Current Payoff
EFP	Expected Future Payoff
ESS	Energy Storage System
EV	Electric Vehicle
G2V	Grid-to-Vehicle
H2V	Home-to-Vehicle
MO	Microgrid Operator
N	Number of Electric Vehicles
PD	Participation Decision
PSO	Particle Swarm Optimization
PV	Photovoltaic
Q	Amount of energy to be exchanged
QF	Future amount of energy to be exchanged
QX	Maximum amount of energy to be exchanged
RES	Renewable Energy Sources
RL	Reinforcement Learning
T	Total number of time slots
t	Time slot
V2B	Vehicle-to-Building
V2C	Vehicle-to-Cloud
V2D	Vehicle-to-Device
V2eG	Vehicle-to-everything-in-the-power-grid
V2G	Vehicle-to-Grid
V2H	Electric Vehicle
V2I	Vehicle-to-Infrastructure
V2M	Vehicle-to-Microgrid
V2N	Vehicle-to-Network
V2P	Vehicle-to-Pedestrian
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-everything
WT	Wind Turbine

1. Introduction

1.1. Background and motivations

The increasing integration of electric vehicles (EVs) in modern urban life is reshaping the way energy demand-side response is perceived and managed [1]. In fact, not only do EVs contribute to a more sustainable mobility but they hold a great asset as a new mobile energy storage system as well. This synergy, also referred to as Vehicle-to-Grid (V2G) technology, allows energy stored in EVs to be fed back and forth into and from the grid to help regulate the energy supply especially in times of peak or low demand.

Both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) systems can be considered as part of energy sharing management schemes incorporating EVs into the smart grid [2]. In practical terms, while G2V studies focus on understanding the behavior of EVs and developing strategies for optimal management and control of the charging operations of EV batteries, V2G researches explores the opportunity of EVs providing ancillary services to the grid by discharging energy from their batteries back into the grid [3]. This bidirectional energy flow allows EVs to contribute to grid stability when demand spikes or when renewable energy sources (RESs) are unavailable, responding almost in real-time. V2G technology derives its effectiveness from the low utilization rate of private vehicles that are primarily used to daily commuting and essential tasks but remain most of the times parked in the streets and driveways [4,5]. In this paper, “V2G system” refers to the technical infrastructure facilitating bidirectional energy flow between EVs and the grid [6], while “V2G program” denotes specific initiatives or policies aimed at promoting or implementing V2G technology [7].

Within the same idea, microgrids, defined as localized energy systems able of operating autonomously or in coordination with the main grid, typically incorporate localized consumption as well as distributed energy sources (DESs). These DESs often integrate various inherently intermittent RESs such as photovoltaic (PV) panels and wind turbines (WT) which may impact the consistency of energy supply [8].

In this context, combined with microgrids, V2G technology can be a substantial game changer in the realm of smart mobility and energy management. By facilitating two-way energy transfer, V2G not only addresses the intermittency challenges of RESs within microgrids, but also encourages a more active way of energy consumption. Additionally, V2G opens new income streams for EV owners, fleet operators and even vehicles manufacturers [9,10], fostering a more balanced and efficient energy ecosystem. In line with this, reference [11] investigates the financial gains obtained from using EVs as a dynamic, temporary energy storage system (ESS) in a microgrid integrating a PV plant. Many existing studies have unveiled the potential of V2G as a promising technology in the matter of peak load shaving and valley filling as in [12,13]. Likewise, it is estimated, in [14], that, by 2030, EVs will contribute by approximately 7.7% of China’s electricity consumption, that uncoordinated charging may increase the peak load to a 12% compared to a scenario with no EVs, and that V2G integration may unleash a considerable potential in flattening the load.

Researches have also explored a myriad of emerging applications of V2G in smart buildings [15,16], frequency regulation [17], fleet management [18], or as a mobile charging stations in case of grid emergencies as in [19]. From the same perspective, reference [20] reviews some of the key participation aspects of EVs in the power grid expanding the concept from V2G to vehicle to everything in the power grid (V2eG). In fact, this concept can be extended and duplicated to encompass the broader Vehicle-to-Everything (V2X) paradigm [21,22]. This umbrella term captures the wide scope of EVs as flexible assets supporting bidirectional data and energy exchanges not only with the grid (V2G) but also with buildings (V2B) [15,16,23], homes (V2H) [16,24], Infrastructure (V2I) [25], and even other vehicles (V2V) [25,26], emphasizing the potential of EVs as DERs. Fig. 1 depicts an overview of the vehicle-to-everything (V2X) technology including the exchange of energy and data between EVs and everything in their surroundings along with a high-level schematic illustration of the V2G and G2V mechanisms.

However, despite the potential of V2G, their upsides may be impacted by some challenges such as battery degradation [27,28] and thermal management [29,30], eventual interoperability hurdles between EVs and grid systems [31] as well as some complex regulatory landscape considerations [32]. A recent study has pinpointed, reviewed and analyzed 23 barriers hampering an eventual widespread of V2G technology, covering technical, business, and user-related obstacles. Authors highlight the interplay between these barriers as well as the associated risks if V2G is not adopted, stressing the need for collaborative efforts to overcome these limitations [33]. Results indicate that barriers related to business modeling issues stand out as particularly critical and must be addressed accordingly to advance V2G technology. Review [34] also investigates business schemes associated with V2G assessing their feasibility and challenges within the market. The study identified three main areas of challenges: technical issues involving communication complexity and battery degradation; economic aspects related to high fixed investment and uncertain market policies; and social concerns such as trust issue and range anxiety.

1.2. Literature review

In the literature, several approaches have been adopted in attempt to manage and optimize the energy sharing and interactions between EVs and the grid. Many of these approaches range from multi-objective optimization and game theory to artificial intelligence and machine learning based techniques.

Optimization methods are widely used in V2G systems, with a multitude of studies incorporating different techniques to tackle specific aspects of V2G challenges. For instance, particle swarm optimization (PSO) is a popular tool used in addressing EVs charging and discharging scheduling problems under V2G, as in references [35,36]. Reference

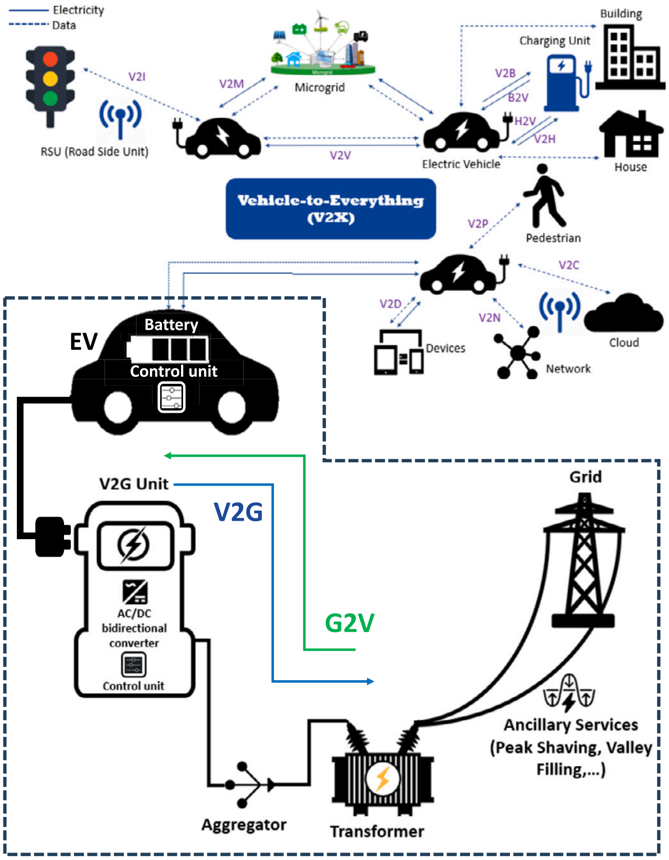

Fig. 1. Comprehensive overview of Vehicle-to-Everything (V2X) technology with a focus on V2G and G2V concepts.

[37] also uses PSO as well as an artificial bee colony to optimize the costs related to the integration of EVs and hybrid renewable sources into the economic dispatch for CO2 emission reduction. Meanwhile, reference [38] introduces a decentralized whale optimization algorithm for a fair, optimal and privacy preserving transactions for EVs involved in the V2G program. Reference [39] suggests a multi-mode optimization technique for EV unidirectional charging stations aimed at reducing the cost of EV charging in an open electricity market, incorporating three operational modes (normal, eco, and boost) to meet varying customer needs and optimize charging schedules. The approach, focusing on shifting EV loads to off-peak hours, shows potential savings. In the context of microgrids, reference [40] develops an EVs charging/discharging algorithm that optimizes grid energy consumption for a microgrid integrating PV generation. Results have shown significant energy savings for a case study of a microgrid system at Jordan University of Science and Technology. Furthermore, references [41,42] introduce novel EV battery wear models to enhance trust among EV owners and encourage their engagement in V2G and G2V synergies. Both papers use modern optimization techniques for an optimal power scheduling of charging/discharging operations, which are respectively the Musical Chairs Algorithm (MCA) and the Gradual Reduction Swarm Size Grey Wolf Optimization (GRSS-GWO) algorithm. Findings across both studies indicates that V2G technology can deliver substantial net annual profits for EV owners while also improving power system performance by efficiently shaving peak loads, despite a slight decrease in battery lifespan, thereby promoting participation in V2G programs.

On the other hand, game theory has been extensively used to model the behavior and interactions of EVs and grid. Reference [43], for example, introduces two different models for scheduling problem of EVs contribution to frequency regulation of the power grid: A non-cooperative approach through a Stackelberg game and a cooperative approach through a potential game. Results have shown that both approaches incentivize EVs to effectively smooth power fluctuations, and that cooperation and information exchange between players increase the grid performance and social welfare. Similarly, study [44] analyses competition among aggregators in the context of V2G applying the Stackelberg Leadership Model and Cournot Competition Model to pinpoint how competition among aggregators influences pricing strategies and optimal behavior. On a more specific level, reference [45] considers Stackelberg game based model to address a user-preference-driven power-scheduling problem, but only in the case of charging from the grid, while [46] tackles the imperfect information scheduling problem of EVs within V2G system and proposes a fictitious self-play game theory framework to address and approximate the Nash equilibrium state. Each of these game theory frameworks uncovered an aspect of the interplay of strategies and interests within V2G systems.

From an alternative perspective, artificial intelligence (AI) and machine learning are also gaining attention of the academia in optimizing V2G systems. Reference [47] investigates AI-driven algorithms to optimize V2G systems. The paper shows that these methods can achieve around 50% reduction in operational grid costs, and improve computation time, and address challenges like battery degradation, scalability, and data privacy concerns. In a similar vein, reference [48] develops a predictive model for V2G services optimization, using a hybrid machine learning algorithm. The model enhances energy security and balance between EV users and the grid. A deep Q-network (DQN)-based reinforcement learning (RL) method is introduced in [49] for V2G-oriented EV charging management, achieving a 98% cost reduction compared to immediate charging. The study also highlights the significance of some key factors such as departure-time and electricity price variability. Moreover, reference [50] implements a V2G strategy for a university campus, achieving 35% average energy savings and up to 65% with consistent participation, using a machine learning algorithm with 94-96% accuracy in energy predictions.

1.3. Contributions

Although previous research has significantly enhanced our understanding of the multifaceted challenges related to V2G technology, only few studies have addressed the inherent stochasticity of some key parameters governing V2G interactions like energy demand, charging prices, and grid conditions [51–53]. Furthermore, behavioral factors influencing the drivers' willingness to engage in V2G transactions, such as perceived payoffs, preferences, concerns over battery state of health and convenience of participation have received limited attention and deserve to be further understood.

In order to address these gaps, this study contributes, most importantly, by the following:

- **Innovative optimization model:** Developing an optimization model for V2G interactions within a microgrid context, accounting for the strategic behavior of both the EV driver and the Microgrid Operator (MO). This approach bridges the gap between traditional deterministic modeling and the dynamic nature of real-world scenarios, where the behaviors and motivations of EV driver can vary.
- **Integration of predictive analytics:** Introducing a basic, yet scalable, illustration of how a prediction system can be integrated within the conceived decentralized optimization framework addressing the stochastic optimization problem of EVs participation in V2G. This predictive ability enhances decision-making process under incomplete information, strengthening the model robustness.
- **Comprehensive impact analysis:** Offering an insightful analysis of the impact of various factors such as microgrid conditions, pricing schemes as well as the number of EVs participating on the system performance under varying conditions.

1.4. Paper organization

The remainder of this paper is structured as follows. Section 2 defines the problem setting, section 3 outlines the proposed solving process involving a two-stage optimization, while section 4 presents and discusses the numerical results.

2. Problem setting

In cooperative game theory, communication between players is typically permitted; however, in non-cooperative games, this is not allowed. In the following, it is assumed that EVs owners do not have access to each other's private information and strategies. In this setting, each EV operates autonomously, making strategic decisions in isolation. Nevertheless, they may keep historical records and statistical data on past occurrences and interactions.

2.1. Model components

The time horizon is segmented into discrete time slots denoted t. T being the total number of time slots. Slot "1" refers to 00:00AM - 00:59AM, slot 2 refers to 1:00AM - 1:59AM and so on. Slot "24" refers to 23:00PM – 23:59PM. N Electric Vehicles (EVs) are considered inside a microgrid managed by a MO who is in charge of the overall operation of the microgrid. At each time slot 't' the MO dynamically calculates the energy demand of the microgrid $D_M(t)$ as the difference between the load $L_M(t)$ and the generation $G_M(t)$ at that time slot, considering key factors like renewable energy generation, energy storage levels and demand forecasts.

$$D_M(t) = L_M(t) - G_M(t) \tag{1}$$

Note that the microgrid can interact with the main grid as well, as explained in Fig. 2, to either obtain additional energy (if V2G obtained energy is insufficient) or sell excess energy to the main grid (if there still be an excess energy after G2V operation).
It is vital to note that prices are designed to motivate a desired behavior. The EV's discharging price should be set higher or at least equal to the EV's charging price. Otherwise, EVs will not be motivated to do any discharging.
On the other hand, the price for discharging should be less than the price of direct energy purchase from the main grid so that the MO is motivated to sell energy from EVs rather than directly from the main grid. Similarly, the price for charging should be higher than the price of direct energy selling from the main grid so that the MO is motivated to buy energy from EVs rather than directly from the main grid. This can be formulated as follows:

$$\forall t \in \{1, 2, \dots, T\} : P_{sG}(t) \le P_c(t) \le P_d(t) \le P_{bG}(t) \tag{2}$$

with:
$P_{sG}(t)$: The price (per kWh) of selling energy to the main grid
$P_c(t)$: The price (per kWh) of charging energy to EVs
$P_d(t)$: The price (per kWh) of discharging energy from EVs
$P_{bG}(t)$: The price (per kWh) of buying energy from the main grid
This structured pricing approach aims to ensure a balanced energy exchange between the microgrid, EVs and the main grid, creating incentives for all agents to engage in V2G interactions.

2.2. Flexibility profile

Each EV owner i has a flexibility profile F_i that can be defined as follows:

$$F_i = \{A_i; C_i; R_{c,i}; R_{d,i}; E_{c,i}; E_{d,i}\} \tag{3}$$

with, for each EV owner i:

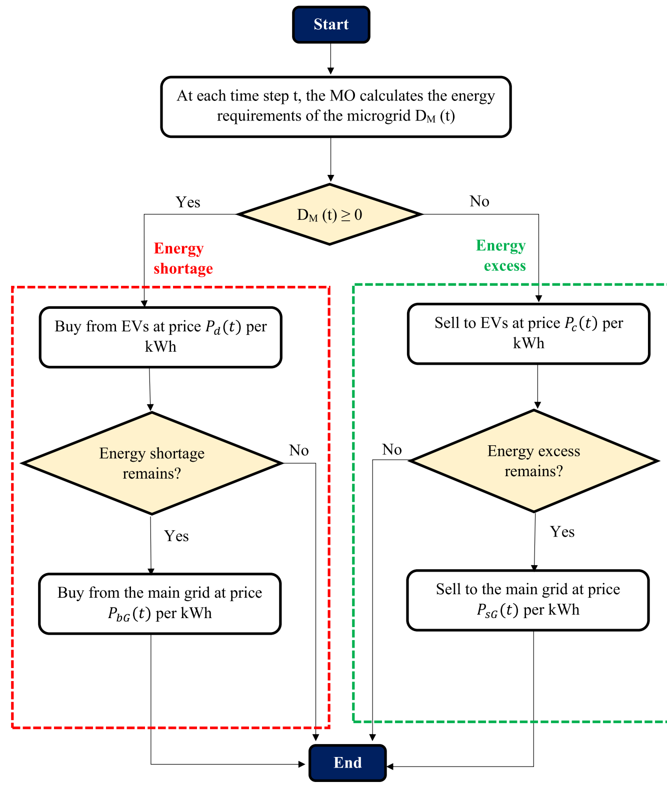

Fig. 2. Process of microgrid interaction with EVs and the main grid.

A_i: Availability function

$$A_i(t) = \begin{cases} 1 & \text{if EV } i \text{ is available at time } t \\ 0 & \text{else} \end{cases} \tag{4}$$

C_i: EV battery capacity (in KWh)
$R_{c,i}$: Allowed charging rate (in KW)
$R_{d,i}$: Allowed discharging rate (in KW)
$E_{c,i}$: Desired energy for charging (in %)
$E_{d,i}$: Desired energy for discharging (in %)
The allowed charging rate reflects the speed at which the EV's battery can be charged (measured in kW), while the desired charging energy is a particular quantity of energy the EV owner desire to acquire (measured in kWh). Similarly, the same thing can be said for the allowed discharging rate and the desired discharging energy.

By way of illustration, Adam owns an EV with a battery capacity of 60 kWh and plans to charge it overnight. The EV has an allowed charging rate of 7 kW, meaning Adam can charge his vehicle at a maximum rate of 7 kW without risking damage to the battery or charging equipment.
Adam intends to charge his EV to a desired level of around 67% State of Charge (SoC), which is the percentage of the battery capacity he wants to achieve.
For common EV drivers, expressing the desired energy as a percentage of the battery capacity is more practical, as it avoids the need to deal with technical terms like energy or power capacity. Instead, drivers focus on the simple and familiar SoC percentage, similar to how they track the charge on their phones or other devices. In this case, 67% SoC corresponds to adding about 40 kWh of energy to the EV's battery during this charging period.
Since the allowed charging rate is 7 kW, Adam plans to charge his EV for approximately $40\,\text{kWh} \div 7\,\text{kW} \approx 5.71$ hours to reach his desired energy target. He begins charging his EV at 9:00 PM and sets a timer to stop charging at around 2:43 AM, ensuring that he reaches his desired State of Charge while remaining within the safe charging parameters.

By following this plan, Adam achieves his desired energy level without exceeding the maximum allowed charging rate.

2.3. Flexibility constraints

As a response to the pricing strategy of the MO, each EV owner i, decides on the charging and discharging energy amounts $q_{c,i}(t)$ or $q_{d,i}(t)$ that maximize their profit with respect to the their flexibility constraints below.

The charging and discharging, at each time slot, should not exceed the desired energy for charging or discharging:

$$SOC_i(t) + \frac{q_{c,i}(t)}{C_i} \leq E_{c,i} \tag{5}$$

$$E_{d,i} \leq SOC_i(t) - \frac{q_{d,i}(t)}{C_i} \tag{6}$$

with $SOC_i(t)$ refers to the state of charge of EV i at time slot t.

As for the constraints related to the charging/discharging rates, it can be expressed as follows:

$$0 \leq \frac{q_{c,i}(t)}{d_{c,i}(t)} \leq R_{c,i} \tag{7}$$

$$0 \leq \frac{q_{d,i}(t)}{d_{d,i}(t)} \leq R_{d,i} \tag{8}$$

with $d_{c,i}(t)$ and $d_{d,i}(t)$ being respectively the durations of charging and discharging amidst the time slot t.

On the other hand, the V2G energy should meet, as much as possible, the microgrid energy requirements, this can be expressed by the following constraint:

$$\sum_{i=1}^{n} q_{c/d,i}(t) \leq |D_M(t)| \tag{9}$$

Note that $q_{c,i}(t)$ and $q_{d,i}(t)$ are both positive values, and that the sign that precedes them that makes the distinction. A negative sign indicates a discharged energy while a positive one indicates a charged energy from an EV's perspective.

2.4. Payoff functions

The gains of the MO at the end of time horizon T can be expressed as follows:

$$\begin{aligned}\pi_{MO} = &\sum_{t=1}^{T}\left(P_c(t)\sum_{i=1}^{n} q_{c,i}(t)\right)\\ &- \sum_{t=1}^{T}\left(P_d(t)\sum_{i=1}^{n} q_{d,i}(t)\right)\\ &+ \sum_{t=1}^{T}\left(P_{sG}(t)\sum_{i=1}^{n} q_{sG,i}(t)\right)\\ &- \sum_{t=1}^{T}\left(P_{bG}(t)\sum_{i=1}^{n} q_{bG,i}(t)\right)\\ &- \mathrm{Cost}_{\mathrm{procurement}} - \mathrm{Cost}_{\mathrm{maintenance}}\end{aligned} \tag{10}$$

with $q_{sG,i}(t)$ representing the energy sold to the main grid and $q_{bG,i}(t)$ representing the energy bought from it at a time slot t.

As for EV owner i, the payoff function at the end of the time horizon T can be expressed as follows:

$$\begin{aligned}\pi_{EV_i} = &-\sum_{t=1}^{T}\left(P_c(t)\cdot q_{c,i}(t)\cdot A_i(t)\right)\\ &+ \sum_{t=1}^{T}\left(P_d(t)\cdot q_{d,i}(t)\cdot A_i(t)\right)\\ &- \mathrm{Cost}_{\mathrm{charge}} - \mathrm{Cost}_{\mathrm{discharge}}\end{aligned} \tag{11}$$

2.5. Best response versus Nash equilibrium

The best response and Nash equilibrium are two fundamental game theory approaches that offer distinct insights into EVs behavior and rationality within strategic interactions, particularly in how they can maximize their payoffs. The best response approach allows each player EV to independently optimize their utility, represented by equation (11), without considering the strategies of other EVs. In contrast, the Nash equilibrium seeks a state where each player's strategy is optimized in response to the strategies of others. This equilibrium provides a stable point where no player has an incentive to unilaterally deviate from their chosen strategy, highlighting the interdependence of all players' decisions. Achieving this equilibrium requires that the MO makes transactions at each time step t with all EVs participating in V2G. These transactions are proportional to the maximum energy each EV can charge or discharge, while adhering to the constraints outlined in equations (5), (6), (7), (8) and (9).

2.6. EV strategic behavior

EVs participating in a V2G may exhibit a strategic behavior that extend beyond immediate payoff maximization. Their decisions to charge or discharge energy during a specific time slot t are influenced not only by the current payoffs but also by expectations of future conditions. They may choose not to charge or discharge energy during a specific time slot t if they expect better conditions for profit in the future. This forward-thinking dimension is key in the strategic decision-making process, where EVs consider multiple factors before engaging in V2G transactions. Three primary factors drive EVs' strategic behavior: the microgrid's energy requirements, the charging and discharging prices, and the number of other EVs participating in V2G. Moreover, EV drivers must account for their mobility needs, as maintaining sufficient energy for travel is paramount. While the mobility need is not modeled as an explicit constraint in this work, it is implicitly reflected in the driver's "desired charging energy" and "desired discharging energy," which account for the energy necessary to meet both immediate and future transportation needs. The decision to participate in V2G is, therefore, influenced by the drivers' desire to ensure they have adequate energy to meet their mobility needs before committing to charging or discharging for profit. This ensures that mobility remains the primary concern while still enabling strategic participation in the V2G framework. Additionally, since EVs behave autonomously and without information exchange, the three parameters mentioned —microgrid demand, prices, and other EVs participation— are treated as stochastic variables from the perspective of an individual EV owner. Consequently, EV drivers adopt a forward-looking strategy based on the expected values of these stochastic parameters, while simultaneously balancing their mobility requirements.

3. Solving process

The main steps followed to solve the formulated V2G problem are outlined in the flowchart in Fig. 3.

3.1. Step 1: Calculation of the energy demand of the microgrid

The Microgrid Operator computes, at each time slot t, the energy demand D_M of the microgrid defined as the difference between the energy generation G_M and the load L_M:

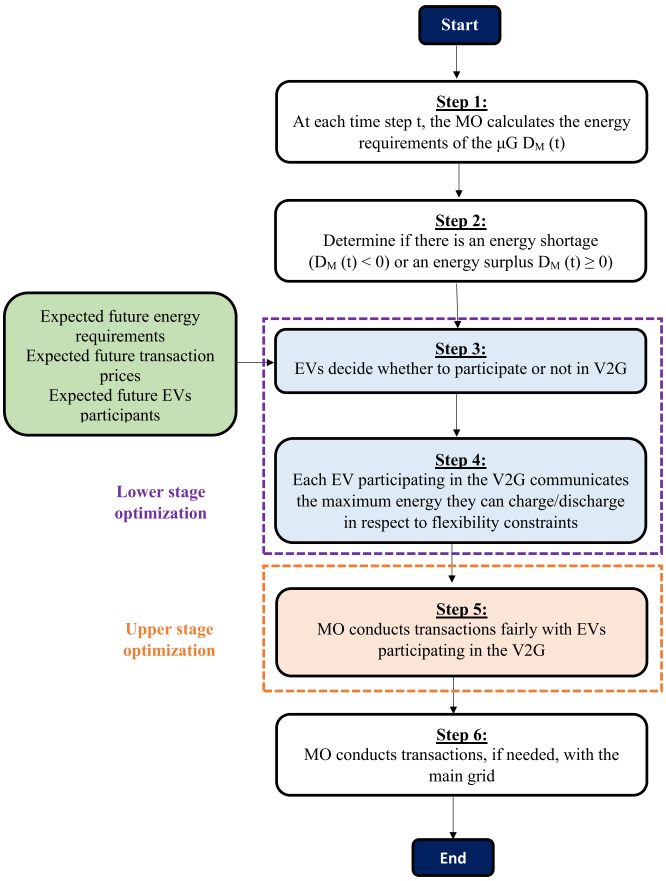

Fig. 3. The process of solving the formulated V2G problem.

$$D_M(t) = L_M(t) - G_M(t) \tag{12}$$

3.2. Step 2: Identification of the selling/buying modes

After defining the microgrid energy demand $D_M(t)$ as in (12), two modes can be discerned:
-A buying mode with $D_M(t) > 0$, where the microgrid looks for EVs capable of discharging to purchase energy from.
-A selling mode with $D_M(t) < 0$, where the microgrid looks for EVs capable of charging to sell excess energy to.

3.3. Step 3: Lower stage optimization - Participation decision

To solve the problem of EVs decision to participate or not in the V2G, a decentralized optimization algorithm was conceived. The optimization consists in examining all future possible time slots for a given EV using the expected values of the stochastic variables which are the energy requirement $D^e_M(t)$ and prices $P^e_c(t)$, $P^e_d(t)$ evolution as well as the expected number of V2G participants $n^e(t)$, and identify the specific time slot that maximizes the payoff in each time slot. The pseudocode for the designed participation decision function is given in Fig. 4.
Note that the expected values are based on their respective probability distributions. These expected values constitute the most likely values or the average for the energy needs, the prices and the number of participants in accordance to the law of large numbers in probability theory.

$$x^e(t) = \begin{cases} \int_{-\infty}^{+\infty} x(t) \cdot f(x(t))\, dx(t) & \text{If } x \in \{P_c, P_d, D_M\} \\ \sum_{i=1}^{N} i \cdot p(x(t) = i) & \text{If } x \in \{\text{number of EVs in the V2G}\} \end{cases} \tag{13}$$

where f is the probability density function for the continuous random variables P_c, P_d, D_M, and p is the probability of the discreet random variable related to the number of participants in the V2G.
It should be noted that the accuracy and reliability of these forecasts are of high importance for effective decision-making and energy management processes.
Several methods can be used to improve these forecasts such as incorporating trends and historical data, making use of advanced data analytics techniques and machine learning algorithms [54–56]. Regular validation and continuous monitoring of the accuracy of forecasts against real-time values can also be of a great help identifying and addressing inconsistencies or discrepancies.

Table 1
Data of Electric Vehicles.

	EV1	EV2	EV3	EV4	EV5
C (KWh) [57]	36	48	60	72	84
Rc (KW) [57]	2	6	4	4	6
Rd (KW) [57]	2	6	4	4	6
Ec (% of Capacity C)	80%	100%	97%	70%	90%
Ed (% of Capacity C)	10%	10%	10%	10%	10%
Initial SOC	100%	100%	100%	100%	100%
Duration of charge dc (min)	20	20	20	20	20
Duration of discharge dd (min)	20	20	20	20	20

3.4. Step 4: Lower stage optimization - EV charge/discharge capacity computation

Each EV participating in V2G operations computes and communicates its maximum capacity in terms of charge/discharge in respect to the aforementioned flexibility constraints.

3.5. Step 5: Upper stage optimization (Nash equilibrium)

Let m be the number of EVs that decided to participate in the V2G at time slot t, and let $q^*_{c/d,i}(t)$ be the maximum energy amount EV_i is capable to trade while respecting the flexibility constraints during time slot t. The MO, with energy requirements $D_M(t)$, should make transaction with all m participants.
Conducting fair transactions with all participating EVs consists on the following sub steps:

- Sub step 1: $R = \min\left(D_M(t), \sum_{i=1}^{m} q^*_{c/d,i}(t)\right)$
- Sub step 2: The MO sort increasingly all EVs based on $q^*_{c/d,i}(t)$;
- Sub step 3: The MO buys/sells $\min\left(q^*_{c/d,i}(t), \frac{R}{m}\right)$ from the EV with lowest $q^*_{c/d,i}(t)$;
- Sub step 4: The MO updates R and m and moves to the next EV with the next lower $q^*_{c/d,i}(t)$;
- Go to Sub step 2 until there are no EV left.

4. Numerical results and discussions

4.1. Case study definition

To assess the suggested optimization approach, a microgrid with 5 EVs are considered. The EVs data, inspired from [57] are given in Table 1. For the microgrid, the same load profile as well as the charging and discharging prices profiles used in [58] are considered as illustrated in Fig. 5 and Fig. 6.
The case study assesses five EVs profiles with different charging behaviors and thus distinct availability patterns as portrayed in Fig. 7.

- The first profile of EVs consists of individuals who commute to their work with no access to charging facilities throughout working hours. This EV type typically depends on public charging or home charging stations.

Algorithm 1: V2G Steps 3 and 4 Algorithm

Data: EV index j; current time step t; current energy demand of the microgrid D; current price of charge/discharge fixed by the microgrid P; availability function A (matrix: $A(t,j) = 1$ if available; $A(t,j) = 0$ otherwise); allowed charging and discharging rates Rc and Rd (in KW); desired energy for charging and discharging Ec and Ed (in %); duration of charging and discharging amidst the time slot dc and dd(in min); capacity of EV's battery C (in KWh); actual state of charge of the EV SOC (in %); vector of expected values of energy demands over 24 hours $Demand\_forecast$; vector of expected charging prices over 24 hours $Forecast\_charging\_prices$; vector of expected discharging prices over 24 hours $Forecast\_discharging\_prices$; vector of expected number of participants over 24 hours $forecasted\_participants$

Result: Participation decision PD, Maximum amount of energy to be exchanged QX

```
if A(t, j) == 1 then
    if D > 0 then
        /* The Microgrid is a buyer.  Calculate Q the energy the EV can discharge */
        Q ← min((SOC − Ed) × C, (Rd × (dd/60)));
        if Q ≤ 0 then
            PD ← 0;
        else
            /* 'ECP' stands for expected current payoff */
            ECP ← min((Q × P), ((D/forecasted_participants(t)) × P));
            for i ← (t + 1) to 24 do
                if Demand_forecast(i) > 0 then
                    Forecasted_price ← Forecast_discharging_prices(i);
                    QF ← min((SOC − Ed) × C, (Rd × (dd/60))); /* QF is the future energy to be exchanged */

                else
                    QF ← min((Ec − SOC) × C, (Rc × (dc/60)));
                    Forecasted_price ← Forecast_charging_prices(i);
                /* 'EFP' stands for expected future payoff */
                EFP ← max(EFP, min((QF × Forecasted_price), ((Demand_forecast(i)/forecasted_participants(i)) ×
                  Forecasted_price)) × A(i, j));
            if ECP > EFP then
                PD ← 1;
            else
                PD ← 0;
    else
        /* The Microgrid is a seller.  Calculate Q the energy the EV can charge */
        Q ← min((Ec − SOC) × C, (Rc × (dc/60)));
        if Q ≤ 0 then
            PD ← 0;
        else
            ECP ← min((Q × P), ((−D/forecasted_participants(t)) × P));
            for i ← (t + 1) to 24 do
                if Demand_forecast(i) > 0 then
                    Forecasted_price ← Forecast_discharging_prices(i);
                    QF ← min((SOC − Ed) × C, (Rd × (dd/60)));
                else
                    QF ← min((Ec − SOC) × C, (Rc × (dc/60)));
                    Forecasted_price ← Forecast_charging_prices(i);
                EFP ← max(EFP, min((QF × Forecasted_price), ((Demand_forecast(i)/forecasted_participants(i)) ×
                  Forecasted_price)) × A(i, j));
            if ECP > EFP then
                PD ← 1;
            else
                PD ← 0;
else
    /* Not participating due to unavailability */
    PD ← 0;
if PD == 1 then
    /* Affect QX the maximum energy that can be exchanged */
    QX ← Q;
else
    QX ← 0;
```

Fig. 4. Pseudocode for the lower stage optimization (steps 3 and 4).

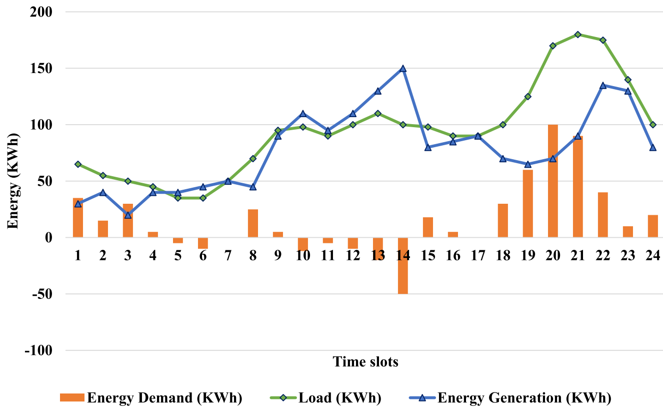

Fig. 5. Microgrid Load, Generation and Energy Demand profiles.

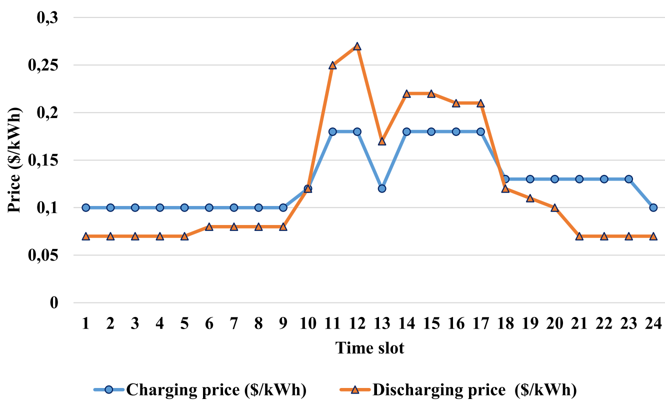

Fig. 6. Charging and discharging prices profiles.

- The second profile also represents people who commute to work but may conveniently access charging facilities at their workplace, allowing them to well plan and streamline their charging schedules and eventually take part at the (V2G) programs.
- The third profile type comprises commuters as well who can access charging facilities during work hours too, but require additional charging capacity since they undertake extended travel distances.
- The fourth profile includes individuals who basically use their vehicles for local short-distance trajectories within their vicinity. People dropping the kids off at school or sporadically running errands are a typical illustration of this profile.
- The fifth profile consists of people working on night shifts. The charging needs of this profile vary significantly from individuals with daytime schedules, likely impacting their contribution in V2G programs.

Each of these 5 EVs holds a private perception about the future energy demand of the microgrid as in Fig. 8, the evolution of charging and discharging prices fixed by the MO as in Fig. 9.
Additionally, they maintain, as shown in Fig. 10, distinct projections of the anticipated number of EVs engaging in future V2G interactions.

4.2. Discussion

The outcome of the decision-making process of step 3 is illustrated in Fig. 11.
As explained earlier, at each time slot, each EV calculates their potential current payoff if they participates immediately in the V2G dynamics and compare it to their projection of their potential future payoff at every future time slots. This process also takes into consideration the availability window of each EV.
It is noticed that, unlike other EVs, EV1 does not participate in V2G at any time slot. This observed behavior can be first explained by the fact that EV1 has a tight availability window spanning only 6 hours from 0 am to 6 am. This restricted availability tightens EV1 opportunities to take part in V2G dynamics compared to other vehicles with longer and more flexible availability windows. In fact, during EV1's availability window, the microgrid is expected to be in buying mode, at each time slot, with a positive energy demand, which indicates a need for energy to be discharged from EVs to the microgrid. Initially, EV1 postpones its participation in V2G throughout the first four time slots of its availability frame. This delay stems from EV1 expectation of potentially better payoff opportunities later in the availability window. Nevertheless, during the last two availability time frames, the microgrid shifts to selling mode since the energy demand turns negative. This Unforeseen shift requires EV1 to charge energy from the microgrid, contrary to what was expected. On the other hand, EV1's initial SOC is at 100%, signifying that it cannot charge any additional energy. As a consequence, it cannot take part in V2G during these last time slots resulting in its non-participation during the 24-hour period.

Fig. 12 depicts, as stipulated by step 4, the maximum available energy that can be traded between the microgrid and the EVs deciding to participate in the V2G in respect to the flexibility constraints expressed in subsection 2.3. Once these maximum values communicated, the MO conducts fair transactions with all available EVs.
Among all EVs, EV2 and EV5 slightly display the highest maximum energy values to be traded with the MO as it can be noticed from Fig. 12. This can be explained by their favorable parameters and features notably their discharging and charging rates *Rd* and *Rc*. In fact, as observed from Table 1, these two EVs have the highest values of *Rd* and *Rc* which influence directly the speed at which a particular EV can discharge or charge energy during the fixed transaction periods *dd* and *dc* of 20 min.

After performing energy transactions with each EV participating in the V2G, the MO may either sell or purchase the remaining needed energy to or from the main electric grid. Fig. 13 draws a comparison between the operations conducted with the main grid, with and without considering V2G transactions.
As it can be seen, the contribution of V2G at mitigating the economic burden of balancing energy requirements typically made with higher charging and discharging prices is noticeable during time slots with EVs participation. However, the contribution is still minimal given that the case study suggested to elucidate the paper approach only considers 5 EVs.

For scalability purpose, and in order to showcase the consistent impact of higher number of EVs adhering to the proposed framework, 100 EVs were considered with 20 EVs from each one of the 5 predefined profiles. The results of the energy traded with the main grid this time is given in Fig. 14.
Specifically, with 5 EVs, the total contribution to the microgrid's energy demand throughout the day, computed by summing the differences between the bar values in Fig. 13, amounts to 20.67 kWh. This value represents approximately 5.5% of the microgrid's total energy requirement. In contrast, when the number of EVs is increased to 100, their contribution, calculated similarly by summing the differences between the bar values in Fig. 14 throughout the day, rises to 199.5 kWh, which accounts for approximately 35.37% of the microgrid's daily energy requirement. This substantial increase underscores the significant impact that a larger fleet of EVs can have on reducing the dependency on the main grid and improving the overall efficiency of the V2G system.

4.3. Sensitivity analysis

In this subsection, a sensitivity analysis is conducted in order to assess the impact of key system parameters variations on the dynamics of the V2G proposed model. Parameters considered include microgrid energy demand D_M and the energy charging and discharging prices $P_{c/d}$. Practically, D_M and $P_{c/d}$ are respectively varied to 50%, 60%, 70%,

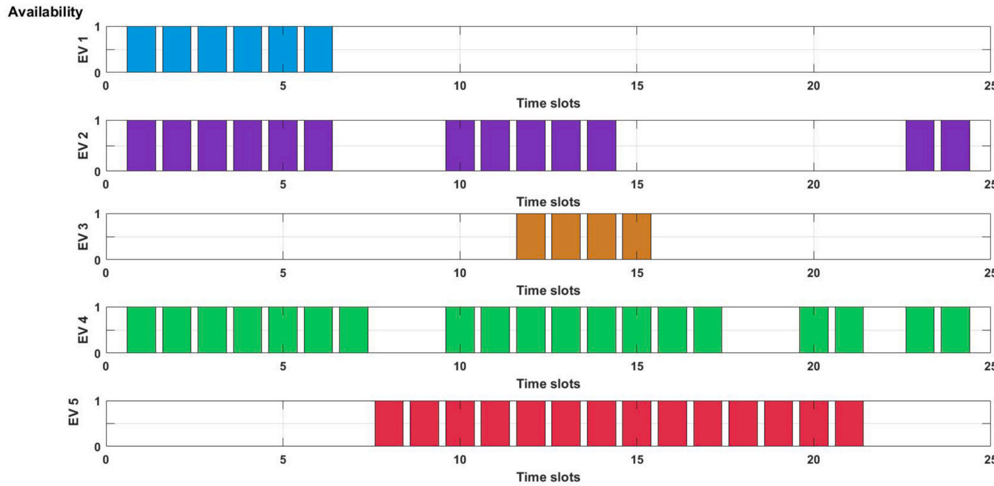

Fig. 7. EVs Availability profiles.

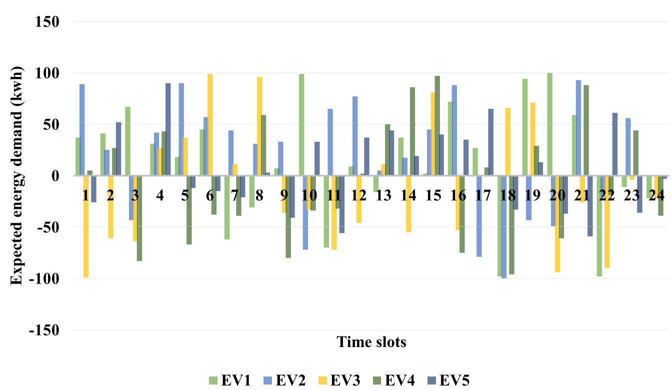

Fig. 8. Expected microgrid energy demand by EVs drivers.

Table 2
Summary of the sensitivity analysis.

Parameter change	Total exchanged energy (kWh)	Relative variation in exchanged energy (%)	Parameter change	Total exchanged energy (kWh)	Relative variation in exchanged energy (%)
50% $D_M(t)$	134.0	0%	50% $P_{c/d}(t)$	168.0	0%
60% $D_M(t)$	144.8	8.06%	60% $P_{c/d}(t)$	168.0	0%
70% $D_M(t)$	157.1	8.49%	70% $P_{c/d}(t)$	168.0	0%
80% $D_M(t)$	162.4	3.37%	80% $P_{c/d}(t)$	168.0	0%
90% $D_M(t)$	167.7	3.26%	90% $P_{c/d}(t)$	173.0	2.98%
100% $D_M(t)$	173.0	3.16%	100% $P_{c/d}(t)$	173.0	0%
110% $D_M(t)$	178.3	3.06%	110% $P_{c/d}(t)$	203.0	17.34%
120% $D_M(t)$	183.6	2.97%	120% $P_{c/d}(t)$	203.0	0%
130% $D_M(t)$	188.9	2.89%	130% $P_{c/d}(t)$	256.3	26.26%
140% $D_M(t)$	194.2	2.81%	140% $P_{c/d}(t)$	256.3	0%
150% $D_M(t)$	199.5	2.73%	150% $P_{c/d}(t)$	256.3	0%

80%, 90%, 100%, 110%, 120%, 130%, 140% and 150% of their values. The results are summarized in Table 2.

From the sensitivity analysis, it can be noticed that variations in charging and discharging prices have the greatest impact on the energy exchanged within the V2G system. Moreover, when the demand is at 50%, the total energy exchanged between the EVs and microgrid is 134 kWh. This exchange of energy steadily increases as demand rises, reaching 199.5 kWh at 150%. The relative rate of change in energy exchange is most pronounced between 50% and 70%, with relative increments of 8.06% and 8.49%, respectively. Beyond 70% demand, the rate of increase diminishes, dropping to 2.73% at 150%. This diminishing rate of energy exchange as the microgrid's demand grows further, suggests that EVs have reached their limitation in supplying or storing additional energy. As demand rises, the EVs' capacity to support the microgrid becomes constrained, highlighting potential limitations in the system's flexibility under higher load conditions and limited involvement of EVs in V2G operations. Similarly, the second part of the analysis examines the impact of varying the EV charging/discharging prices from 50% to

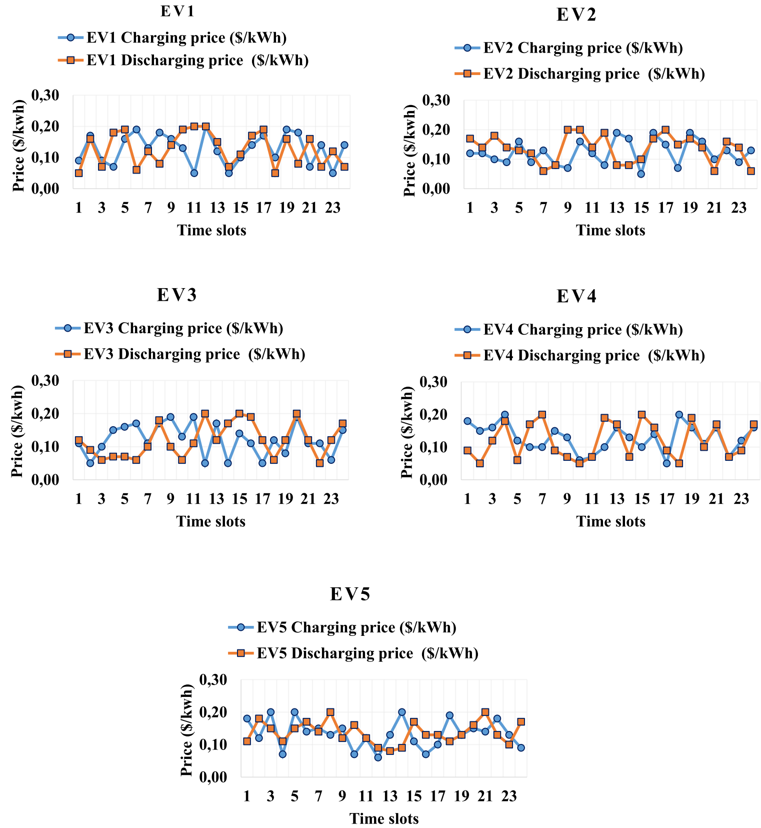

Fig. 9. Forecast of the evolution of charging and discharging prices.

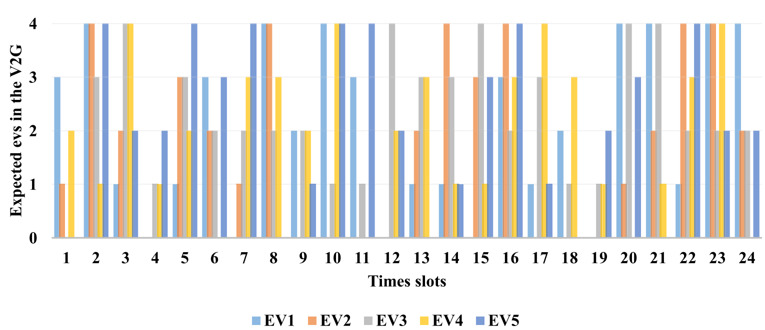

Fig. 10. Forecast of the number of EVs engaging in the V2G.

150% of the baseline. The results indicate that when the V2G transaction prices increase, EVs are more incentivized to engage in V2G operations and thereby the energy exchange increases. Furthermore, as the power profile increases to 130%, the total energy exchange reaches 256.3 kWh with a maximum relative rate of 26.26%. This suggests that the energy exchanged between the microgrid and EVs is more sensitive to changes in the EV charging/discharging prices. Overall, the sensitivity analysis highlights the system's responsiveness to variations in microgrid energy demand and EV charging/discharging prices. The diminishing rate of change in energy exchange with increasing microgrid demand indicates that while the system can efficiently adapt to moderate demand fluctuations, it becomes less responsive as demand grows significantly. On the other hand, the high increase in energy exchange with higher EV charging/discharging prices suggests that the system is particularly sensitive to changes in the V2G transaction prices.

5. Conclusion

This paper developed an approach allowing Electric Vehicles, with different profiles and preferences, to strategically and effectively engage in Vehicle-to-Grid (V2G) programs within a microgrid environment. The proposed framework takes into consideration the distinct characteristics of each EV, such as availability to participate, energy charging and discharging rates, and the desired levels of charge and discharge to be maintained. The suggested framework relies on a decentralized optimization conducted by EVs throughout a forward-thinking analysis. The optimization uses a forecasting approach for key stochastic parameters enabling EVs to make informed decisions regarding their imminent or delayed participation in the V2G synergy.

Numerical results from the simulations demonstrate that under the proposed framework, 5 EVs contribute a total of 20.67 kWh to the microgrid's energy demand over a typical day, representing approximately

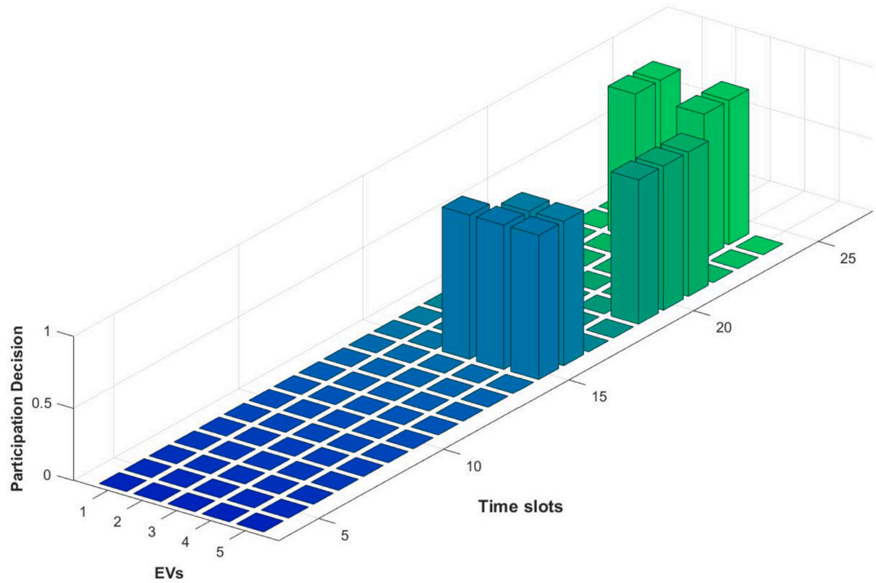

Fig. 11. Decision outcomes of EVs in terms of V2G engagement.

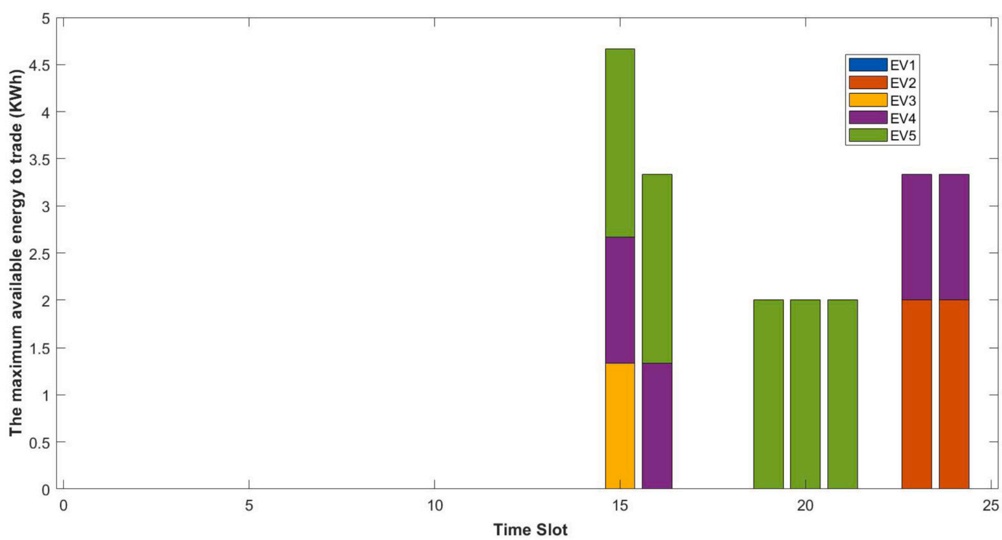

Fig. 12. Maximum energy to be traded between the microgrid and EVs engaging in the V2G.

5.5% of the microgrid's total energy requirement. When the number of EVs is increased to 100, their contribution rises significantly to 199.5 kWh, accounting for about 35.37% of the microgrid's daily energy requirement. These results highlight the substantial potential of V2G operations to enhance grid stability, sustainability, and economic viability.

Although this study presents a robust framework for optimizing strategic V2G interactions within microgrids, certain limitations should be acknowledged. The framework relies on historical data and basic predictive mechanisms, which may limit its accuracy in highly dynamic environments where more sophisticated machine learning models might be necessary. Additionally, a detailed economic analysis of implementation costs needs to be further explored. Future work should focus on addressing these limitations by incorporating more comprehensive stochastic modeling, real-time data integration, and cost-benefit analyses.

CRediT authorship contribution statement

Ayoub Zerka: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Mohammed Ouassaid:** Validation, Supervision, Project administration, Methodology. **Mohamed Maaroufi:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

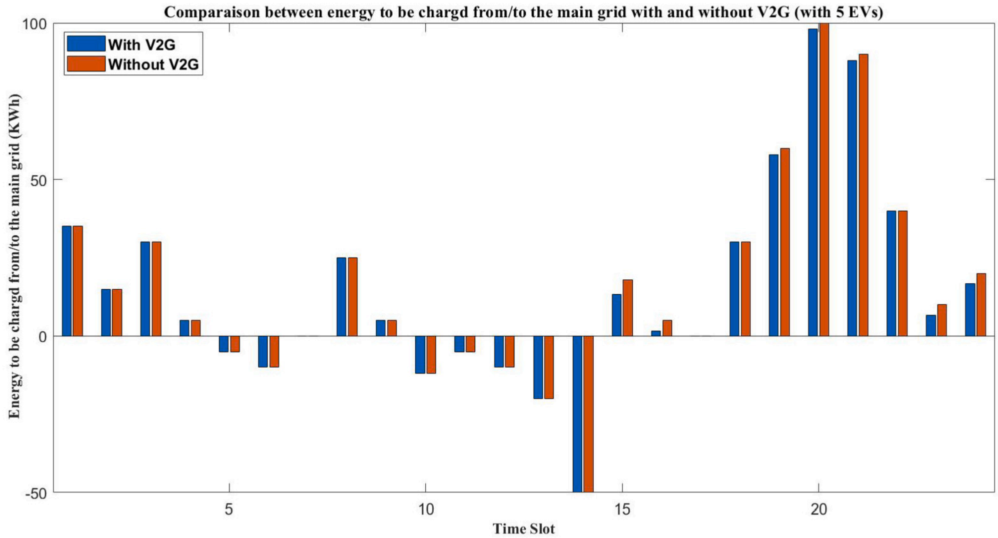

Fig. 13. Energy traded directly with the main grid with and without participation in V2G transactions (with 5 EVs).

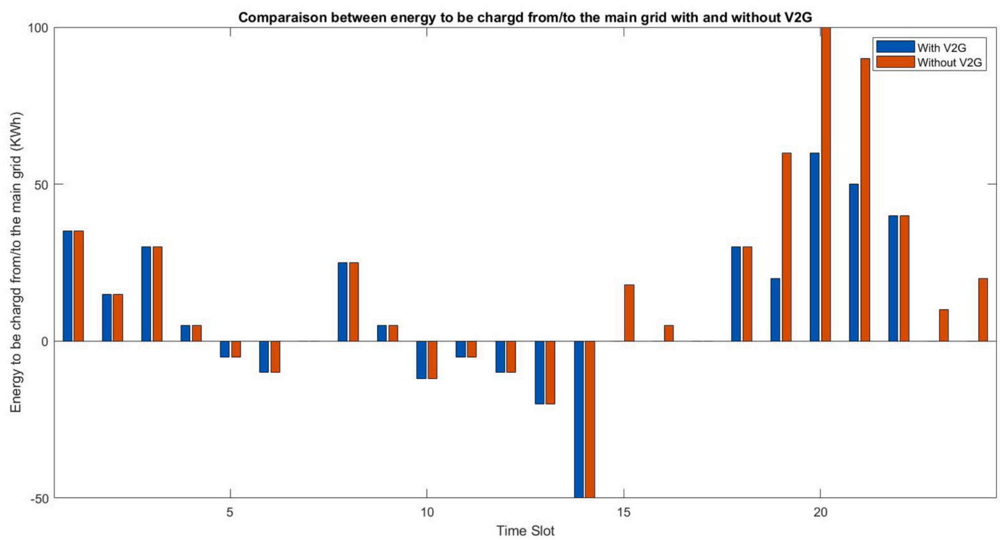

Fig. 14. Energy traded directly with the main grid with and without participation in V2G transactions (with 100 EVs).

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