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RESEARCH ARTICLE

A Novel Electric Vehicle Charging Management With Dynamic Active Power Curtailment Framework for PV-Rich Prosumers

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ABSTRACT Prosumer communities are integrating renewable energy sources to reduce energy costs and carbon emissions for sustainable and clean energy awareness. However, increasing solar photovoltaic penetration in low-voltage distribution networks leads to serious power quality challenges, such as overvoltage for grid operators and prosumers. Integrating electric vehicles (EVs) as deferable loads can reduce prosumer costs and maximize environmental benefits as EV charging is managed. Therefore, this paper proposes a novel EV charging management that maximizes prosumer communities' power quality and benefits PV-rich prosumers by applying a dynamic active power curtailment framework. The methodology calculates each prosumer's maximum power injection into the grid based on their voltage sensitivities. The performance of the developed charging management is examined on the European 906 bus low-voltage distribution networks under unmanaged, managed, and vehicle-to-grid (V2G)-empowered scenarios. The prosumers' individual and aggregated economic cost-benefit results are analyzed considering increasing EV penetration. The results show that the proposed method considering fair active power curtailment could increase self-consumption and renewable fraction for prosumers. It is observed that increasing EV penetration could reduce the curtailed energy by 14.6%. The V2G-empowered method also increased up to 20% more renewable energy for charging EVs, improved self-consumption and renewable fraction up to 11% and 19.4%. Moreover, the V2G option reduced total costs by up to 37.93%. This work can potentially promote renewable energy sources by modifying consumers' charging behaviors to be more sustainable and environmentally friendly.

INDEX TERMS Active power curtailment, vehicle charging management, self-consumption, over-voltage mitigation, sensitivity matrix.

I. INTRODUCTION

Due to the growing worldwide awareness of sustainable, environment-friendly, and on-site energy generation, prosumer communities are increasingly integrating renewable energy sources (RES) to reduce energy costs and carbon emissions [1]. Despite all advantages, the increased penetration of PV in low-voltage distribution networks (LVDN) leads to serious power quality challenges, like overvoltage, for both network operators and prosumers due to the time mismatch of renewable energy generation and the demand [2], [3]. The reverse power flow increases the voltage at the prosumer's node due to surplus energy. The cable impedance may increase the overvoltage effects in nodes far from the power supply. Active power curtailment (APC) in LVDN is a highly effective method for over-voltage

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mitigation. APC generally curtails a certain amount of clean and renewable power regardless of the prosumers' location and interaction with LVDN. Thus, current standard droop-based APC techniques use local voltage and power measurements to prevent over-voltages, resulting in direct renewable energy losses and unfair power curtailment. Since the line resistances in LV systems are more significant, the relationship between voltage and active power is more dominant than in reactive power [4], [5]. Several studies on APC have been proposed to control the active and reactive power injected by PV units using droop control to share the curtailed power among the prosumers uniformly [6], developing a distributed control scheme [7] and determining a voltage bandwidth for each prosumer for over-voltage mitigation [8]. Although APC has been explicitly evaluated in various studies, these APC methods generally result in an unfair power curtailment when mitigating overvoltage. Simply curtailing active power will result in more renewable energy losses for prosumers in the sensitive parts of the grid compared to those close to the substation transformer [9]. On the other hand, some studies [10] apply the same sense of power curtailment for all prosumers of the same feeder in a particular part of the electricity grid at every instant. Since all prosumers are responsible for the overvoltage at different nodes, it is unfair to curtail different active power for each user depending on the connection voltage. Thus, the unfairness asks for an approach to curtail the power equitable among the prosumers based on predefined fairness. Fair APC can become equality in curtailed power, PV production, or power export among prosumers. If all prosumers curtail the same power, a smaller percentage is curtailed from prosumers whose exported power is higher. Furthermore, uniform export curtails more power for the same prosumer. So, curtailment based on PV production finds the middle ground. Thus, it can be concluded that deciding on a suitable fairness method depends on the requirements of the prosumers since there are trade-offs between various factors that determine fairness [10]. Therefore, a droop-control-based APC was presented to provide fair curtailment among prosumers controlling each prosumer's inverters. Nevertheless, this method leads to more power curtailment than unfair methods, reducing overall energy export [9]. Therefore, the study has focused on equalizing the loss of revenue for each prosumer in designing a fair APC algorithm [11]. This technique considers only economic fairness, avoiding fairness in total curtailed power. It recommends fair APC as a ratio of active power and the injected actual power by different prosumers, even if leading to more power curtailment [10]. Nevertheless, these effective APC methods mitigate over-voltages in LVDN and cause significant renewable energy loss. Sensitivity-based approaches can be more helpful for fairness in APC regarding prosumers' needs. Several studies have used sensitivity-based APC using primary load flow results to calculate sensitivity indices for LVDN and a perturb-and-observe-based algorithm to estimate sensitivities for overvoltage mitigation [12]. However, these techniques need more computational effort and are hard to implement. On the other hand, analytical methods can efficiently and quickly implement and estimate sensitivities [13]. However, a few presented analytical solutions apply to balanced three-phase LVDN. An APC method can minimize renewable energy losses and equitably share the curtailed power among prosumers for more attractiveness. Also, APC methods aim to reduce the net energy exchange with the grid and enhance the prosumers' energy independence [6].

Similarly, electric vehicles (EVs) have been recognized as a significant step in decarbonization and improving power grid flexibility [14], [15]. EVs are expected to increase rapidly due to global encouragement for expanding EVs to achieve net-zero emission targets. Many countries have witnessed dramatic increases in grid energy prices over the past decade [16]. Furthermore, a growing number of awareness-raising projects are encouraging public commitment to environmental sustainability. As a result, local renewable energy production is expanding across European countries, accompanied by a proliferation of subsidies to offset costs [17]. However, increasing unmanaged and unpredictable EV charging demand, especially in residential, can cause a substantial adverse impact on distribution systems, such as voltage deviations and additional power losses [18], [19]. Charging management can postpone charges to off-peak times. Smart charging may use renewable and cheaper energy, improving benefits for both the prosumer and network, compared to immediate unmanaged charging [20]. Existing research on EV charging management mainly focuses on centralized and decentralized power control to minimize its effect on the distribution system assets and reduce transmission congestion and greenhouse gas (GHG) emission via integrating RES into charging management [21]. Charging management methods optimize the charge level, location, and duration [22], [23], considering arrival-departure times, arrival and desired state of charge (SOC) of EVs, RES availability, power constraints, and loading conditions of the grid [24], [25], [26], [27]. By implementing charging coordination, prosumers self-consumption increases to 65% for vehicle-to-grid (V2G)-enabled smart charging. Thus, this leads to higher revenues and autarky using PV energy rather than grid power [28].

RES-integrated smart EV charging strategies can minimize renewable energy curtailment to improve the self-consumption of prosumers equipped with a solar photovoltaic where excess energy injection into the distribution system is not allowed for reducing network congestion [29]. Smart EV charging seems more feasible and cost-effective than local and stationary energy storage systems (ESS). Because this approach has achieved reducing 76% in energy curtailment and 67% in daily savings compared to a traditional consumer of the same size and characteristics without smart charging [30]. EV charging management smooths load profile effectively and reduces charging cost in a short computational work and is applicable for large-scale EV charging, avoiding higher transformer capacity costs without hampering EV owners' SOC desires and charge durations [31]. Coordinated EV charging can lighten the negative impact of uncoordinated EV charging. Managing EV charging to facilitate RES in California reduces curtailment by up to 40%. Overnight charging saves the cost but raises curtailment [32]. The decentralized managed EV charging mitigated the charging impact of 100 EVs with a rated power of 7 kW charged simultaneously on power grids successfully, safely, and effectively. It can be extended with vehicle-to-grid (V2G) functionality exchanging information between EVs [33]. Due to loading uncertainties and unpredictability in EV charging, a charging approach for large irregular EVs to minimize the degradational effects on the distribution system and reduce transmission congestion and GHG emission has been proposed to determine the maximum number of vehicles that should be charged during the next hour avoiding increasing the loss of life (LOL) of the transformer or degrade the reliability of the system. Power system-level communication must be improved to implement the proposed work [34]. However, this approach needs to improve the scheduling of each EV based on the battery state of charge and their V2G availability. Moreover, EV owners may suffer from charging anxiety, which refers to the stress of reaching the destination if they participate in V2G [35]. Full participation of the EV fleet in managed charging and V2G integration allows for supplying 4% and 11.1% of the system load from zero-emission sources, respectively [36]. Increasing EV battery sizes or charging power together does not provide additional flexibility, as charging times do not change [37].

Prosumers have different PV power in real life. However, most works have assumed that all prosumers have the same PV power [38], [39]. Most studies have not considered high PV penetration rates that significantly cause overvoltage in the LVDN and grid dynamics, such as voltage profile and capacity utilization. In addition, even though most consider grid power quality, they do not consider the improving economic benefits through fair APC when investigating prosumer benefits at high RES penetration. To this end, the required power curtailments for prosumers having different PV power are determined by considering critical self-consumption rates (SCRs) to eliminate the overvoltage. Moreover, the increase in EV numbers affecting the cost-benefit analysis of SCR and V2G options has not been focused on sufficiently in the recent literature [40], [41], [42], [43]. This study investigated the effects of increasing EV numbers considering individual energy exchange. All seasonal variations have been evaluated in terms of self-consumption. The main contributions of this study are as follows:

- Developing a novel electric vehicle charging management with a dynamic fairness active power curtailment framework for PV-rich prosumers.
- Investigating the relationship between SCR and daily travel range under high renewable energy penetration.
- Analysis of the impact of an increase in the EV population on evening charging peaks when the vehicle-to-grid (V2G) strategy is applied.
- Examination of the potential reduction of curtailed energy associated with increases in the EV population under high RES penetration conditions.

This paper has been organized as follows. Section I presents the motivation behind the fairer APC method empowered with EV charging management and summarizes the recent related studies, indicating the research gap and the paper's main contributions. The APC method combined with voltage sensitivity analysis for fairness is described and applied to the charging management framework in Section II. Several case studies are introduced, and their results are discussed in Section III. Finally, Section IV concludes the study by giving future suggestions.

II. METHODOLOGY

A. THE PROPOSED DYNAMIC APC-BASED CHARGING MANAGEMENT STRATEGY

The same droop coefficients control PV inverters with standard droop-based APC. V_{cri} is defined as the voltage at which the curtailment starts. The PV inverter active power (P_{PV}) is reduced linearly with the local voltage. Starting from V_{cri} until the low boundary of voltage limit (V_{lb}), PV inverters should not inject any power into the grid. The coefficient m is obtained from Equation (1) by dividing the power in kW to be reduced during this time by the voltage change.

$$m = \frac{P_{PV,\max}}{V_{\text{cri,pu}} - V_{\text{lb,pu}}} \quad (1)$$

The disadvantage of the standard droop-based APC method is that prosumers far from the transformer inject less of their excess power into the grid. For example, prosumers near the transformer could inject all their PV power even during maximum power generation. However, prosumers far from the transformer could only export 35% of their PV power at the time of maximum power generation. Therefore, the PV revenues of these prosumers are lower than other prosumers, creating an unfair situation [9]. Prosumers at the most distant nodes are more likely to suffer from overvoltage and, thus, higher active power curtailments when PV power injection increases. However, the prosumers closer to the transformer are not curtailed due to the radial nature of most LVDNs. It is known as an unfair curtailment of renewable energy. Therefore, the proposed method uses sensitivity to redistribute the curtailed power more equitably among prosumers.

In dynamic APC, inverters are controlled by separate droop parameters and power losses are shared equally among all inverters. Here, the design of droop coefficients is based on the voltage sensitivity determined using power flow analysis. The sensitivity analysis is used to understand the effect of the active and reactive power variation of the inverters on the voltage variation of the radial distribution feeder. The sensitivity matrix, which is the inverse Jacobian matrix of the network, measures the voltage magnitude and angle variations considering active and reactive power fluctuations. Namely, it shows the dependencies between bus voltage and power flow. Jacobian-based methods are commonly used for the analysis of voltage sensitivities. Three-phase AC power flow are provided in Equations (2)-(6) for determining power flow among the prosumer community.

$$P_{G_{i,t}} - P_{D_{i,t}} = \sum_{j=1}^{N} V_{i,t} \cdot V_{j,t} \cdot Y_{ij} \cdot \cos\big(\theta_{ij} + \delta_{j,t} - \delta_{i,t}\big), \quad \forall i, j, t, b \tag{2}$$

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

$$I_{ij,t} = |Y_{ij}| \cdot \left[V_{i,t}^2 + V_{j,t}^2 - 2 \cdot V_{i,t} \cdot V_{j,t} \cdot \cos\left(\delta_{j,t} - \delta_{i,t}\right)\right]^{1/2}, \quad \forall i, j, t \tag{4}$$

$$P_{\text{loss}} = \sum_{j=1}^{N} I_{ij}^2 \cdot r_{ij}, \quad \forall i, j \tag{5}$$

$$V_{\min} \leq V_{i,t} \leq V_{\max}, \quad \forall i, t \tag{6}$$

In Equation (2), the generated and demand active powers at bus i at time t are expressed as ($P_{G_{i,t}}$) and ($P_{D_{i,t}}$), respectively, for describing active power flow. In Equation (3), describing reactive power flow, the generated and demand reactive powers at bus i at time t are expressed as ($Q_{G_{i,t}}$) and ($Q_{D_{i,t}}$), respectively. Y_{ij} and θ_{ij} are the amplitude and angle of the admittance between buses i and j. Equation (4) represents the line current ($I_{ij,t}$) from bus i to bus j using the voltage amplitude ($V_{i,t}$) of bus i at time t and angle ($\delta_{i,t}$). Equation (5) calculates the total active power losses on all lines where r_{ij} is line resistance between buses i and j. Equation (6) is the voltage constraint commonly used in DN stability. The slack bus voltage is 1, and its angle is 0 ($V_{i,t} = 1, \delta_{i,t} = 0$). According to the results of power flow analyses, the voltage sensitivity matrix can be derived like Equation (7).

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \cdot \begin{bmatrix} \Delta \delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial V} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial V} \end{bmatrix} \cdot \begin{bmatrix} \Delta \delta \\ \Delta V \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} \Delta \delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} \frac{\partial \delta_2}{\partial P_2} \cdots \frac{\partial \delta_2}{\partial P_N} & \frac{\partial \delta_2}{\partial Q_2} \cdots \frac{\partial \delta_2}{\partial Q_N} \\ \vdots \ddots \vdots & \vdots \ddots \vdots \\ \frac{\partial \delta_N}{\partial P_2} \cdots \frac{\partial \delta_N}{\partial P_N} & \frac{\partial \delta_N}{\partial Q_2} \cdots \frac{\partial \delta_N}{\partial Q_N} \\ \frac{\partial V_2}{\partial P_2} \cdots \frac{\partial V_2}{\partial P_N} & \frac{\partial V_2}{\partial Q_2} \cdots \frac{\partial V_2}{\partial Q_N} \\ \vdots \ddots \vdots & \vdots \ddots \vdots \\ \underbrace{\frac{\partial V_N}{\partial P_2} \cdots \frac{\partial V_N}{\partial P_N}}_{\text{voltage sens. at P}} & \underbrace{\frac{\partial V_N}{\partial Q_2} \cdots \frac{\partial V_N}{\partial Q_N}}_{\text{voltage sens. at Q}} \end{bmatrix} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{8}$$

$$S_V = \begin{bmatrix} \frac{\Delta \delta}{dP} & \frac{\Delta \delta}{dQ} \\ \frac{\Delta V}{dP} & \frac{\Delta V}{dQ} \end{bmatrix} \tag{9}$$

The voltage sensitivity matrix (S_V) consists of 4 sub-matrixes ($S_{V_{mn}}; m = 1, 2; n = 1, 2$) with partial derivatives showing variations in the voltage magnitude and angle of buses, as shown in Equations (8) and (9). The sub-matrix $S_{V_{21}}$ is used to analyze the voltage variation as a function of the active power variation. Equation (10) calculates bus voltages after curtailment ($V_{C_{i/i+1}}$) using voltages before curtailment ($V_{i/i+1}$) and total curtailments depending on the voltage sensitivity. Then, the m coefficient is calculated in Equation (11).

$$V_{C_{i/i+1}} = V_{i/i+1} - \Delta P \sum_{j} \frac{\Delta V_{P_{i/i+1}}}{\Delta P_{P_{j/j+1}}} \tag{10}$$

$$m_{i/i+1} = \frac{\Delta P}{V_{C_{i/i+1}} - V_{cri}} \tag{11}$$

Since an APC method is adopted to mitigate overvoltage effectively, the sub-matrix $S_{V_{21}}$ is of primary interest, as it refers to the voltage variations against the active power injections ($\Delta V / \Delta P$). The sensitivity theory is based on, Firstly, reducing the computational complexity for low execution times and, secondly, obtaining a good numerical result regardless of the network non-linearities.

Vehicle charging management (VCM) is suggested for a fairer curtailment of the excess renewable power considering each prosumer's position within the network, given in Figure 1. The proposed VCM adjusts the curtailment energy of prosumers according to the voltage sensitivity matrix. For this reason, EV profiles, including charging and traveling behaviors, have been implemented in VCM for presenting a real driving consumption and V2G availability of prosumers' EVs.

In the first stage of the close loop optimization framework, the operational cost of prosumers has been minimized without network constraints using a mixed integer linear programming (MILP) solver via Gurobi. Gurobi optimizer is one of the best performance solvers for MILP problems in terms of returning high-quality and feasible solutions due to advanced searching algorithms in Gurobi. Reducing the number of variables and constraints can accelerate the solution time in MILP. Gurobi is very sensitive to changes in the number and order of constraints and variables. Thus, several buses have violated the voltage constraints and exaggerated prosumer profits. The results of this case will be used to compare the superiorities of the proposed VCM. According to the results of the first stage, violated buses have been determined to calculate the network sensitivity matrix (NSM). Therefore, the computed total curtailment active renewable power is distributed among prosumers considering the NSM. Namely, NSM dispatches the curtailed power regarding each prosumer's contributions. So, each prosumer's curtailed power is founded by Panda Power and proceeded to the second stage. In the second stage of the close loop optimization framework, the total operation costs

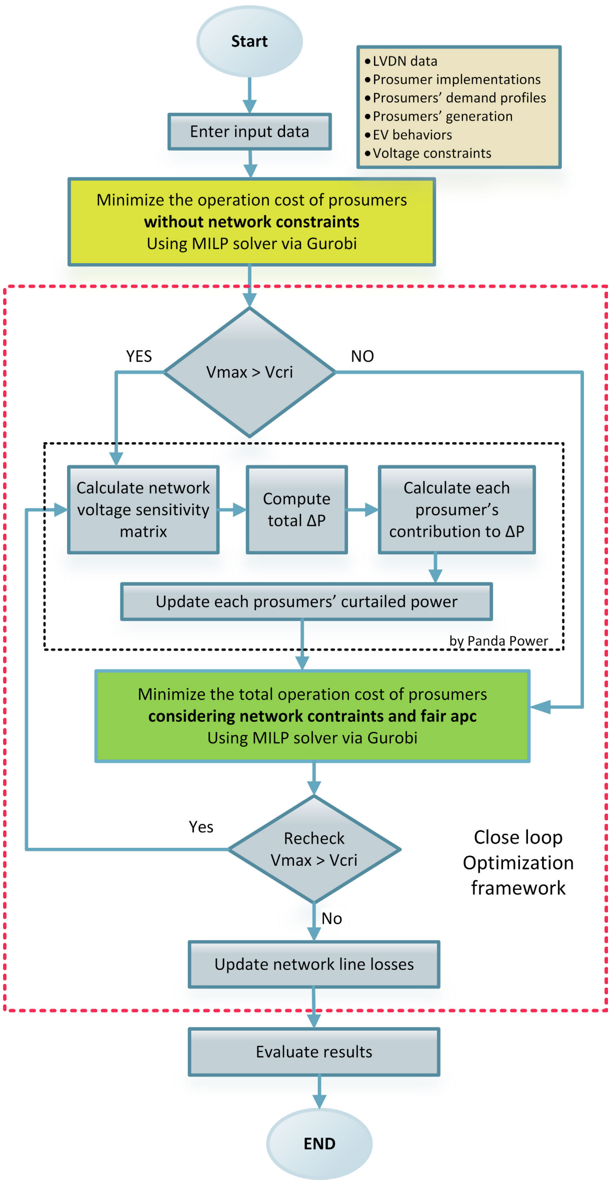

FIGURE 1. Charging management framework.

of prosumers have been minimized considering network constraints and fair APC. Thus, no bus violated the voltage constraints, and curtailment of surplus renewable energy has been minimized and distributed equitably among the prosumers. Also, after rechecking buses for voltage violations, total line losses have finally been updated to evaluate the overall results. An unmanaged VCM has been compared to managed and bidirectional VCMs to present the superiorities of the proposed VCM with fair APC. Additionally, this paper evaluates the impacts of increasing charging power and battery size of EVs in the proposed VCM framework. A possible increase in EV numbers has also been considered. Furthermore, the implementation of common ESS in the prosumer community has been investigated.

The energy purchase price at time t from the grid p_t^{buy}, the energy sale price from PV $p_t^{PV_{sell}}$, and from EV is $p_t^{EV_{sell}}$. The grid powers flowing to the load and EV of prosumer k at time t are $P_{t,k}^{G2L}$ and $P_{t,k}^{G2EV}$. The powers of PV and EV discharge belonging prosumer k at time t delivered to the grid are $P_{t,k}^{PV2G}$ and $P_{t,k}^{EV2G}$.

$$P_t^L = \sum_{k=1}^{nodes} \left(P_{t,k}^{G2L} + P_{t,k}^{EV2L} + P_{t,k}^{PV2L}\right), \quad \forall k,t \quad (12)$$

$$P_{t,k}^{G_{injected}} = P_{t,k}^{PV2G} + P_{t,k}^{EV2G}, \quad \forall k,t \quad (13)$$

$$P_{t,k}^{G_{used}} = P_{t,k}^{G2EV} + P_{t,k}^{G2L}, \quad \forall k,t \quad (14)$$

The total system load at time t fed from the grid, EV ($P_{t,k}^{EV2L}$) and PV ($P_{t,k}^{PV2L}$) is given in Equation (12). The powers injected to ($P_{t,k}^{G_{injected}}$) and supplied by the grid ($P_{t,k}^{G_{used}}$) are given in Equations (13) and (14).

$$P_{t,k}^{PV_{gen}} = P_{t,k}^{PV_{used}} + P_{t,k}^{PV2G} + P_{t,k}^{PV_{cur}}, \quad \forall k,t \quad (15)$$

$$P_{t,k}^{PV_{used}} = P_{t,k}^{PV2L} + P_{t,k}^{PV2EV}, \quad \forall k,t \quad (16)$$

The total PV generation of prosumer k at time t ($P_{t,k}^{PV_{gen}}$) is either transferred to load ($P_{t,k}^{PV2L}$), EV charging ($P_{t,k}^{PV2EV}$) or injected into the grid ($P_{t,k}^{PV2G}$), as shown in Equations (15) and (16). If excess power exists, ($P_{t,k}^{PV_{cur}}$) is curtailed to keep the bus voltage within the limit.

$$P_{t,k}^{EV2L} = P_{t,k}^{EV2G} = 0, \quad \begin{cases} t \in [06, 18] \\ t \in [22, 06] \end{cases} \quad (17)$$

For minimizing EV battery degradation due to V2G operations, power discharges to the load or the grid are prevented during non-peak load times, as given in Equation (17).

$$P_{t,k}^{PV2G} + P_{t,k}^{EV2G} \leq M \cdot u_{t1}, \; V_{min} < V_k < V_{max}, \quad \forall t \quad (18)$$

$$P_{t,k}^{G_{used}} \leq M.(1 - u_{t1}) \quad (19)$$

In Equations (18) and (19), the unit step function (u_{t1}) prevents bidirectional energy flow at the same bus and time. For prosumer k at time t, using grid power ($P_{t,k}^{G_{used}}$) is not possible, while PV power injection ($P_{t,k}^{PV2G}$) or discharging EV power ($P_{t,k}^{EV2G}$) into the grid at the same bus. M is a sufficiently large number.

$$P_{t,k}^{EV_{chr}} \leq c.u_{t2}, \quad c \in \{7\} \quad (20)$$

$$P_{t,k}^{EV_{dischr}} \leq c.(1 - u_{t2}), \quad c \in \{7\} \quad (21)$$

$$P_{t=0,k}^{EV_{chr}} = P_{t=0,k}^{EV_{dischr}} = 0, \quad \forall k \quad (22)$$

The unit step function (u_{t2}) in Equations (20) and (21) ensures that EVs are not charged and discharged simultaneously. The coefficient c refers to the charging power of 7 kW. Equation (22) defines the initial (t = 0) charge ($P_{t,k}^{EV_{chr}}$) and discharge ($P_{t,k}^{EV_{dischr}}$) powers for each EV.

$$P_{t,k}^{EV_{chr}} = P_{t,k}^{G2EV} + P_{t,k}^{PV2EV} + P_t^{ESS2EV}, \quad \forall k,t \quad (23)$$

$$P_{t,k}^{EV_{dischr}} = P_{t,k}^{EV2G} + P_{t,k}^{EV2L}, \quad \forall k,t \quad (24)$$

In addition to the grid and PV power, the charging power from the shared ESS is given in Equation (23). When there is no shared ESS, $P_t^{ESS2EV} = 0$. Similarly, the EV discharge ($P_{t,k}^{EV_{dischr}}$) towards the grid ($P_{t,k}^{EV2G}$) and the prosumer load ($P_{t,k}^{EV2L}$) is seen in Equation (24).

$$SoE_{t,k}^{EV} = SoE_{t-1,k}^{EV} + P_{t,k}^{EV_{chr}} \cdot \eta_{chr} - \frac{P_{t,k}^{EV_{dischr}}}{\eta_{dischr}}, \quad \forall k, t \tag{25}$$

$$SoE_{\max,k}^{EV} \geq SoE_{t,k}^{EV} \geq SoE_{\min,k}^{EV}, \quad \forall k, t \tag{26}$$

The state of energy at time t for the EV at prosumer k ($SoE_{t,k}^{EV}$) is given in Equation (25). The charging efficiency is η_{chr}, and the discharging efficiency is η_{dischr}. Equation (26) expresses the maximum ($SoE_{\max,k}^{EV}$) and minimum SoE ($SoE_{\min,k}^{EV}$) values for each EV.

$$P_{t,k}^{PV2G} \leq P_{t,k}^{PV2G_{APC}}, \quad \forall k, t \tag{27}$$

Finally, Equation (27) expresses the maximum PV power that can be injected into the grid according to the fair curtailment power determined for each prosumer at each time t by the proposed APC method.

The proposed method minimizes the total cost of the system in Equation (28). The optimization model considers two types of network constraints: voltage deviations and network capacity. $p_t^{EV_{sell}}$ covers both operational costs and degradation costs of EV battery. $p_t^{PV_{sell}}$ covers both PV's operational and maintenance costs. Furthermore, the objective function incorporates $c.P_{t,k}^{PV_{cur}}$, which minimizes the amount of curtailed energy. An important point is that curtailed energy costs are subtracted from the minimized total cost after optimization. c is a very small cost constant, and $P_{t,k}^{PV_{cur}}$ is the amount of power curtailed. Additionally, the objective function in Equation (28) was utilized to minimize the system's total cost, irrespective of whether grid constraints were considered. However, the constraint in Equation (18) was excluded from the optimization model, which did not incorporate grid constraints. Therefore, there is no need for energy curtailment because surplus energy can be totally sold to the grid in this scenario.

$$\text{minimize} \sum_{k=1}^{K} \sum_{t=1}^{T} \Big(p_t^{buy} \big(P_{t,k}^{G2L} + P_{t,k}^{G2EV} \big) - p_t^{PV_{sell}} \cdot P_{t,k}^{PV2G} - p_t^{EV_{sell}} \cdot P_{t,k}^{EV2G} \Big) + c.P_{t,k}^{PV_{cur}} \tag{28}$$

Self-consumption rate (SCR) and renewable fraction (RF) are already considered in various technical and economic evaluation works. SCR is defined as the amount of directly self-consumed PV energy (E_{PV}^{cons}) over the total PV production (E_{PV}^{gen}), as expressed in Equation (29). Renewable fraction (RF) shows the total annual RES energy rate transferred to the load, as in Equation (30). Where RF is renewable energy fraction (%), and E_{nonren} is the conventional energy source (kWh/yr). The ratio between the total PV generation directly transferred to the load and charging demand and the annual total demand gives the self-supply rate (SSR), as in Equation (31).

$$SCR = \frac{\sum E_{PV}^{cons}}{\sum E_{PV}^{gen}} \tag{29}$$

$$RF = 1 - \frac{\sum E_{nonren}}{\sum E_{served}} \tag{30}$$

$$SSR = \frac{\sum E_{PV}^{cons}}{\sum E_{load}} \tag{31}$$

III. SIMULATION RESULTS AND DISCUSSIONS

Firstly, the system under study is presented. Afterwards, distinct scenarios are presented for consideration. The first scenario examines the impact of charging coordination on both charging management and the potential for V2G over a year. The daily results have demonstrated the impacts of coordinated charging and increased V2G participation on the grid power quality, including line loading, voltage drop, and energy losses. The second scenario also illustrates the impact of an increase in EV numbers on the prosumer and the grid in terms of curtailed energy reduction, total cost reduction, and the increasing injected power from EV to the grid, in addition to the benefits of renewable energy utilization.

A. SYSTEM UNDER STUDY

The IEEE European LVDN represents a radial distribution network suitable for simulating distributed power supply voltage/reactive power controls [44]. The test network comprises 906 buses, 55 single-phase residential loads, and an 11/0.416 kV delta-wye medium voltage transformer. The IEEE European LVDN has been modified by adding 55 prosumers to randomly selected buses and has been used to simulate the proposed novel VCM with fair APC. Each prosumer's PV power was defined by considering the E_{PV}/E_{load} ratios. In addition, considering the space constraints of residential prosumers in LVDN, the maximum PV power was determined as less than 15 kW. A total of 465 kWp PV installed power is defined in PV-rich LVDN. Also, PV productions were obtained from NASA. The number of EVs in the scenarios is determined by increasing from 20% (11 EVs) to 80% (44 EVs) of 55 prosumers. The battery capacities of EVs are created by considering the different EV sales rates in the Turkish market and are randomly assigned to each prosumer. The selected EV battery capacities are between 52 and 89 kWh. The time-of-use (TOU) pricing structure, as determined by the utility company of Türkiye, is comprised of three distinct rate periods: flat (6 AM-5 PM), peak (5-10 PM), and valley (10 PM-6 AM). The corresponding rates are 0.11, 0.18, and 0.056 $/kWh.

B. DAILY PERFORMANCE EVALUATION OF CONTROL METHODS

In contrast to uncoordinated EV charging as soon as it is plugged in or at random times, off-peak or smart charging makes it possible to charge with renewable and cheaper energy. Thus, it is possible to complete charging under more beneficial conditions for both the user and the grid. This study optimizes the proposed control method and charging process by considering EVs' arrival and departure times, SOC values during critical hours, daily range requirements, RES availability, charging power constraints, and grid loading conditions. The interaction of the prosumer with the grid in the case of uncoordinated EV charging for a low-voltage grid with high RES installed capacity is detailed with technical and economic aspects. The uncoordinated EV charging caused morning peaks in the grid. In addition, the charging demand in the evening hours, when domestic loads are at their maximum, poses a problem in terms of both economic and grid capacity constraints. Moreover, the absence of a charging demand at noon, when RES power generation is at its peak, misses the opportunity to utilize both cheap and renewable energy sources. While this situation increases the unit energy costs of the users, it also leads to a move away from the environmental zero-carbon targets. SCR increased by 7% and RF by 10% for a sample clear day due to coordinated charging. Thus, renewable energy loss due to overvoltage and curtailment is reduced. Grid power quality is improved with the APC method applied to prevent overvoltage. However, this resulted in up to 35% curtailment in some prosumers.

The daily results of coordinated charging management and V2G potential are shown in Figure 2. The excess energy generated at noon, when PV generation (yellow line) is highest, is curtailed (orange line) by the APC method. However, for the prosumer, part of the curtailed energy was used to charge the prosumer's EV (black dotted line) with the managed charging method.

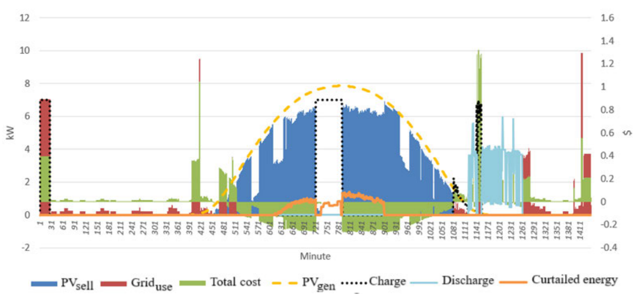

FIGURE 2. Coordinated charging management and V2G potential.

Table 1 shows the LVDN impacts of the EV fleet with V2G participation for a sample day. The lines were overloaded in the scenario without V2G participation, and the voltage dropped below 95%. On the same day, because of the EV support to the grid via V2G, line loading could be reduced below 80%, and bus voltages could be kept above 95%. Line losses were also reduced by up to 40%.

C. THE IMPACT OF INCREASING EV NUMBERS

Demand response practices such as TOU pricing to minimize EV charging loads are not the optimal solution. Moreover, at high EV penetrations, second peaks may occur due to price-based demand response practices, and new power system capacity and efficiency problems may occur. Therefore, EV charging rates and times should be optimized by considering grid dynamics and targets to use the power system more efficiently. In particular, approximately half of the generated energy can be curtailed when the network average SCR falls below 30%, depending on the load profile and grid constraints. Conversely, the optimization method ignores power system constraints so that almost all excess energy can be sold to the grid. Thus, misleading increases in grid energy sales revenues can reduce total costs by up to 100%. Therefore, smart charging algorithms that eliminate the negative impacts of high RES installed capacity and EV penetration on the distribution system should be developed to maximize the benefits for utilities and EV owners. This section analyzes power system performance and individual and collective economic cost-benefit analyses of prosumers in unmanaged, managed, and managed-V2G scenarios considering grid power constraints. In the unmanaged EV charging scenarios, it is observed that up to 57% of the generated energy is generated as excess energy due to grid constraints at high PV installed capacities. The consequences of increasing EV penetration are detailed in Table 2. Figure 3 shows that increasing EV penetration rises the energy transferred from PV directly to EVs by up to 5 times and reduces the excess energy by up to 9.16%. Thus, the increase in EV penetration from 20% to 80% increases the SCR from 19.8% to 25.2%, as shown in Figure 4. On the other hand, the increase in EV penetration decreased the SSR by 4.1% to 27.8%, increasing grid dependency.

In the case of managed charging, the excess energy generated in the unmanaged scenario at low EV penetrations takes similar values and improves only up to 2%. However,

TABLE 1. The V2G potential.

V2G share	Max. loading (%)	Losses (kWh)	Min. Voltage (pu)
0	102.45	178	0.941
25%	99.74	130	0.942
50%	92.12	121	0.947
75%	85.10	113	0.952
100%	79.00	107	0.957

TABLE 2. The results of increasing EV penetration.

EV rate	Method	CE* (%)	TCost (K$)	V2G (MWh)	RF (%)	SCR (%)
20%	Unmanaged	–	12.8	0	31.8	19.8
	Managed	1.7	12.1	0	36.2	21.9
	V2G	2.1	10.7	16.4	38.0	22.4
40%	Unmanaged	–	17.4	0	30.0	21.6
	Managed	1.1	16.4	0	35.2	24.6
	V2G	5.8	12.5	34.1	41.3	27.2
60%	Unmanaged	–	21.2	0	28.2	23.4
	Managed	3.9	19.5	0	37.0	29.2
	V2G	7.7	14.2	51.2	44.3	31.5
80%	Unmanaged	–	25.1	0	27.8	25.2
	Managed	7.6	22.1	0	39.1	33.7
	V2G	11.3	15.6	68.8	47.7	36.2

*The decreasing CE is calculated according to the base case (unmanaged).

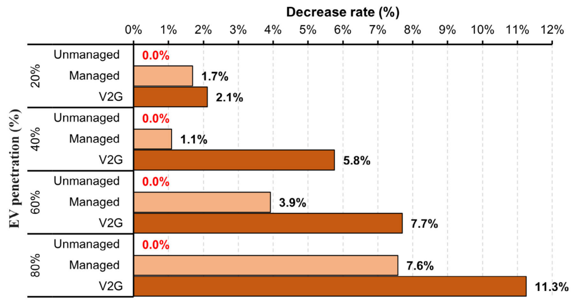

FIGURE 3. The impacts of increasing EV penetration on curtailed energy.

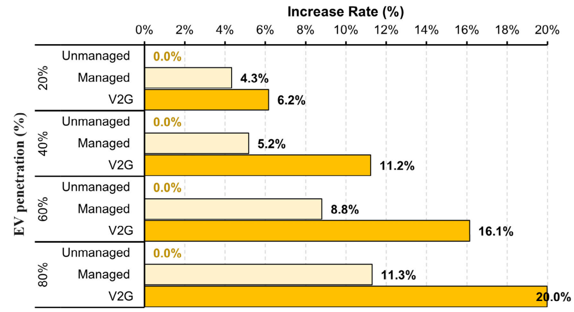

FIGURE 5. The impacts of increasing EV penetration on RF.

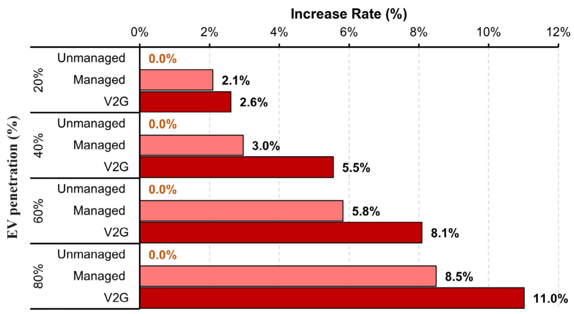

FIGURE 4. The impacts of increasing EV penetration on SCR.

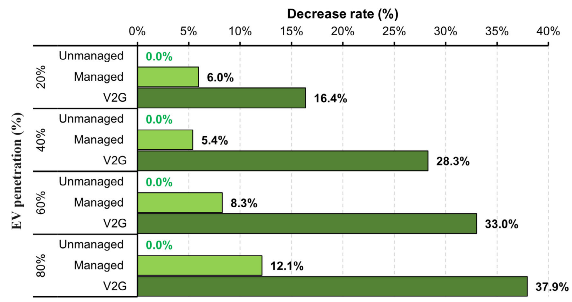

FIGURE 6. The impacts of increasing EV penetration on the total cost.

increasing EV penetration improved the SCR by up to 8.5% compared to the unmanaged scenario, reaching 33.7%. In this way, the total cost could be reduced by up to 12.1% compared to the unmanaged scenario. Moreover, controlling EV charging times increased the energy transferred from PV directly to EV up to 2.31 times. RF, which decreased up to 27.8% in the unmanaged case due to increased EV penetration, increased to 39.1% due to charging coordination. Moreover, Figure 5 shows that the increase in EV penetration in the unmanaged case decreases the RF by up to 4%. In contrast, it increases by up to 2.9% in the managed scenario. In addition, with increased EV penetration, excess energy was reduced by 14.6%, and the curtailed energy was reduced by up to 7.6% compared to the unmanaged case. Thanks to the V2G option, the energy transferred from PV to EV can be increased by up to 20% compared to the managed scenario. This increase improved the SCR by 11% and 2.5% compared to the unmanaged and managed scenarios.

In the managed-V2G scenario, the energy transferred from PV to the grid could be reduced by up to 13% and excess energy by up to 18% due to increased EV penetration. With an increase in EV penetration to 80%, the energy transferred from PV to the grid decreases by 13.82% compared to the unmanaged scenario. However, the curtailed energy due to high PV installed capacity can be reduced by 11.25% compared to the unmanaged scenario. In addition, RF increased by 19.4% compared to the unmanaged scenario. With the increase in EV penetration, the energy transferred from EV to the grid increased by 2.02% to 12.60% of the total charging power. SSR, which was as low as 27.8% in the unmanaged case, can be increased up to 47.7% in the managed-V2G scenario, and grid energy dependency can be reduced by up to 20%. Moreover, Figure 6 shows that the V2G option reduced total costs by 37.93% and 29.36% compared to the unmanaged and managed scenarios, respectively.

The analysis shows that despite the same installed capacity and load profiles, prosumers can increase their individual grid dependency by up to 2 times depending on the seasons. For example, for the P5 prosumer with the E_{PV}/E_{load} ratio of 0.28, the SSR decreased by 8.55% in winter and increased up to 15.86% in summer. Moreover, its SCR varies in a wide range of 36-53% depending on climatic conditions. Due to unmanaged charging, only 6% of the annual PV energy can be transferred to EV, while 36% of the generated energy is excess energy. On the other hand, 69% of the curtailed energy was generated in the summer months. The 88.39 kWh of curtailed energy generated in July decreased by more than 50% to 26.62 kWh in February. Furthermore, 68.9% of the renewable energy was sold to the grid between April and September. However, almost all the PV energy was used for prosumer load in the fall and winter months. As a result, energy costs in summer are 20% lower than in winter. The unmanaged curtailed energy could be reduced up to 16.51% thanks to the managed charging. Thus, the average SCR increased by 10% compared to the unmanaged case. The managed-V2G method reduced the curtailed and grid-to-load energy by 25.6% and 28.3% compared to the unmanaged method. The V2G option increased the SCR by up to 12.62% and 4.91% compared to the unmanaged and managed scenarios. In addition, RF is increased up to 25%.

Since the E_{PV}/E_{load} ratio is 1.18, the SSR for the P8 prosumer is 37.75%, and the curtailed energy is 46%. Thus, unmanaged charging transfers only 12.3% of PV energy to EVs. Due to the APC constraint, RF could not be increased, and only 22% of the total PV generation was transferred to the grid. Due to the high PV installed capacity, the energy curtailment of P8 is 10% higher than that of P5 prosumer. On the other hand, the total cost in summer months is up to 52% lower than in winter months. The managed method reduced the curtailed energy of P8 by 21.2%. Moreover, with managed charging, the energy sold from PV to the grid decreased by 16.5%, and the average SCR increased up to 48%. Furthermore, 28.2% of the EV charging demand can be met directly from PV in the unmanaged charging method, compared to 69.2% in the managed scenario. In the summer months, the SSR increases up to 76%. Thus, the total energy cost decreases by 19.5% compared to the unmanaged scenario. In addition, the energy cost decreases only by 12% in winter compared to the unmanaged scenario but by 70% in July. In the control-V2G scenario, 18% of the total charged energy was discharged during the evening peak demand to meet the energy demand. Furthermore, the energy transferred from PV directly to the EV was increased by 17.8%, thus increasing the SCR to 51.44%. Moreover, the curtailed energy is reduced by up to 12.6% and 31% compared to the unmanaged and managed scenarios. Energy costs could be reduced by up to 58% and 27.8% by reducing the energy purchased from the grid by up to 33.9% and 11.58% according to the unmanaged and managed scenarios, respectively.

P11 contributed more to the overvoltage as the prosumer E_{PV}/E_{load} ratio was 1.87. In P11, 51.6% of curtailed energy occurred. The curtailed energy in July is 2.4 times higher than in December. On the other hand, in the unmanaged scenario, the energy transferred directly from PV to EV increased by 8.2% compared to other prosumers. It reached up to 14% of the total PV generation. Thus, 35% of P11 EV charging energy is provided directly from PV. EV charging demand accounts for 76% of the total load demand of P11 due to long-range travel behavior. On the other hand, during the summer months, the SCR drops to 15%, negatively impacting both P11 economics and grid power quality. Due to unmanaged charging, SSR only increased up to 33.77%. In fact, this ratio drops to 21% in the winter months, and P11's energy cost in February is 2.54 times higher than in July. In the managed charging strategy, the curtailed energy decreased by 15%, and the energy transferred directly from the PV to the EV increased up to 29.21%. In addition, the energy purchased decreased by 40%. However, the SSR decreased to 37% in winter and increased to 74% in summer. Compared to the unmanaged scenario, SCR increased by 16.5%, and energy cost decreased by 35.3%. Moreover, SCR increases up to 46% in winter and decreases to 21.63% in summer due to increased PV generation. 68% of the curtailed energy is realized between April and September. In the control-V2G scenario, P11 V2G participation is limited due to its longer average daily travel range and technical and environmental outputs are not improved at the desired level compared to our managed scenario. In P11, 8% of the charged energy was transferred to the load and the grid thanks to V2G. However, this rate is 18% in P8. Thus, the total energy cost for P8 in the managed scenario with the V2G option is reduced up to 27.8%, while for P11, it is 22.38%.

The system's availability is the primary factor determining the feasibility of V2G implementation. To realize the envisaged benefits through V2G, the EV must be at home and connected to charging, and the user must volunteer for V2G participation. It has been revealed that privacy and loss of control concerns have decreased V2G program participation by 7-12% for every 20% decrease in the reliable driving range [45]. Integrating EVs alters load patterns and provides improved opportunities for energy storage for EV charging. Thus, some governments will promote bidirectional EV charging that supports benefits via V2G. As the EV charging infrastructure is tightly interconnected in terms of both electrical (physical) and information flow (cyber), an attack on the charging system can significantly compromise both the reliability of the charging process and information security. The electric Vehicle Supply Equipment (EVSE) determines the EV charge/discharge rate using a protocol. The EVSE interacts with the Distribution System Operator (DSO) and payment method to control the energy flow and charging bill. EV-grid integration, which involves communication and control interactions, can increase the risk of cyber-attack vulnerabilities. Additionally, using different standards and protocols to manage EV-grid charging and discharging operations can further increase the potential for cyber-attacks. Therefore, future studies may focus on enhancing bidirectional charging capabilities, cyber-security issues, and the willingness to participate in V2G to investigate further the feasibility of EV-grid integration benefits.

IV. CONCLUSION

For sustainable and environmentally friendly energy production and consumption, prosumer communities are turning to using RES to reduce energy costs and carbon emissions. However, increasing PV penetration in the low-voltage distribution grid leads to serious power quality challenges, such as overvoltage for both grid operators and prosumers. Integrating EVs with renewable energy sources, whose charging loads can be shifted, reduces prosumer costs and maximizes environmental benefits. However, unplanned EV charging loads will also lead to voltage problems. Thus, a novel EV charging management is developed that maximizes the power quality and benefits of a prosumer community with high renewable energy penetration by applying a fair power curtailment that considers voltage sensitivities. The performance of the developed charging management is analyzed under three scenarios: unmanaged, managed, and managed-V2G. The prosumers' individual and collective economic cost-benefit analyses are analyzed by considering the EV penetration increase. In unmanaged EV charging scenarios, it is observed that the curtailed energy is up to 57%, and RF is 27.8% due to grid constraints under high renewable penetration. On the other hand, a 60% increase in EV penetration reduces the curtailed energy up to 9.16% and increases the self-consumption by 6%. Nevertheless, it increases grid dependency. In managed scenarios, increasing EV penetration could reduce curtailed energy by up to 7.6% and total cost by up to 12.1% compared to unmanaged scenarios. The managed-V2G method could increase the direct energy transferred from PV to EV by up to 20% and the self-consumption by up to 2.5% compared to the managed scenario. The increase in EV penetration could reduce the energy transferred from PV to the grid by up to 13%, the curtailed energy by up to 18%, and grid dependency by up to 20%. Moreover, the V2G option reduced total costs by up to 37.93% and 29.36% compared to unmanaged and managed scenarios, respectively. Policy-makers should consider grid dynamics with high renewable energy generation to expand EV use. Investigating easy and powerful EV charging management methods is important for sustainable energy and environmental goals. Future studies should explore the potential impact of increasing EV battery capacities on overall system performance within the current V2G framework. Additionally, future research will focus on developing a multi-objective energy management strategy that simultaneously addresses both consumer and network benefits.

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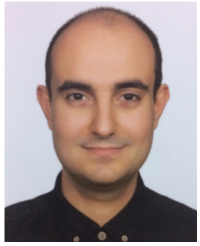

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