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Boosting the Usage of Green Energy for EV Charging in Smart Buildings Managed by an Aggregator Through a Novel Renewable Usage Index

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ABSTRACT The growing trend of electric vehicles (EVs) and building integrated photovoltaics (BIPVs) is a promising means to reduce related climate change issues. EV loads can be managed via an aggregator to maximize the usage of green energy produced by photovoltaic units (PV) through smart charging strategies that exploit controllable EV demand connected to BIPV. Previous works have focused on the EV charging coordination in a smart BIPV, although without an optimization that encourages EV charging with the energy produced by the PV units. This paper proposes an aggregation strategy that maximizes a green energy index (GEI) for the smart charging coordination of EVs, which takes advantage of periods with high PV availability to charge the EV batteries; moreover, a post-processing stage for the GEI provides EV owners with information about the percentage of charged energy, period by period, that comes from PV generation. The results for a case study with 510 EVs integrated with 17 smart BIPVs show that the strategy effectively optimizes the usage of the energy produced by the PV units to charge the EVs, contributes to reduce non-renewable energy consumption of the building sector, and satisfies the EV owners' energy requirements for transportation.

INDEX TERMS Aggregator, building integrated photovoltaic, electric vehicles, green energy index, local energy market, smart charging.

NOMENCLATURE

INDICES

n	Index for nodes.
s	Index for scenario of PV generation.
t	Index for time.
v	Index for vehicles.

PARAMETERS

$\bar{E}_v^{EV}$	Battery capacity of EV v.
$\underline{E}_v^{EV}$	Minimum battery level of EV v.
E_v^{SOC}	Initial state of charge of EV v.
$\underline{E}_v^{Trip}$	Energy requirement for trip of EV v.
f_t^{pv}	PV generation factor at time t.
$\bar{P}_v^{CH}$	Rated power of the EV charger v
P_n^L	Active power demand for loads of the building at node n.

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$\bar{P}^{pv}_{n}$	Active power capacity of PV at node n.
$P^{PV}_{n,t,s}$	Active power injected by PV unit at node n, time t, and scenario s.
$s_{v,t}$	Binary parameter corresponding to the state of EV v (1 when the EV v is on trip and 0 otherwise).
$\zeta_{v,t}$	Binary parameter corresponding to the availability for charging EV v (1 when available to charge the battery and 0 otherwise).
ϑ^{N}_{v}	Connection node of the EV v.
α^{PV}_{t}	Price of energy from PV units at time period t.
α^{SE}_{t}	Price of energy from substation at time period t.
π_s	Probability of scenario s.
Δ_t	Duration of time period t.
ξ_t	Demand factor of the buildings loads at time period t.

VARIABLES

$\mathcal{C}^{EV}_{s}$	Cost that EV owners have to pay to the DNO at scenario s.
$\mathcal{C}^{L}_{s}$	Cost that building users have to pay to the DNO at scenario s.
$E^{EV}_{v,t}$	Battery level of EV v at time t.
$P^{EV}_{v,t}$	Active power charging of EV v at time t.
$P^{ex}_{t,s}$	Positive variable for the exporter power at time t and scenario s.
$P^{im}_{t,s}$	Positive variable for the importer power from the main grid at time t and scenario s.
$\mathcal{R}^{EV}_{s}$	Cost that EV owners have to pay to the aggregator at scenario s.
$\mathcal{R}^{L}_{s}$	Cost that building users have to pay to the aggregator at scenario s.
$\mathcal{E}$	Green energy index.
$\Im$	Variable related to the total energy imported/generated in the system.
$\wp$	Variable related to the total energy produced by PV units.
$\delta^{GEI}_{t,s}$	Proportion of green energy in the system at time t and scenario s.
φ^{GEI}_{s}	Proportion of green energy in the system for all time periods and scenario s.
$\mu^{GEI}_{v,s}$	Proportion of green energy for a particular EV v at scenario s.

I. INTRODUCTION

Important sectors in society, such as electricity, transportation, and building, have a high petroleum dependence, which makes them partially responsible for climate change issues [1]. In 2019, the electrical sector was responsible for 40% of total emissions of worldwide greenhouse gas emissions (GGE), while the transportation sector also presented a significant part of the total GGE, (around 22% in 2019) [1], which has garnered significant attention in recent years. Likewise, the building sector produced approximately 28% of the global GGE and consumed around one-third of the final energy consumption in 2020 [2]. Therefore, from the perspective of helping with the decarbonization of those sectors, electric vehicles (EVs) and the smart building integration with renewable energy sources (RESs), particularly photovoltaic technologies (PV), have been raising attention around the world in recent years [3], [4]. This can be verified by the 40% increase of the global EV market share registered in 2019 [3]. In regard to the smart buildings integrated with RES, PV units are the most attractive technology due to their cost reduction year after year, the improvement of the performance, and their unlimited supply [4]. A new trend in which the PV modules are installed into the building, also known in the literature as building integrated photovoltaic (BIPV), has been receiving more attention during the last few years due to its low energy consumption and improvement of energy management in cities and communities [4]. These buildings can be residential, commercial, or industrial buildings [5]–[7]. Various works have investigated applications for BIPVs, such as pitched roofs of residential and commercial buildings, external building walls and curtain walls in commercial and public buildings, and double skin façade integrating photovoltaic. A numerical model for a double skin façade integrating photovoltaic was developed in [8] aiming to minimize the heating and cooling demand of the system. The authors in [9] defined the BIPV as a potential tool for reaching the nearly zero energy building and zero-emission buildings of the near future.

EV and BIPV systems can produce benefits for their inhabitants, EV owners, and the environment due to the possibility of reducing the electric consumption fueled by coal and gas in the context of smart cities; on the other hand, the future for buildings' energy demand is expected to be mainly covered by local electricity generation [4]. This integration of smart building and EVs could be exploited through charging in the workplace, which is an alternative for the promotion of EV adoption since the users of a commercial building can take advantage of the possibility of charging its EV batteries during work time; this can be crucial for the implementation of BIPVs and EVs. Additionally, the local use of PV energy could be encouraged due to the high interest in reaching zero direct emissions and the possibility of reducing the energy requirements from the power grid (still highly dependent on fossil fuels), contributing to an increase in the usage of green energy by the community [10]. On the other hand, BIPVs and EVs can help to reduce peak energy consumption and the energy cost of a smart building, which is attractive for both building users and EV owners [11].

Despite all the advantages of BIPVs and EVs, the uncertain nature of RESs and the increased energy demands of EVs and smart buildings require the efficient utilization of those resources, motivating the development of energy management strategies that can help to cope with the corresponding challenges [12]. Hence, comprehensive energy management systems need to be developed to better integrate distributed energy resources. In that context, an aggregator can serve multiple purposes in the management of those resources [13], [14]. For instance, the aggregator can control the charging of EVs and manage the energy produced by the PV units. In the case of EVs, the aggregator can manage the resulting demand associated with the EV charging. Hence, an aggregator can control the time intervals of the EV charging and reduce the consumption of energy to avoid issues related to congestion in the network, peak demand, and voltage profile out of statutory limits [15]. Moreover, an aggregation strategy for the EV charging coordination can be integrated with the management of the energy produced by PV units to boost the usage of renewable energy by implementing workplace EV charging in smart buildings. Notwithstanding, this is an area that still has significant room for research [16]. There is a lack of proposals and strategies that improve the opportunity of aggregators to manage BIPVs and EVs. Furthermore, new optimization models that allow this kind of transaction are needed [4]. Some works have focused on the integration between smart buildings and EVs for the enhancement of energy sharing and use of renewable sources [11], [17]–[19]. Furthermore, the authors in [6] described a systematic analysis of different energy management systems and control strategies regarding the energy interaction among smart buildings and EVs; those strategies allowed for a lessening of the energy demand during peak hours and improved the energy efficiency and economic performance, but neither the EV charging coordination nor the management of the integration with smart buildings was carried out considering the role of an aggregator. A multi-objective proposal is presented in [20] aiming to minimize the peak load and the total energy consumption cost in smart buildings, considering EV charging and discharging coordination; the multi-objective optimization is based on the Pascoletti-Serafini scalarization approach to obtain the Pareto front solutions, although the optimization is not managed via an aggregator. The authors in [11] formulated a collaborative decision model based on mixed-integer linear programming to study the energy interaction between various buildings and EV charging stations. The optimization model considered different building categories and driver behaviors, as well as EV discharging to the building. Additionally, the proposed model analyzed the economic performance of this interaction; nevertheless, the smart buildings are not integrated with PV units, for which the use of green energy is not taken into account as an opportunity to enhance the sharing of energy between the EVs and the loads of the buildings.

Analyses on BIPVs and EVs have been carried out aiming at different purposes, such as the development of optimization methods/strategies to find the ideal operation of the interaction between them, and the settlement of energy management strategies for improving the energy exchange among all users (building and EV owners) [21]–[23]. For instance, a two-stage stochastic programming model to study the energy distribution among a group of buildings, EV charging stations, and the main grid is proposed in [24], in which the effects of the integration between the BIPVs and the EV charging stations are analyzed, considering uncertainties related to the energy demand in order to minimize the overall system cost. Although the authors have adopted stochastic programming, the energy sharing between BIPVs and EVs is not managed through an aggregator; furthermore, the energy produced by PV units was not encouraged to be used for the charging of EVs.

The use of indices that can quantify how much energy is shared between BIPVs and EVs is a research topic addressed by some authors aiming to identify the advantages of using energy from RESs, e.g., the stress reduction in the main grid [25], [26]. A methodology with a series of flexibility indices of energy is presented in [25]; the adopted indices quantified how much renewable energy could be stored in electrical storage devices to help reduce the peak of consumption of the grid, although without assessing the usage of green energy for EV charging. In [26], an algorithm for a solar-friendliness index is proposed to increase the usage of energy from RESs; however, that proposed index neither considers a smart building environment nor management through an aggregator, nor does it quantify how much renewable energy is used for EV charging.

The literature review indicates that most of the studies have analyzed the integration between smart buildings and EVs to exploit the sharing of energy and renewable sources; their aims are different, however, such as reducing peak demand, alleviating the stress of the main grid, enhancing energy efficiency, and increasing economic performance. Some approaches consider BIPVs and EVs to encourage the usage of green energy and to minimize the overall cost to the electrical system. Nevertheless, the idea of boosting the usage of the energy produced by RESs for EV charging and adopting an index to measure the amount of green energy that is used by both conventional and EV demands via the management of a centralized aggregator is yet to be developed. Table 1 shows a summary of the studies addressing this research area. To the best of the authors' knowledge, none of the prior studies have developed an optimization model in which an aggregator manages, in a centralized manner, the interaction between BIPVs and EV systems in a smart city environment. To fill this research gap, this paper proposes a novel aggregation strategy for EV users through workplace EV charging coordination, aiming to boost the usage of renewable energy via the maximization of a green energy index (GEI). Moreover, the strategy makes available this energy for the use of the conventional loads of BIPVs. Additionally, a post-processing stage calculates how much of the energy consumed by both the EV owners and building users was produced by the PV units, considering sharing between various BIPVs. The main contributions of this work are summarized as follows:

- An aggregation strategy for EVs and BIPVs implementing workplace EV charging coordination that takes advantage of the solar energy produced by PV units in periods of higher availability.

TABLE 1. Main works related to BIPVs and EVs.

Reference	Optimization of a green energy index	Joint optimization of BIPVs and EVs	Inclusion of the main grid power injection	Management by an aggregator	Preferences of EV users	Workplace EV charging coordination
[7]		✓	✓			
[11]		✓	✓		✓	
[12]		✓	✓		✓	
[13]			✓			✓
[16]		✓	✓			
[19]		✓	✓		✓	
[23]		✓	✓			
[24]		✓	✓			
[25]		✓	✓			
[26]	✓					
[33]		✓				
This proposal	✓	✓	✓	✓	✓	✓

- A green energy index that provides information to both the EV owners and building users about the source of the energy used to serve the daily consumption.
- A mathematical formulation for the proportion of green energy that provides information to EV owners about the source of the energy used to serve the daily energy required for transportation.
- An optimization model based on a transaction in the local energy market in which an aggregator, as the owner of various PV units, can manage the energy consumption of a pool of EV users of various BIPVs to offer PV energy for the building users and help with the decarbonization of small communities.

The remaining part of this paper is organized as follows: Section II presents the problem and the mathematical formulation, Section III introduces the case study, and Section IV provides numerical results and a discussion, followed by the conclusions in Section V.

II. MATHEMATICAL MODEL FOR AGGREGATION STRATEGY

The increase in electrical mobility has led to a rise in power demand from the distribution network. On the other hand, the implementation of PV generation on-site and the adoption of smart buildings are trends that have received great attention in recent years. Therefore, an interest in developing strategies for taking advantage of the energy produced by PV units that can contribute to decarbonization and alleviate grid congestion led to the emergence of BIPV. In this context, a quadratic programming model is developed here to define a workplace EV charging coordination via an aggregator, aiming to boost the charging of the EV batteries with energy produced by the PV units integrated into the buildings. In this way, the time intervals to charge the EV batteries are controlled, taking advantage of the available generation from PV units. In the proposed control strategy, the aggregator reduces the usage of energy required from conventional non-renewable generation sources. The proposed model assumes that the aggregator is the owner of the PV units integrated into the buildings and makes a centralized management of the BIPVs and EVs. Hence, the aggregator has a commitment with the users of EVs and BIPVs based on a transaction in the local energy market. In regard to the former, the aggregator attempts to charge EV batteries with the highest possible amount of PV energy, while guaranteeing the EV owners the energy requirements for motion [27]. Regarding the BIPV, the aggregator strategy offers the possibility of serving loads using renewable energy.

EV owners and BIPV users will pay the energy consumption in a separate way, i.e., the amount of total energy that was served by the PV units is paid to the aggregator. The remainder of the energy will be paid to the distribution network operator (DNO). Furthermore, the aggregator will receive a fee from the EV owners, since the aggregator coordinates the charging, taking advantage of PV generation. Figure 1 shows the strategy proposed for BIPV and EV management.

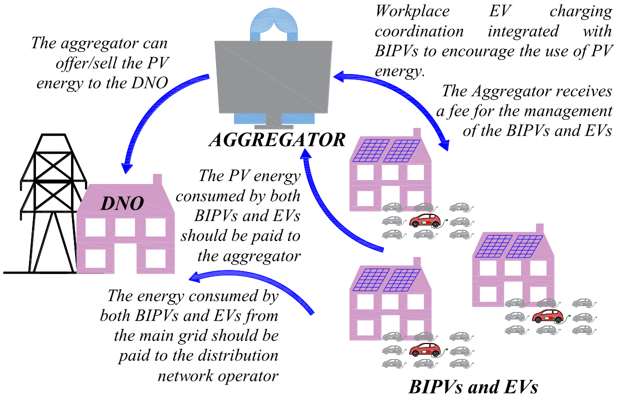

FIGURE 1. Aggregation strategy proposed for the energy shared between BIPVs and EVs.

The strategy implemented by the aggregator is mathematically formulated as a quadratic programming model, which allows finding optimal solutions within a reasonable computational time.

A. OPTIMIZATION OF THE GEI

The proposed GEI ($\mathcal{E}$) is a mathematical expression that optimizes the usage of green energy for all time periods and scenarios of PV generation. The GEI ($\mathcal{E}$) is calculated through two quantities. The first one represents the total energy from PV units that was used by the system ($\wp(kWh)$), which is written in terms of the square of the power generated by the PV units ($P^{PV}_{n,t,s}(kW)$) and the probability of scenarios (π_s), as expressed by (1). The second quantity represents the total energy generated or imported in the system, i.e., both energy from PV units and energy imported from the substation ($\Im(kWh)$), which is written in terms of two values: the square of the power imported by the substation ($P^{im}_{t,s}(kW)$) and the square of the power generated by the PV units ($P^{PV}_{n,t,s}(kW)$), including the probability of scenarios (π_s), as indicated by (2). The squares in the expressions represented by (1) and (2) are required to encourage EV charging in periods of high PV generation, leading to smooth rates of green energy across the given time periods; this can be verified by the calculation of those rates for each period and scenario (represented by the variable $\delta^{GEI}_{t,s}(\%)$ as indicated by (14)). Thus, the optimization of the GEI ($\mathcal{E}$) can be made by using a fractional expression, as shown in (3). It should be highlighted that the proposed model aims to maximize the GEI ($\mathcal{E}$) given in (3), whose mathematical representation is naturally nonlinear due to the fact that $P^{im2}_{t,s}$ in (2) is a variable. Therefore, to obtain an equivalent quadratic model for the optimization of the GEI, it becomes necessary to minimize the inverse expression of $\mathcal{E}$, as specified by (4).

The PV energy is exported to the system only in the case it cannot be locally used by both the EV owners and users of the BIPVs. Nevertheless, this exported power $P^{ex}_{t,s}$ is not considered in the optimization of the GEI due to the fact that the maximization of $\mathcal{E}$ is focused on encouraging the local usage of the PV energy by the owners of the EVs and the users of the BIPVs.

$$\wp = \sum_{s\in S}\sum_{t\in T}\sum_{n\in N}\pi_s\Delta_t P^{PV2}_{n,t,s} \tag{1}$$

$$\Im = \sum_{s\in S}\sum_{t\in T}\pi_s\Delta_t P^{im2}_{t,s} + \sum_{s\in S}\sum_{t\in T}\sum_{n\in N}\pi_s\Delta_t P^{PV2}_{n,t,s} \tag{2}$$

$$\mathcal{E} = \frac{\wp}{\Im} \tag{3}$$

$$\min \frac{1}{\mathcal{E}} = \frac{\sum_{s\in S}\sum_{t\in T}\pi_s\Delta_t P^{im2}_{t,s} + \sum_{s\in S}\sum_{t\in T}\sum_{n\in N}\pi_s\Delta_t P^{PV2}_{n,t,s}}{\sum_{s\in S}\sum_{t\in T}\sum_{n\in N}\pi_s\Delta_t P^{PV2}_{n,t,s}} \tag{4}$$

B. CONSTRAINTS FOR THE BIPV OPERATION

The operation of the BIPVs is formulated by (5)–(8). Equation (5) represents the power balance between the generation and the demand in the distribution system. Exported and imported power to/from the substation or the main grid are included ($P^{ex}_{t,s}$ and $P^{im}_{t,s}$). Exporting is necessary in case the PV units produce more power than required to meet the loads in the system; thus, the surplus energy can be offered/sold to the transmission network operator, the distribution network operator, and other stakeholders. Additionally, Figure 2 illustrates the representation of the power balance, which takes into account the accumulated PV generation and demands (conventional load of the building and EV charging) of all nodes of the system. The power produced by the PV units is given by (6), written in terms of the parameter π_s, corresponding to the probability of PV generation in terms of a set of scenarios [28], the factor of irradiance ($f^{pv}_{t,s}$), and the generation capacity ($\overline{P}^{pv}_n(kW)$) of each PV. The imported and exported powers through the substation are positive variables, as indicated in (7) and (8).

$$P^{im}_{t,s} - P^{ex}_{t,s} + \sum_{n\in N} P^{PV}_{n,t,s} = \sum_{n\in N} P^L_n \xi_t + \sum_{n\in N}\sum_{\substack{v\in V:\\ \vartheta^N_v = n}} P^{EV}_{v,t}, \quad \forall t, s \tag{5}$$

$$P^{PV}_{n,t,s} = \pi_s \overline{P}^{pv}_n f^{pv}_{t,s}, \quad \forall\, n, t, s \tag{6}$$

$$P^{im}_{t,s} \geq 0, \quad \forall t, s \tag{7}$$

$$P^{ex}_{t,s} \geq 0, \quad \forall t, s \tag{8}$$

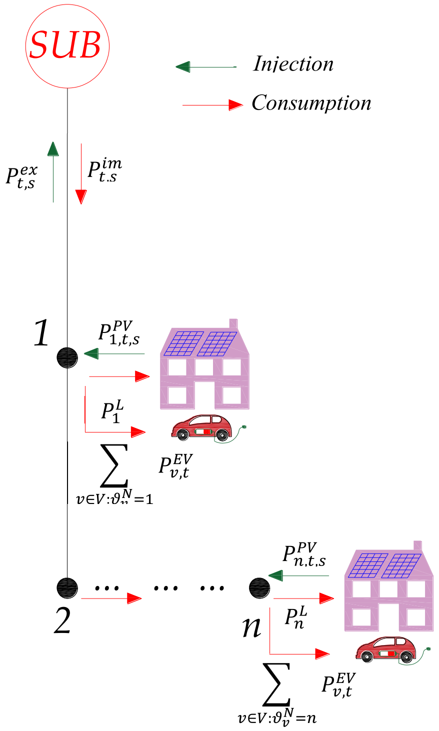

FIGURE 2. Representation of the power balance.

C. CONSTRAINTS RELATED TO THE EV OPERATION

The set of equations (9)–(13) represents the workplace EV charging coordination carried out by the aggregator [27]. These constraints allow the aggregator to guarantee the energy requirement for motion of EVs. Furthermore, through these expressions, the aggregator can schedule the charging of EV batteries in the hours of highest availability of PV generation. The power limit for each EV charging is established by (9), according to the maximum charger power $\overline{P}_v^{CH}(kW)$; the charging power required by each EV depends on the availability state, which is represented by the binary parameter $\zeta_{v,t}$: 1 if the EV is available for charging, and 0 if it is not connected to the system [29]. The energy stored in the initial period of the charging control is expressed by (10) and depends on the initial state-of-charge ($E_v^{SOC}(kWh)$); the power consumption of the EV ($P_{v,t}^{EV}(kW)$); the energy required for daily motion $E_v^{Trip}(kWh)$; and the state related to transportation, represented by the binary parameter $s_{v,t}$, which indicates whether the EV is on a trip ($s_{v,t} = 1$) or not ($s_{v,t} = 0$). Expression (11) represents the energy stored in each EV battery at time intervals different from the first one. Constraint (12) establishes that the energy stored in the EV battery should be at least equal to the energy required for motion in each time period. Moreover, (13) defines the lower and upper limits for the energy stored in the EV batteries.

$$0 \leq P_{v,t}^{EV} \leq \zeta_{v,t}\overline{P}_v^{CH}, \quad \forall v, t \tag{9}$$

$$E_{v,t}^{EV} = E_v^{SOC} + \left(P_{v,t}^{EV}\Delta t - E_v^{Trip}\frac{s_{v,t}}{\sum_{k\in T} s_{v,k}}\right), \quad \forall v, t = t_1 \tag{10}$$

$$E_{v,t}^{EV} = E_{v,t-1}^{EV} + \left(P_{v,t}^{EV}\Delta t - E_v^{Trip}\frac{s_{v,t}}{\sum_{k\in T} s_{v,k}}\right), \quad \forall v, t > t_1 \tag{11}$$

$$E_{v,t}^{EV} \geq E_v^{Trip}\frac{s_{v,t}}{\sum_{k\in T} s_{v,k}}, \quad \forall v, t \tag{12}$$

$$\underline{E}_v^{EV} \leq E_{v,t}^{EV} \leq \overline{E}_v^{EV}, \quad \forall v, t \tag{13}$$

D. POST-PROCESSING STEP AFTER IMPLEMENTING THE AGGREGATION STRATEGY

After the aggregation strategy has been implemented, the expressions (14)–(16) are executed in a post-processing step. These expressions make it possible to calculate how much of the green energy was used by the system. Hence, equation (14) represents the proportion of green energy used by both EV owners and building users at each time interval and scenario ($\delta_{t,s}^{GEI}(\%)$); thus, through this expression, it is possible to provide information about the source of the energy consumption in a particular period and scenario. Additionally, the proportion of green energy used in the system for all time periods and each scenario $\left(\varphi_s^{GEI}(\%)\right)$ is expressed by (15), which provides information to EV owners and users of the buildings about the daily source of their energy consumption for each scenario. Finally, the expression in (16) indicates the proportion of green energy of a single EV for all time periods and a particular scenario ($\mu_{v,s}^{GEI}(\%)$), which allows the owner of the EV to know its percentage of renewable energy consumption.

$$\delta_{t,s}^{GEI} = \frac{\sum_{n\in N} P_{n,t,s}^{PV}\Delta_t}{P_{t,s}^{im}\Delta_t + \sum_{n\in N} P_{n,t,s}^{PV}\Delta_t}, \quad \forall s \tag{14}$$

$$\varphi_s^{GEI} = \frac{\sum_{t\in T}\sum_{n\in N} P_{n,t,s}^{PV}\Delta_t}{\sum_{t\in T} P_{t,s}^{im}\Delta_t + \sum_{t\in T}\sum_{n\in N} P_{n,t,s}^{PV}\Delta_t}, \quad \forall s \tag{15}$$

$$\mu_{v,s}^{GEI} = \frac{\sum_{t\in T} P_{v,t}^{EV}\Delta t\delta_{t,s}^{GEI}}{\sum_{t\in T} P_{v,t}^{EV}\Delta t}, \quad \forall v, s \tag{16}$$

The costs that both EV owners and building users have to pay daily and for a single scenario are calculated based on transactions in the local energy market in a post-processing stage, taking into account the expressions (17)–(20), which are established in terms of the energy price from PV units ($\alpha_t^{PV}(\$/kWh)$) and the energy price from the substation ($\alpha_t^{SE}(\$/kWh)$). Expressions (17) and (18) represent the daily costs that EV owners and buildings have to pay to the aggregator for a single scenario, $\mathcal{R}_s^{EV}(\$)$ and $\mathcal{R}_s^{L}(\$)$, respectively. Hence, after expression (17) has been defined, the aggregator's fee is calculated. Expressions (19) and (20) represent the daily costs that EV owners and building users have to pay to the DNO for a single scenario, $\mathcal{C}_s^{EV}(\$)$ and $\mathcal{C}_s^{L}(\$)$, respectively.

$$\mathcal{R}_s^{EV} = \sum_{n\in N}\sum_{\substack{v\in V:\\ \vartheta_v^N=n}} \alpha_t^{pv}P_{v,t}^{EV}\Delta_t\delta_{t,s}^{GEI}, \quad \forall s \tag{17}$$

$$\mathcal{R}_s^{L} = \sum_{n\in N}\sum_{t\in T}\alpha_t^{pv}P_t^{L}\xi_t\Delta_t\delta_{t,s}^{GEI}, \quad \forall s \tag{18}$$

$$\mathcal{C}_s^{EV} = \sum_{n\in N}\sum_{t\in T}\sum_{\substack{v\in V:\\ \vartheta_v^N=n}} \alpha_t^{SE}P_{v,t}^{EV}\Delta_t(1-\delta_{t,s}^{GEI}), \forall s \tag{19}$$

$$\mathcal{C}_s^{L} = \sum_{n\in N}\sum_{t\in T}\alpha_t^{SE}P_t^{L}\xi_t\Delta_t(1-\delta_{t,s}^{GEI}), \quad \forall s \tag{20}$$

It is necessary to clarify that a continuous adaptable power rate has been adopted in this proposal for the EV charger. This is technically feasible and has the advantage of avoiding binary variables to represent the state of the EV charging, which would increase the computational complexity of the optimization problem [27]. Classical optimization techniques can be applied to solve the problem and to obtain the optimal solution for the management of BIPVs and EV charging through an aggregator, as will be shown in the following section.

III. CASE STUDY

To validate the effectiveness of the proposed method, a case study is carried out in an environment of BIPVs and EVs in which the aggregator controls the charging of 510 EVs in a centralized manner. EV owners are users of 17 smart BIPVs connected in a 34-bus distribution system (adapted from [30]) including the buildings connected in the medium-voltage level, as illustrated in Figure 3. The mathematical model has been implemented in AMPL [31] and solved via the commercial solver CPLEX [32], using a computer with an Intel i7-7770 processor, 16GB of RAM, and Windows 64 bit. The test cases and the results are discussed below.

A. TEST SYSTEM

The users are interested in the possibility of charging their EV batteries using green energy produced by PV units

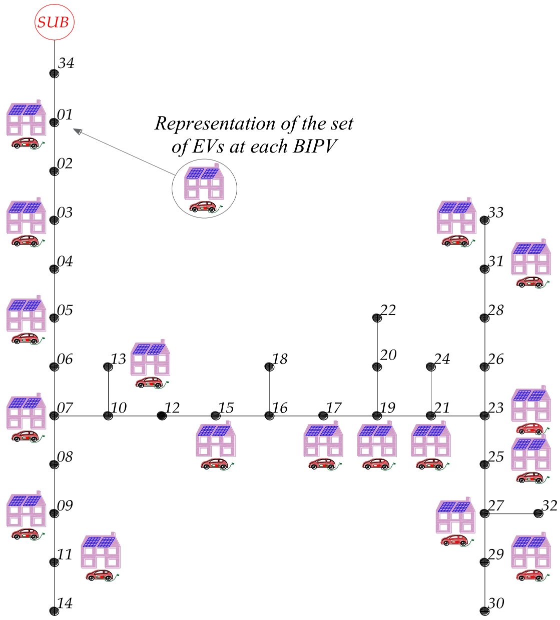

FIGURE 3. Topology of the distribution system with connected EVs and BIPVs.

while their vehicles are parked at the workplace. Furthermore, the aggregator can offer PV energy to both the EV owner and building users at a fixed energy price equal to 0.068 $/kWh [33]; this price is fixed between the aggregator and the consumers (contracted price) and it is more competitive than the grid, which is dynamic along the day; Figure 4 shows the energy price from the substation and the energy price of the PV units [33], [34]. Moreover, the aggregator receives a fee from the EV owners through the workplace EV charging coordination and the optimization of the GEI. Thus, the aggregator establishes a fixed fee for the workplace EV charging coordination, which is assumed to be 20% of the cost that the EV owners must pay to the aggregator for their energy consumption that comes from the PV units; this fee is applied in case the climatic conditions allow the PV generation to be taken advantage of (e.g., during a sunny day). On the other hand, when the weather conditions are poor (e.g., during a cloudy day), the fee established by the aggregator for the EV users is fixed at 5%; the percentage of the fee is low during poor climate conditions since in this scenario it is not possible to take advantage of the PV generation and, consequently, the aggregator does not receive a competitive fee. The aggregator receives a fee for the workplace EV charging coordination since the active power consumption of the EVs is managed by the aggregator to take advantage of the PV generation, while the conventional loads of the BIPVs are not managed by the aggregator, but they can use the green energy and lessen the use of conventional generation.

Each of the BIPVs has a charging infrastructure composed of 30 chargers to meet the EV demand. The PV units are integrated into the smart buildings, and the maximum active power is 450 kW for each unit. Furthermore, four scenarios related to the energy produced by the PV units illustrated in Figure 5 have been adopted, each with a probability of 0.25 [28]; scenario I is the representation of a sunny day, while scenario IV corresponds to a cloudy day. The BIPVs represented in the model have typical loads, such as heating ventilation and air conditioning, exterior and interior lighting, outside air temperature, and electric equipment [35]. Three EV models have been adopted in the tests: the BYD E6, the Nissan Leaf 2019, and the Tesla Model S [35]. It is assumed that E_v^{SOC} is updated at the beginning of the charging control through communication devices [36]. The total number of EV users is 510 and the corresponding information is detailed in Table 2.

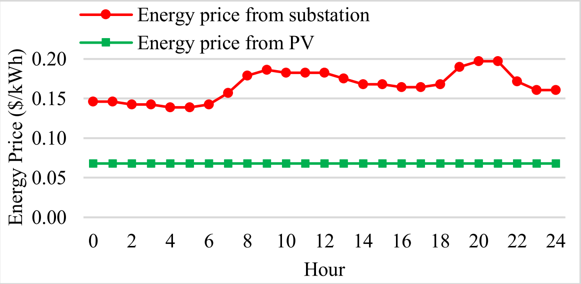

FIGURE 4. Energy price from the substation and energy price from the PV units.

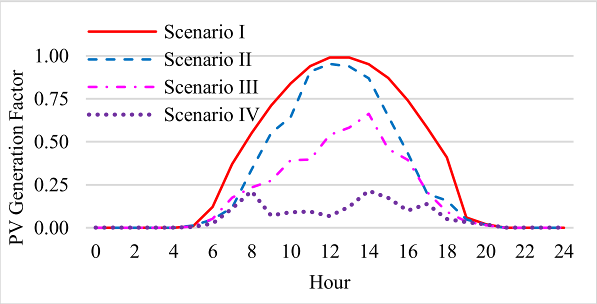

FIGURE 5. PV generation factor for each scenario.

B. TEST CASES

Two cases are proposed to validate the performance of the aggregation strategy considering workplace EV charging during a weekday in which the EV owners are available to charge their EV batteries between 7:00h and 19:00h.

Case I represents operation without aggregator management (dumb charging), while Case II implements the management of the aggregator. Furthermore, the duration of the time period $(\Delta t(h))$ is set as 1h.

IV. NUMERICAL RESULTS AND DISCUSSION

A. CASE I: OPERATION WITHOUT AGGREGATOR MANAGEMENT (DUMB CHARGING)

Workplace EV charging coordination is not considered in this case; hence, the aggregator does not manage the energy

TABLE 2. **EV information.**

Description	EV Model		
	BYD E6	Nissan Leaf	Tesla Model S
Rated power of the EV charger (kW)	6.6	6.6	10
Energy requirement for EV trips (kWh)	30	30	50
EV battery capacity (kWh)	61	62	85
Minimum battery level (kWh)	3.6	3.6	3.6
Numbers of EVs	255	170	85

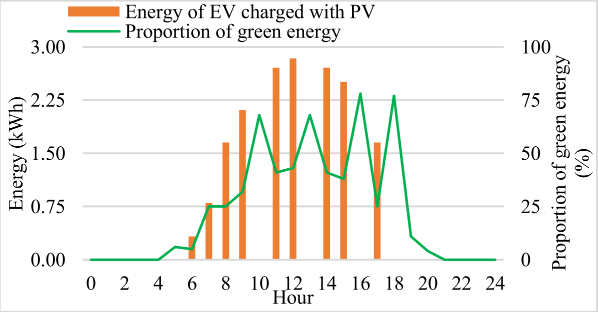

FIGURE 7. **Proportion of green energy for EV#12 without the aggregator strategy (scenario I).**

shared between the BIPVs and EVs. The objective function corresponds to a dumb charging, i.e., charging when the connection to the grid is available and without maximizing the usage of the PV generation. The EV owners can charge their batteries using either green energy or energy coming from the main grid indistinctly. Therefore, for this case, and considering scenario I, the results showed that the φ_s^{GEI} in the system was 31%. Figure 6 illustrates the power shared between the buildings for this case; the green line in Figure 6 shows the $\delta_{t,s}^{GEI}$ at each control interval. In fact, it can be observed that the curve of the $\delta_{t,s}^{GEI}$ is not uniformly distributed across the day, which means there are low percentages of the index, even when the PV units produce more energy (e.g., the $\delta_{t,s}^{GEI}$ was just 38% at noon and 59% at 13:00h); this can be explained by the absence of the maximization strategy of the GEI. Figure 6 also shows that the power required to serve the transportation requirements of the EVs does not follow the PV generation curve and results in a poor performance of the usage of green energy. To further illustrate this, Figure 7 shows the performance of the usage of green energy for EV #12 without aggregator management and under scenario I. Hence, it is possible to note that, since the power required to serve the transportation requirements of the EVs does not follow the PV generation curve; the energy charged with PV is not uniformly distributed across the day, resulting in a $\mu_{v,s}^{GEI}$ of 31% at the end of the EV charging period.

Finally, for scenario I, the energy produced by the PV units used to meet the demand of both the EVs and the loads of the buildings was 14.11MWh. The imported energy from the substation was 30.42MWh, while the exported energy was 3.39MWh; this indicates that, since not all of the energy produced by the PV units was used to charge the EVs, part of it was exported to the main grid. The cost that the EV owners had to pay to the DNO for charging their EVs was $4875.64, while the users of the building had to pay $2987.91. On the other hand, due to the fact that no aggregation management was carried out, neither a payment for the PV energy nor a fee from the EV charging coordination was paid to the aggregator.

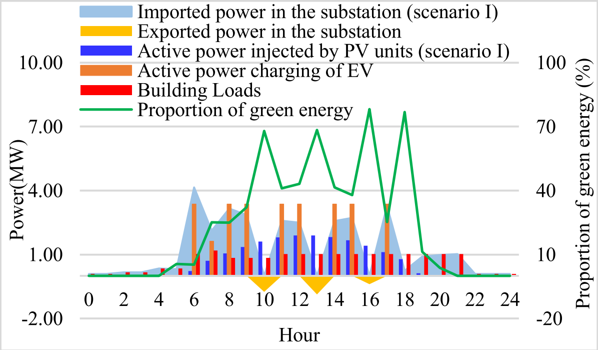

FIGURE 6. **Power sharing in the BIPVs and EVs without aggregator management (scenario I).**

B. CASE II: OPERATION WITH AGGREGATOR MANAGEMENT

Case II includes the aggregator coordination and management. The results suggest substantial improvement in comparison with the previous case without coordination. In fact, for scenario I, the imported energy from the substation is reduced from 30.42MWh to 26.18MWh, without presenting exported power. The energy of the PV units used to meet the demand of both the loads of the building and the EV batteries was 17.50MWh; moreover, the φ_s^{GEI} was 40%. Figure 8 shows the information associated to power sharing between the BIPVs and the EVs under scenario I, in which the PV generation is related to a sunny day. The green line in Figure 8 illustrates the $\delta_{t,s}^{GEI}$ at each control interval, which was 70% at noon and 69% at 13:00h; it demonstrates the effectiveness of the proposed strategy to encourage the usage of the energy produced by the PV units. Additionally, it is possible to verify the uniform distribution of the $\delta_{t,s}^{GEI}$ among the periods. The orange bars represent the power required by the EVs for transportation; it can be observed that the aggregator manages the EV charging to maximize the usage of the PV energy.

The results for a cloudy day (scenario IV) are illustrated in Figure 9. Under this scenario, the energy of the PV units used to meet the demand of both the loads of the building and the EV batteries was 2.93MWh, while the imported energy from the substation was 40.76MWh; there was not exported energy. Finally, the φ_s^{GEI} was 7%. These results show that, due to the adverse weather conditions, the proposed model indicates the supply of the required energy for both the BIPV

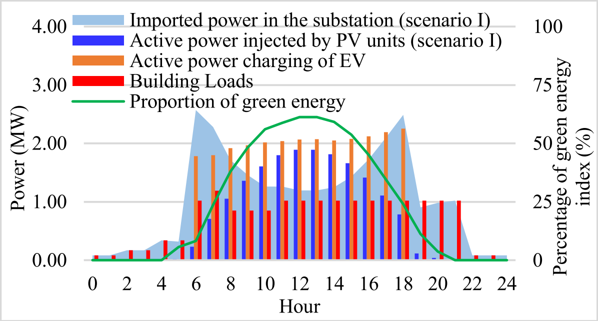

FIGURE 8. Power sharing in the BIPVs and EVs under the control of the aggregator (scenario I).

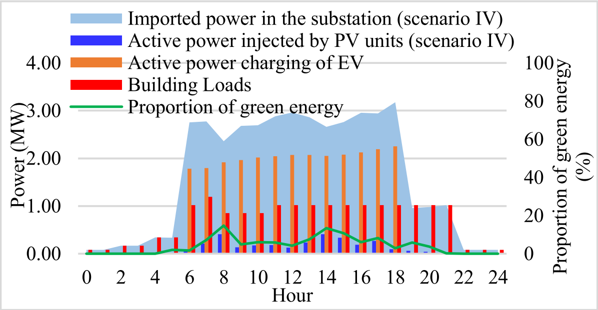

FIGURE 9. Power sharing in the BIPVs and EVs under the control of the aggregator (scenario IV).

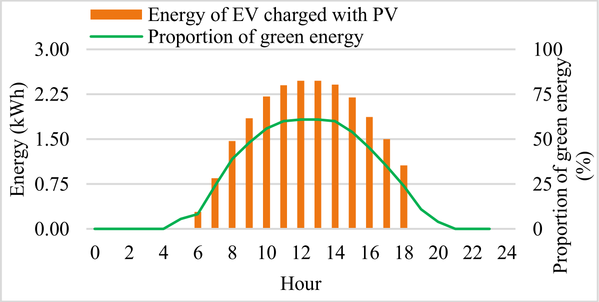

FIGURE 10. Proportion of green energy for EV#12 (scenario I).

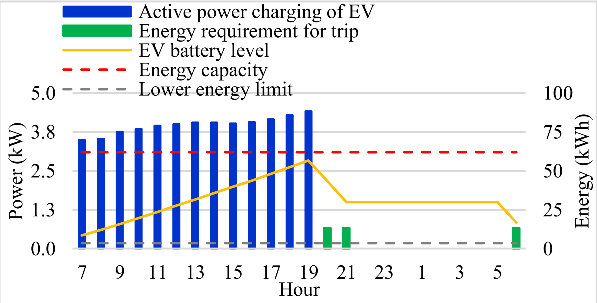

FIGURE 11. Charging behavior of EV#12 (scenario I).

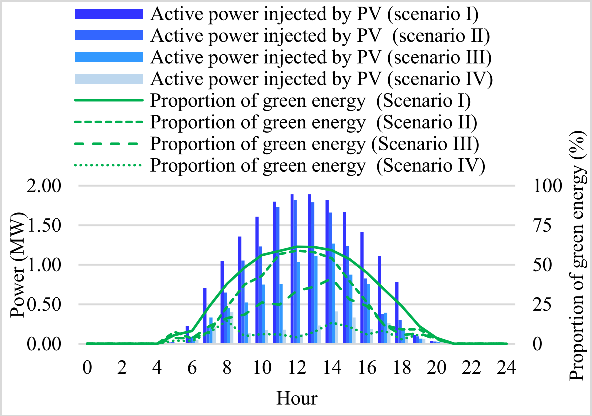

FIGURE 12. Proportion of green energy in each scenario of PV generation.

users and the EV owners through the increase of the imported power from the substation.

Additionally, the proposed strategy demonstrates how much of the energy produced by the PV units was used to charge the EV batteries. For instance, Figure 10 illustrates the periods in which a single EV battery (EV#12) is charged with green energy. The orange bars indicate, period by period, the amount of energy that the EV charges with energy produced by the PV units. At noon, the EV took greater advantage of the PV energy and its $\delta_{t,s}^{GEI}$ was 61%. For this particular EV, the $\mu_{v,s}^{GEI}$ was 45% at the end of the EV charging period, which is an increase of 14% compared with the case without the aggregator coordination. Moreover, Figure 11 shows the charging behavior of EV#12 under scenario I, in which it is possible to verify the effectiveness of the aggregation strategy regarding the compromise between the aggregator and the EV owners. Note that this EV reaches the energy required for transportation; furthermore, the energy capacity (upper and lower) is always maintained within the established limits.

Figure 12 illustrates the performance of the $\delta_{t,s}^{GEI}$ for the four scenarios; when the PV generation is low due to cloudy conditions (scenario I), the), the $\delta_{t,s}^{GEI}$ is low at each of the control intervals and results in a φ_s^{GEI} of 7%; for scenarios II and III, which represent better climatic conditions, the φ_s^{GEI} was 30% and 20%, respectively. However, when the PV generation is high (scenario I), the performance of the φ_s^{GEI} was much better, resulting in 40%. Likewise, the performance of the GEI at each scenario follows the PV generation curve, which demonstrates the effectiveness of the optimization strategy developed to encourage the usage of green energy.

Aiming to demonstrate the importance of the consideration of the squares in $P_{t,s}^{im}$ and $P_{n,t,s}^{PV}$ in expressions (1) and (2) for the optimization of the GEI ($\mathcal{E}$), an additional test for Case II and scenario I without those squares has been considered. In Figure 13, it is possible to note that the performance of the $\delta_{t,s}^{GEI}$ at each period is not homogenous; therefore, the EVs are not taking into account the PV generation for the charging of the batteries. For instance, at 10:00h, 15:00h, and 16:00h, the PV energy is relatively high, but the power charging scheduling of the EVs is low. On the other hand, there is no exported power, which confirms that the PV generation was completely used but was not maximized for EV charging.

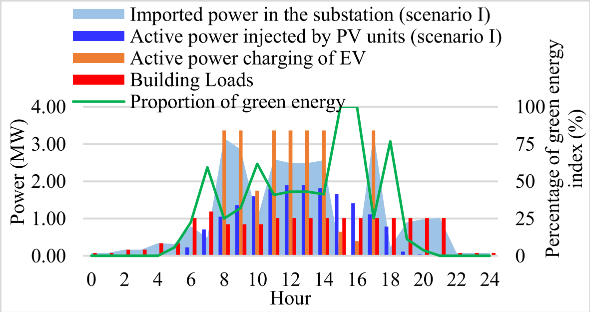

FIGURE 13. Power sharing in the BIPVs and EVs under the control of the aggregator and without the squares in the objective function (scenario I).

The optimization of the GEI through the aggregation strategy proposed enables a reduction in energy consumption from the main grid and can be interesting for both users of EVs and of buildings. It may be possible that the users of the buildings and EVs have to pay a more expensive bill in cases of poor weather conditions since green energy is not available in the same manner on a cloudy day as it is on a sunny day; therefore, the users of the system will use more energy from the main grid and the cost of the energy might be more expensive. Nevertheless, the proposed optimization method of the GEI made it possible, even in cases of poor weather conditions, for users to pay a competitive cost for the energy.

In this context, for this case and for scenario I, the EV owners had to pay $2457.26 to the DNO for the energy provided by the substation. Moreover, the EV owners had to pay $959.73 to the aggregator ($799.77 for consumption of energy provided by PV units and $159.95 corresponding to the fee).

On the other hand, the users of the building had to pay $1972.70 to the DNO for the conventional energy consumption (conventional loads), and the aggregator received $396.82 for meeting the loads of the buildings through the energy produced by the PV units. To summarize, Table 3 shows a comparison of the cost that the users had to pay, including the aggregator's fee. Case I (without aggregator management) and Case II (with aggregator management) are shown in this comparison, namely, the costs for scenarios I and IV. Thus, it is possible to observe that, due to the absence of aggregator coordination (Case I), the users had to pay the same cost, regardless of the scenario. Case II under scenario I presents the best competitive cost, even considering the aggregator's fee. To illustrate the economic performance of the proposed aggregation strategy, a comparison between Case I (scenario I) and Case II (scenario I) for the costs that users had to pay is detailed below. EV owners had a 30% reduction in the total cost that they had to pay in Case II (scenario I) compared with Case I (scenario I).

The building users had a reduction of 21% for Case II (scenario I) in terms of the cost that they had to pay compared with Case I (scenario I). In essence, even under scenario IV, Case II was cheaper than Case I (scenario I). Table 4 shows the costs that both the EV owners and building users had to pay, taking into account a single building. Based on the results previously discussed, it can be concluded that the proposed aggregation strategy can reduce bills for people using electric mobility in a smart building environment.

TABLE 3. Daily cost comparison ($).

	Case I (scenario I)	Case I (scenario IV)	Case II (scenario I)	Case II (scenario IV)
Cost that EV users have to pay to the DNO	4875.64	4875.64	2457.26	4177.43
Cost that EV users have to pay to the aggregator	0	0	799.77	129.49
Cost that building users have to pay to the DNO	2987.92	2987.92	1972.70	2808.75
Cost that building users have to pay to the aggregator	0	0	396.82	70.39
Aggregators' fee from EV users	0	0	159.95	6.47
Aggregators' total revenue	0	0	1356.54	206.35
Total cost for users	7863.56	7863.56	5786.50	7398.88

TABLE 4. Daily cost comparison ($) for a single building.

	Case I (scenario I)	Case I (scenario IV)	Case II (scenario I)	Case II (scenario IV)
Cost that EV users have to pay to the DNO	286.80	286.80	144.54	245.73
Cost that EV users have to pay to the aggregator	0	0	47.04	7.62
Cost that building users have to pay to the DNO	175.76	175.76	116.04	165.22
Cost that building users have to pay to the aggregator	0	0	23.34	4.14
Aggregators' fee from EV users	0	0	9.4	0.38
Aggregators' total revenue	0	0	79.78	12.14
Total cost for users	462.56	462.56	340.39	423.09

Finally, the total revenue of the aggregator is the sum of the payments received from the users, i.e., the cost of EV users, including the fee, and the cost of the building users.

Therefore, Case II under scenario I was the more interesting for the aggregator. On the other hand, when the climatic conditions are poor (scenario IV), the aggregator did not receive a competitive revenue. This comparison highlights that, with aggregator management, the users of the EVs and BIPVs not only are able to improve green energy usage while contributing to energy decarbonization, but also pay a reduced energy bill. The cost for scenarios II and III is not presented, but the numerical results have a similar behavior.

V. CONCLUSION

An aggregation strategy implemented in a workplace's electric vehicle (EV) charging coordination environment for the optimization of a green energy index (GEI), considering the interaction between several building integrated photovoltaics (BIPVs), has been proposed in this paper. The proposed method made it possible to encourage the GEI and measure how much of the energy produced by the photovoltaic units was used to meet the energy consumption of the BIPV users and EV owners.

The GEI was maximized by using the green energy produced by the PV units, taking advantage of periods with high solar energy available to meet not only the energy requirements from EV owners, but also the energy consumption from users of the smart buildings. Furthermore, the users are able to know the proportion of green energy that was used for both charging the EV batteries and for meeting the loads of the buildings.

The results suggest that the aggregation strategy encourages EV charging with green energy, since in the case under the aggregator management the proportion of green energy in the system for all time periods and scenario 1 was 40% compared with 31% in the case without the aggregator management. On the other hand, the aggregation strategy promotes the reduction of energy consumption from the main grid; for instance, when the aggregation strategy is implemented, all the PV energy available was used by the EV owners and the users of the BIPVs. Moreover, the exported power was 0W compared with 3.69MW in the absence of the aggregation strategy. Furthermore, it was demonstrated that the proposed strategy maximizes the GEI, while the preferences of EV owners (i.e., energy for motion) are guaranteed; it also encourages building users to use more sustainable energy sources.

The aggregation strategy implemented by an aggregator in a centralized manner makes it possible to manage the energy sharing between the BIPVs and the EVs so that the aggregator can benefit through the fees paid by the EV owners due to EV charging coordination. Furthermore, this benefit can be increased by offering the energy produced by the PV units to meet the load consumption from the users of the BIPVs, since, as under the aggregation strategy the total cost that both the EV owners and building users had to pay for the total energy consumption was \$5786.50 compared with \$7863.56 without the aggregation strategy.

In the future, the authors intend to implement the aggregation strategy considering the stochastic behavior of EV owners, renewable generation, and loads of the building. Likewise, aspects related to the reduction of greenhouse gas emissions will be considered in the mathematical model, not only demonstrating how much of the energy consumption comes from green energy, but also confirming how much is contributed to decarbonization.

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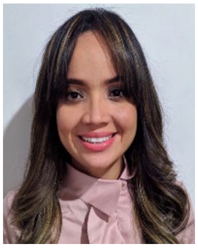

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