Energy Optimization System based on storage potentials of distributed Electric Vehicles

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***Abstract*—Renewable generations are practical options to tackle the problem of cost and environmental damages of traditional energy production ways. Although green alternatives are cheap and clean, a precise consumption plan is mandatory to take the highest advantage of them. This paper proposes a novel optimization strategy where the produced energy of PV and grid is stored during valley hours on electric vehicles that are parked. Then, this saved energy is consumed when the grid is experiencing peak demands. This research uses consumption, PV generation, and parking data of Escuela Técnica Superior de Ingenieros de Telecomunicación at Universidad Politécnica de Madrid. The obtained results show that the electricity cost of the building will be reduced by following the proposed strategy. Moreover, EVs will take the advantage of the proposed strategy by means of receiving free charge.**

Keywords—green energy, photovoltaic, electric vehicles, saving energy, battery.

I. Introduction

Photovoltaic (PV) energy is an attractive renewable energy, whose cost is not meaningfully different from the retail one [1], providing the potential to reduce the overall cost of energy. However, to take full advantage of PV generated energy, it must be integrated with energy storage units and demand-response schemes [2-4].

If a building is equipped with PV units, there are two different scenarios that can happen during a day. The first situation is when the consumer demands less energy than the PV generated energy, while the second situation happens when the demand is higher than PV generation. In the first situation, which can be considered as the best-case scenario, the cost of energy is very low in comparison with the price of the grid. Moreover, in this situation, the remained energy from PV can be saved in storage units. Then, this saved energy will be injected into the gird when the demand increases. The second situation happens when PV generated energy is not enough to cover the demand of the consumer. Obviously, in this situation, the lack of energy must be covered by the energy from the grid. Therefore, the consumer must pay the energy cost imported from the grid. In any case, the overall cost of energy consumption can be reduced by means of optimization and scheduling techniques.

This paper proposes a novel strategy to optimize the cost of energy in the case of grid import. This strategy has been developed under the scenario creation of the eNeuron project [5]. Saving energy based on the price of the grid is the backbone idea of the Energy Optimization System (EOS). In other words, the proposed strategy optimizes the consumption of PV generated energy for the objective of reducing the overall energy cost of a building. In this strategy, PV energy is saved when the price is low, and it is consumed during peak demands when the price is high. Even though the proposed optimization strategy starts with saving PV energy, in the case of having an empty storage capacity, it saves cheap energy from the grid, as well.

Since saving energy is the core idea of the proposed strategy, energy storage is a vital part of it. There are different options for storing [6]. However, the price of storage units is its main disadvantage, because it increases the overall cost of the system. In order to mitigate it, in this paper, we use Electric Vehicles (EVs) as dynamic batteries. EVs have endless possibilities to help environment by means of reducing the level of greenhouse gas emission, if being charged by renewable energies [7, 8]. Even though, using batteries of EVs can result in overall cost reduction, mobility of EVs can affect the system in a negative way. Because of mobility of EVs, the number of accessible batteries is variable along the day. Furthermore, the challenges of designing an optimization strategy are not restricted just to mobility. Capacity of each battery, power rate, State of Charge (SoC), and the level of charge that each EV needs are other effective factors. Along with the mentioned parameters, the price of the energy from the grid, the level of the generated energy by PV, and the level of consumption influence the optimization process. With all the mentioned factors, the optimization strategy decides how to channel the energy flow to minimize the cost of energy.

The rest of this paper is organized as follows. Section II describes the implementation environment. Section III details the proposed optimization strategy. Section IV is devoted to results of EOS, and finally, main conclusions are presented in section V.

II. IMPLEMENTATION ENVIRONMENT

The proposed algorithm has been run on the information from Escuela Técnica Superior de Ingenieros de Telecomunicación (ETSIT) of Universidad Politécnica de Madrid (UPM), Spain.

A. *PV generation and electricity consumption*

ETSIT is equipped with 13.1kWp PV cells. The PV panels are installed on the roof and facades of its buildings. The tilt of the panels is $\theta_{tilt} = 26^{\circ}$ and are oriented south. Figure 1 shows the generated PV and consumption (kW) from 1st January 2019 to 31st December 2019 on hourly basis. As the figure illustrates, the generated PV is far from being sufficient to fulfil the electricity demand of the school. The maximum generated PV is 12.293 kW while the minimum consumption is 32.163 kW in 2019 that shows the level of difference.

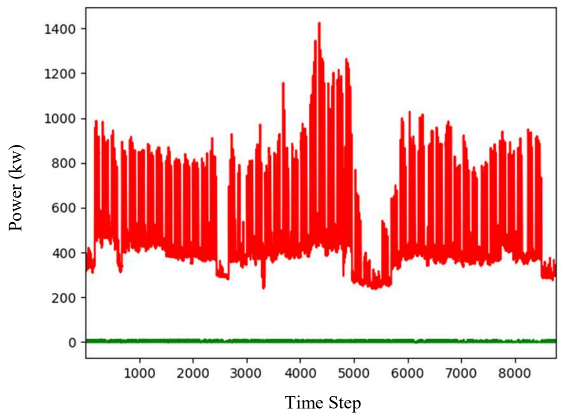

Fig. 1. Hourly PV generation (green) and electricity consumption (red)

B. *Electricity Price*

It is straightforward that the main part of electricity demand must be supplied by the grid. There are three defined tariffs for the grid energy in Spain [9]: normal rate 2.0 A, night rate 2.0 DHA, and EV rate 2.0 DHS. Moreover, the price of each tariff changes every hour. Figure 2 is an example of the change of the tariffs throughout a day.

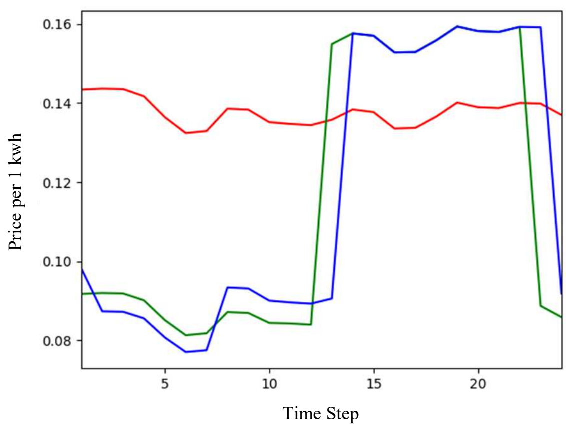

Fig. 2. Tariffs A (red), DHA (green), DHS (blue)

C. *Mobility Information*

As aforementioned, batteries of EVs are the storage infrastructure of the proposed energy optimization strategy. To this end, the availability of EVs for charging and discharging is an important factor. There are some parking spaces at ETSIT where employees park their vehicles. To find out the number of available vehicles at each hour, data of the parking is extracted from [10]. The extracted data is in the format of "Arrived", "Leave", which determine the arrival and leaving time.

In addition to availability information of EVs, there are other important factors that must be considered such as the battery capacity, SoC, and power of each battery. Nonetheless, the daily need of each vehicle must be taken into consideration because every EV must end up the day with at least that amount of energy. Except for the arriving and leaving time, the rest of parameters are produced randomly in this research. Furthermore, it must be emphasized that this paper uses uniform distribution to produce random numbers.

This paper assumes that all the parked vehicles are electric powered ones. To determine battery capacity and power of EVs, two EV models namely, Nissan Leaf and BMW i4 are considered in this research. Table 1 details the properties of these EVs [10, 11]. The shares of these EV models in the parking are randomized.

TABLE I. PROPERTIES OF EV MODELS

Model	Capacity (kWh)	Power (kW)
Nissan Leaf	30	3.7
BMW i4 eDrive 40	80	11

Not only the model of each parked EV is determined randomly, also, the daily need of each EV is produced in a random way. To define charge each EV needs during a day, the distance that each EV covers in a normal day is obtained, first. Based on a survey done among employees of ETSIT each EV travels 30 km per day, on average [10]. Then, the consumption of considered EV models must be extracted. Information related to the Nissan Leaf is reported in [10]. Based on this information, the lowest consumption of the EV is 3.26 kWh per 100 km while the maximum recorded consumption is 22.91 kWh per 100 km. This paper uses [12] to obtain BMW i4 daily consumption. It is a website where consumers record their daily consumptions under real driving conditions. Based on analyzing 20 records of BMW i4, the minimum consumption is 17 kWh/100 km and the maximum consumption is 25.12 kWh/100 km. Since the average traveling distance of the employees of ETSIT is 30 km, the minimum and the maximum needs of a normal day for each EV are shown in Table 2. This paper produces a random number in between the maximum and minimum needs of each EV type to determine the charge that each EV needs for traveling during the corresponding day.

TABLE II. MAXIMUM AND MINIMUM NEED OF ETSIT EMPLOYEES

Model	Maximum (kWh)	Minimum (kWh)
Nissan Leaf	6.8	1
BMW i4 eDrive 40	7.5	5.1

To determine the SoC of each EV when arrives, we must pay attention to the maximum and minimum need of each EV, again. Table 3 shows the minimum and maximum SoC that each EV needs to satisfy its daily consumption after work. Subsequently, a random integer number in between the lowest and the highest is produced.

TABLE III. MAXIMUM AND MINIMUM SOC OF ETSIT EMPLOYEES

Model	Maximum (%)	Minimum (%)
Nissan Leaf	23	4
BMW i4 eDrive 40	10	7

EVs are divided into two main categories: consumer and storage. If an EV at the arrival has enough energy to satisfy its daily needs, this EV is considered as a member of the storage category. On the other hand, if the current charge is not enough for its daily needs, this EV is considered as a member of the consumer category. Regardless the category, EVs must be interested to participate in the program. In fact, the program must be attractive enough to get permission for storing and subtracting energy from the vehicles. EVs in the consumer category need energy. Therefore, the possibility of charging is the incentive for them. However, in the case of EVs in the storage category, charging is not enough attractive. This paper considers an amount of free charge for EVs in the storage category to attract them to the program.

III. Energy Optimization System

Table 4 explains the parameters of the proposed optimization strategy.

TABLE IV. Parameters of EOS

Symbol	Description
k	time step
p_k	Price of the grid at the current time step
p_θ	Threshold price of EOS
pv_k	Generated PV by the building at the current time step
con_k	Consumption of the building at the current time step
pot_{batt}	Empty capacity of the batteries at the current time step
ev_i	i[th] Electric vehicle
t_i	Minutes ev_i stays in the parking
ε_p	Potential PV energy ev_i can receive
ε_r	PV energy that ev_i receives
B_p	Battery power of ev_i
B_e	Empty capacity of ev_i
$bonus_i$	Energy bonus for ev_i
ε_n	Lack of energy
B_r	Extracted energy from batteries

Algorithm 1 shows the whole process of the designed optimization strategy. As the algorithm shows the process of EOS starts with categorizing EVs into storage and consumer. If a vehicle is in consumer category, the system charges it directly from the grid, regardless the other parameters. The main idea of charging consumer category is that these EVs can shift to battery in the next time steps. Subsequently, EOS will use these EVs capacity to save energy.

Then, EOS receives the grid price of the current time step (p_k). Time step (k) is fixed to one hour because the price of the grid energy changes at this frequency. Then, EOS receives the current PV (pv_k) and the current consumption (con_k) at the same time step. Based on p_k, two different scenarios will be followed. If the price of the energy is less than the price threshold (p_θ), pv_k will be channeled toward the batteries. Otherwise, pv_k must be consumed in the building.

If p_k is less than the threshold, EOS measures the empty battery capacity (pot_{batt}) of the EVs in the storage category to charge them by PV generated energy. To charge the batteries, EOS pays attention to different factors. The most important factor is the stay duration (t_i). EOS considers higher level of energy for an EV that will stay longer than the others because there is a higher chance to have access to this EV during peak demands. Equation 1 shows the relationship between duration of stay and the potential received energy. In this equation, t_i is the time in minutes that an EV (ev_i) will stay in the parking and ε_p is the potential energy that it can receive.

$$\varepsilon_p = \frac{t_i}{\sum_{j=1}^{number\ of\ batteries} t_j} \times p_k \tag{1}$$

It must be mentioned that the EV's battery power (B_p) along with its empty capacity (B_e) is another important factor in charging the battery. If the considered ε_p cannot be saved in the battery of ev_i because of B_p or B_e, the additional energy will be transferred to the next battery.

In charging EVs in the storage category, there are two possible scenarios, $p_k > pot_{batt}$ and $p_k < pot_{batt}$. If $p_k > pot_{batt}$, EOS fill the batteries at first, and the remained PV will be consumed in the building.

On the other hand, if $p_k < pot_{batt}$, the process gets one more critical step. In this scenario, EOS fills the batteries with p_k, first. Afterwards, EOS tries to fill the rest of the remained capacities with the grid energy if the price is low enough. To this end, EOS checks the price of energy for the next time step (p_{k+1}). If $p_k < p_{k+1}$, EOS does not charge the empty capacity of the batteries. If $p_k > p_{k+1}$ but $p_{k+1} < p_\theta$, EOS considers it as an opportunity. In this situation, batteries with SoC < 80% are charged to reach 80%. Finally, if $p_{k+1} > p_\theta$, it shows an emergency case where all the batteries must be filled with the lower price energy. Figure 3 shows the diagram of EOP when p_k is low.

Creating an incentive for the vehicles to take part in the EOS process is an important aspect. To fulfil this goal, EOS considers a bonus ($bonus_i$) for every ev_i in the storage category because of using its battery. Moreover, the considered bonus is in the format of energy. In other words, each EV that is in storage category receives free charge up to a maximum value.

The behavior of EOS in the case of experiencing a high price is as follows. When p_k is higher than p_θ, EOS discharges the batteries with respect to $bonus_i$. In this situation, EOS calculates the lack of energy (ε_n) which is the difference between pv_k and con_k. This energy must be gained from batteries and in the case of not having enough battery response (B_r) it will be supplied by the grid. Also, if $B_r > \varepsilon_n$, EOS sells the extra energy to the grid. Unlike the charging process, where longer stay EVs receive higher energy, discharging process starts with EVs that will stay shorter. Also, all the generated PV will be channelled to the building consumption. Figure 4 depicts the diagram of EOP when p_k is high.

It must be emphasized that the proposed optimization strategy runs on the data of 2019. Therefore, all the parameters like the price of the next time step are known. In the case of not knowing these parameters, a prediction methodology is required to forecast them.

IV. Results

This section explains the outcome of EOS on the extracted data. In this section, the results of using EOS for 24 hours are analyzed at first. Then it runs on a full year data and will be compared with different strategies. As algorithm 1 shows, the pre-defined threshold for the peak price determines the behavior of EOS at each time step. The threshold price is considered 0.14 per kWh. Figure 5 analyzes the result of running EOS on DHA tariff for a random day.

As Figure 5 (a) shows, the empty capacity of batteries changes during a day based on the number of EVs in the battery category. As Figure 5(c) depicts, the first price higher than the threshold happens at 13:00 in this day.

A particular emphasis must be placed on this time step, since the plots change meaningfully at this point. Based on the process of EOS, in the case of having a peak in the price of the grid at the next time, we must save as much energy as possible. As Figure 5(b) illustrates, the energy from the grid is used to fill batteries exactly before the peak. In addition, Figure 5(b) clarifies that the saved energy from the grid is used at the upcoming peaks to reduce the overall cost of energy.

This paper compares EOS with two other strategies to evaluate the performance of the proposed optimization strategy. The first strategy is Normal Behavior (NB) of the building where all PV generated energy is sent to the building, directly. The second strategy is PV Saved (PS). In this strategy, only generated energy from PV is saved into the batteries when p_k is less than p_θ. Creating an incentive for EVs to participate in the program is an important aspect of EOS and PS strategies. We start the comparison between the strategies with considering no bonus and then, the bonus will be changed to observe the effects. In the case of having no bonus, each EV must pay the received energy during the parking hours.

Algorithm 1:

begin:
For k in the range of (0, 8760): (365 days and 24 hours per each day)
Split EVs into Battery and Consumer Categories
Read p_k, p_θ, pv_k, con_k, $EVs\ status$
if $p_k < p_\theta$:
Calculate pot_{batt} of EVs in Battery Category for charging
if $pot_{batt} < pv_k$:
Charge batteries with respect to t_i, B_e, and B_p
Consume the remained PV energy in the building
if $pot_{batt} > pv_k$:
Charge batteries with respect to t_i, B_e, and B_p
if $p_{k+1} \geq p_\theta$:
Charge batteries with the grid (Emergency)
if $p_k > p_{k+1}$:
Charge batteries with $SoC < 80\%$ (Opportunity)
if $p_k < p_{k+1}$:
Do not charge batteries with grid
if $p_k \geq p_\theta$
Consume pv_k
Compute ε_n
Compute B_r
Discharge batteries from shorter stay to longer stay
if $B_r > \varepsilon_n$:
Sell $B_r - \varepsilon_n$ to the grid
else:
$Grid\ Need = con_k - pv_k - B_r$
Charge EVs in Consumer Category from Grid
end

Reducing the overall cost of energy is the main purpose of the proposed optimization strategy. To find out which scenario saves more, the three cases are compared based on different tariffs. Figure 6 shows the results of implementing three mentioned strategies on tariff 2.0 A for a random day.

As it can be observed, in some hours, particularly when the price of the grid is not high, EOS costs more than the other two cases. It happens because EOS is trying to save energy as much as it can. In this way, more energy is available for the peak demands. In addition, Figure 6 shows that in some hours the cost of EOS is negative. It shows that in those hours the extracted energy from batteries plus pv_k is greater than $ener_{need}$ and the additional energy is sold to the grid. In the other words, not only the electricity is free for the building during those hours, but also, the building can make money with selling to the grid. Furthermore, Figures 7 depicts the results of the implementations on 2.0 DHA and 2.0 DHS tariffs, respectively.

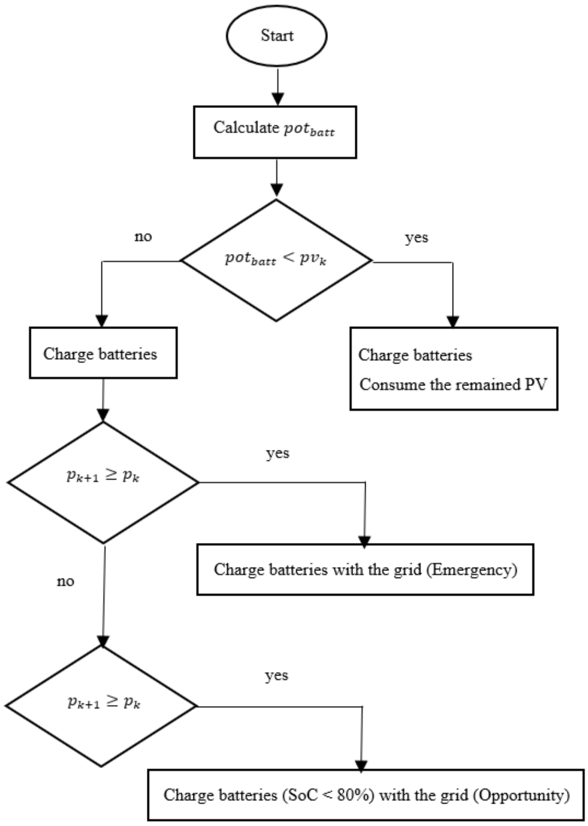

Fig. 3. Diagram of EOS with low p_k

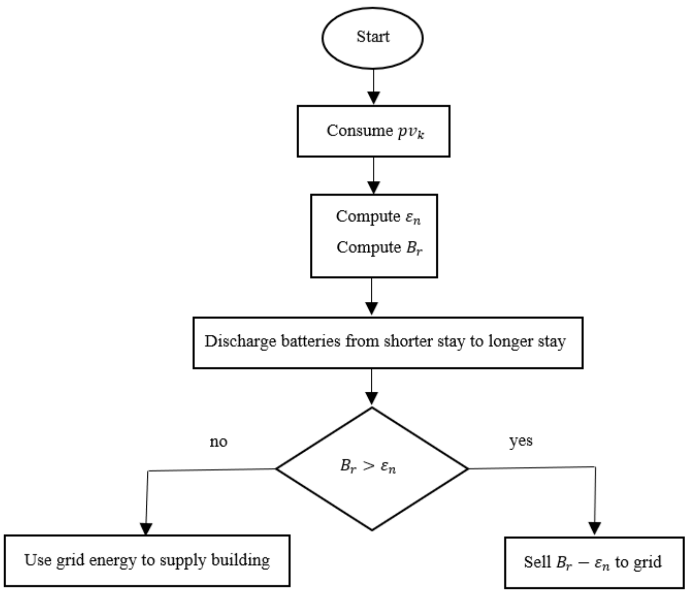

Fig. 4. Diagram of EOS with high p_k

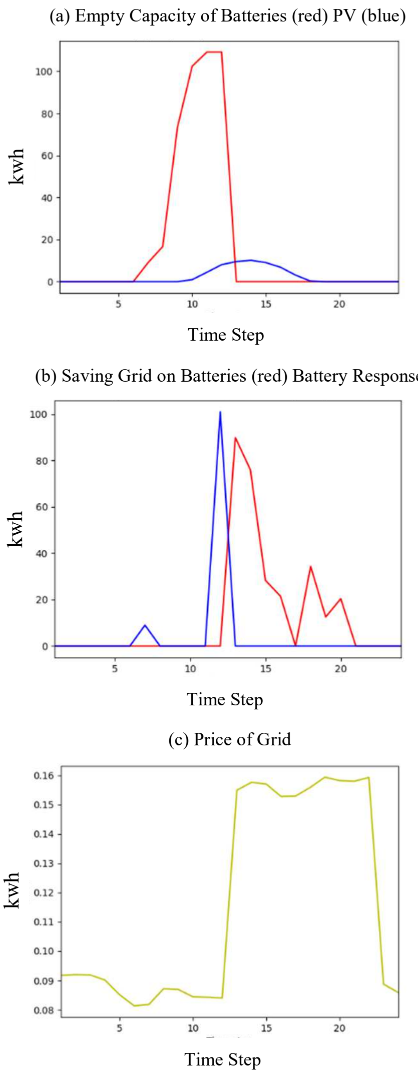

Fig. 5. Running EOS on DHA tariff for one day (a) comparison of empty capacity of batteries and PV (b) saving grid on batteries and battery response (c) DHA price

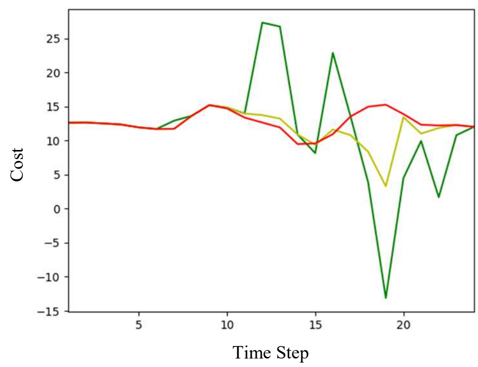

Fig. 6. Results on tariff 2.0 A without bonus, NB (red), PS (yellow), EOS (green)

Table 5 draws a comparison between the three strategies in terms of annual cost of electricity when no bonus is considered for PS and EOS strategies. The proposed optimization strategy has the best performance in all the tariffs. Based on the results, the annual cost reduction of EOS in comparison with NB is 1.7%, 7.1%, and 7.09% on tariffs 2.0 A, 2.0 DHA, and 2.0 DHs, respectively. The reduction rate of EOS in comparison with PS is 0.19%, 2.7%, and 2.7% on tariffs 2.0 A, 2.0 DHA, and 2.0 DHs, respectively. Also, the results proved that saving just PV energy is a better strategy than consume it directly in the building. In addition to the comparison on an annual basis, seasonal comparison is important, too. To perform seasonal comparison between the strategies, one day from each season is selected. Table 6 details the selected days of each season along with the results of running the strategies on the different tariffs.

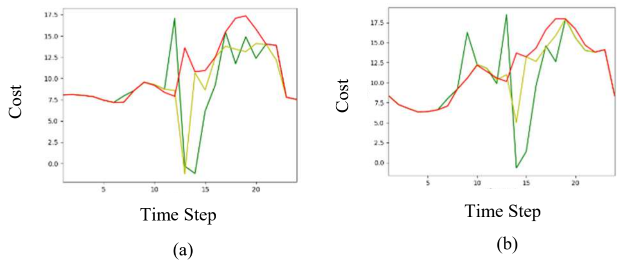

Fig. 7. a) Results on tariff 2.0 DHA without bonus, NB (red), PS (yellow), EOS (green) and b) Results on tariff 2.0 DHS without bonus, NB (red), PS (yellow), EOS (green)

TABLE V. ANNUAL COST OF ELECTRICITY WITH NO BONUS

	Strategies		
Tariffs	***NB***	***PS***	***EOS***
2.0 A	175512.2407	172866.9152	**172521.3187**
2.0 DHA	146624.2999	143101.0129	**139127.0208**
2.0 DHS	147025.0312	143501.7353	**139534.8400**

TABLE VI. SEASONAL COST OF ELECTRICITY WITHOUT BONUS

Season	Date	Strategy	2.0A	2.0DHA	2.0DHS
Winter	1/1/2019	EOS	283.60	219.53	215.37
		PS	285.12	225.24	228.95
		NB	303.57	254.38	256.60
Spring	1/5/2019	EOS	389.02	302.96	305.33
		PS	388.67	311.01	312.79
		NB	396.85	322.75	324.40
Summer	1/8/2019	EOS	298.09	219.54	222.82
		PS	298.94	246.26	248.42
		NB	308.67	259.50	261.57
Autumn	1/10/2019	EOS	548.83	433.55	437.36
		PS	551.38	447.36	450.74
		NB	565.82	466.11	469.41

As Table 6 proves, EOS can reduce the cost in almost all the tariffs and all seasons. Cost rate during spring and tariff 2.0 A is the only exception where PS has better performance than EOS. According to this table, the best performance of EOS compared to NB on tariffs 2.0 A, 2.0 DHA, and 2.0 DHS happens in winter when the overall cost is reduced by 6.57%, 13.69%, and 16.06%, respectively. The reduction rates of EOS and PS in comparison with the normal behavior of the building are in Table 7.

TABLE VII. SEASONAL REDUCTION RATE WITHOUT BONUS

		Reduction (Comparison with NB)		
Season	***Strategy***	***2.0A (%)***	***2.0DHA (%)***	***2.0DHS (%)***
Winter	EOS	6.57	13.69	16.06
	PS	6.07	11.45	10.77
Spring	EOS	1.97	6.13	5.87
	PS	2.06	3.63	3.57
Summer	EOS	3.42	13.39	14.81
	PS	3.15	5.10	5.02
Autumn	EOS	3	6.98	6.82
	PS	2.55	4.02	3.97

To evaluate the performance of EOS, it is run with different percentage of the bonus. It must be emphasized that $bonus_i$ for ev_i, is a percentage of its battery capacity. In this paper, the bonus is set to 5%, 10%, and 15%. In addition, if an EV receives energy higher than the considered bonus, it must pay the cost of that energy. On the other hand, there is a possibility that an EV leaves the parking before receiving full bonus. Table 8 shows the results of running EOS with bonus on different tariffs. Also, this table compares the results of EOS with PS and NB, as well. As Table 8 shows, increasing the rate of the bonus increases the cost of the building in the case of using EOS. It happens because the cost of the bonus must be paid by the building.

Table 9 shows the annual reduction rate when considering different bonus. According to the results, if we consider 5% bonus for EVs in storage category, the annual cost of EOS increases but still it has the best performance on tariffs 2.0 DHA and 2.0 DHS. Also, on tariff 2.0 A, even though it performs better than NB, it is not as good as PS. Increasing the bonus to 10% changes the performance quality of EOS in comparison with the other strategies. Although EOS still has the best performance on tariffs DHA and DHS, it isn't as good as PS and NB on tariff 2.0 A. Implementation results show that increasing the bonus to 15% leads to diminishing in the performance of EOS on all the tariffs. Furthermore, it can be deduced from these results that if we increase the bonus, EOS will result in more cost than the other strategies. Because, with increasing the bonus, smaller portion of the saved energy, which is paid by the building, can be re-used.

TABLE VIII. ANNUAL COST OF ELECTRICITY WITH BONUS

		Tariffs		
Bonus Rate	***Strategy***	***2.0A***	***2.0DHA***	***2.0DHS***
5%	EOS	175475.45	142643.37	143018.55
	PS	174798.18	145406.15	145785.86
	NB	175512.24	146624.29	147025.03
10%	EOS	178181.57	145769.09	146158.88
	PS	176001.88	146759.57	147148.92
	NB	175512.24	146624.29	147025.03
15%	EOS	180551.35	148508.79	148907.20
	PS	176738.74	147571.53	147974.64
	NB	175512.24	146624.29	147025.03

TABLE IX. ANNUAL REDUCTION RATE WITH BONUS

		Reduction (Comparison with NB)		
Bonus	***Strategy***	***2.0A (%)***	***2.0DHA (%)***	***2.0DHA (%)***
5%	EOS	0.02	2.71	2.72
	PS	0.4	0.83	0.84
10%	EOS	Not Reduced	0.58	0.58
	PS	Not Reduced	Not Reduced	Not Reduced
15%	EOS	Not Reduced	Not Reduced	Not Reduced
	PS	Not Reduced	Not Reduced	Not Reduced

V. CONCLUSIONS

In this paper, a novel optimization strategy to reduce the cost of energy consumption is presented. The proposed strategy saves PV and cheap grid energy into batteries of the parked electric vehicles. When the price of the grid energy is high, the saved energy is fed back into the building. In this way, the overall cost of the building is reduced. Moreover, the proposed strategy considers free charge for participated EVs to create incentive for them. The proposed optimization strategy is tested on the information from Escuela Técnica Superior de Ingenieros de Telecomunicación of Universidad Politécnica de Madrid on three available tariffs in Spain. Moreover, different levels of free charges for EVs are tested. According to the obtained results, the proposed optimization strategy can reduce overall energy cost even if we consider 5% free charge for each EV. Also, in the case of considering 10% free charge for EVs, still the overall cost of the school is reduced on tariffs DHA and DHS. In addition, the results show that even saving just PV energy when the price is low can reduce the overall energy cost of the building, too. Finally, a more extended scenario of EOS will be analyzed under one of the innovative use cases reported in the eNeuron project.

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