Multi-Criteria Optimization of Vehicle-to-Grid Service to Minimize Battery Degradation and Electricity Costs

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Abstract—Increased use of renewable energy sources in energy sector as well as improvements and electrification in transportation sector significantly contribute to reduction of green-house gasses emissions and mitigation of problems with fossil fuel dependency. Optimal integration of electric vehicles (EVs) into the grids and their charging/discharging schedules have to be realized in accordance with electricity demand, day-ahead electricity market prices and intermittency of photovoltaic and wind generators electricity production. A microgrid that includes non-deferrable loads, renewable energy sources, EV fleet and its charging station is analyzed in this paper. Its Vehicle-to-Grid (V2G) service is optimized with the aim of minimizing the operational costs and obtaining peak load shaving and valley filling of the load curve, which is especially effective in the case of EVs fleet with occupational time intervals known in advance.

Optimized schedule of EVs charging and discharging is obtained as a result of the procedure that uses multi-criteria optimization function. These criteria include minimization of microgrid electricity costs as the local aggregator's benefit, maximization of the flattening of total microgrid demand curve as main grid operator's benefit, and minimization of battery degradation (due to a number of charging/discharging cycles) as EVs owner's benefit which is the novelty of this paper. Experimental analysis is performed on several scenarios and program Lingo is used to solve the optimization problem.

Index Terms—Cost function; Electric vehicles; Microgrids; Optimization; Renewable energy sources.

I. INTRODUCTION

In 2020, due to the Covid-19 pandemic situation, global carbon dioxide (CO_2) emissions declined by 5.8 % compared to the previous year. That was a drop of 2 Gt of CO_2. However, global energy-related CO_2 emissions remained at 31.5 Gt in 2020, resulting in the highest ever average annual concentration of CO_2 in the atmosphere that is now about 50 % higher than at the beginning of the

industrial revolution. In 2021, global energy-related CO_2 emissions were projected to rebound and grow at least by 5 % due to economic recovery [1]. Although renewable energy sources increased their share in global electricity generation from 27 % in 2019 to 29 % in 2020, there is still a very long way to go to reach the goal of zero net emissions by the 2050, as projected by IEA. Additionally, energy prices in the electric markets increased for more than 100 % from July 2021 to October 2021 [2].

The common belief is that renewably energy sources, together with electric vehicles (EVs) and technologies such as V2G (Vehicle-to-Grid), V2B (Vehicle-to-Building), and V2H (Vehicle-to-Home) [3], [4] can result in mitigation of global warming crisis, but these have to be supported by the efforts to use all resources optimally. This was the motivation for applying optimization procedures in the scheduling of charging and discharging EVs [5]–[7] to reduce the energy costs. There were also efforts to include battery degradation costs [8]–[11].

The authors of this paper considered a microgrid of one company having EVs fleet and its charging station with available V2G service, non-deferrable loads, PV panels, and wind turbines [12], [13]. Two-objective optimization problem was translated into single-objective optimization problem by weighted linear combination of two functions in [14], but battery degradation costs were not considered. However, charging and discharging of EVs has to take into account the battery degradation costs. In this paper, it is shown that these costs are very important for the scheduling of EVs charging/discharging. Another important issue, which is also considered in this paper, is flattening of the electricity demand curve of the microgrid.

Multi-objective genetic algorithm solver in MATLAB is used in [15] for the optimization of energy efficiency and energy management of buildings. Renewable energy tracking is treated in [16], [17]. In this paper, LINGO program [18] is used for minimization of the multi-criteria costs function that is a linear combination of the three functions. One function represents the electricity costs that

should be minimized for the benefit of microgrid owner or aggregator, the other represents costs of battery degradation and should be minimized for the benefit of the EVs owner, and the third represents costs of non-flattened load demand curve to be minimized for the mains operator's benefit.

II. PROBLEM FORMULATION

There are many potential benefits of using V2G service for power systems, microgrids, and EVs owners. For power systems, such benefits include: frequency regulation, voltage support, peak load shaving, avoiding unexpected outages, and enhancing integration of renewable energy sources [5].

In some smart grid concepts, decentralized generation and consumption are managed and controlled locally by aggregators. They coordinate microgrid's operation and contribute to the optimal operation of the entire power system. Main benefits of using V2G service for microgrids and aggregators are: increasing power system reliability by mitigating the intermittency of wind and solar generators, reducing the electricity costs and storage devices costs.

Main benefit of V2G service for EVs owner is using incentives and lowering the electricity costs, but not at the price of exceeding EVs battery degradation costs due to charging or discharging. It has to be taken into account that battery costs are remarkable portion of the total EV's costs, although battery costs decreased for several times in the last decade. Batteries lose their capacity irreversibly due to calendar aging and the growing number of charging and discharging cycles. The battery has to be replaced when it reaches its End-of-Life (EoL), which occurs in the case that it lost about 20 %–30 % of its capacity. This is important for considering the number of charging/discharging cycles to optimally use V2G technology. Charging and discharging schedule for EVs fleet with its occupational time intervals given in advance is obtained in this paper and the optimization of electricity costs is achieved. This is important for reducing costs of the companies owning microgrids and EVs fleets, and for the smart control of their microgrids.

If the cost, safety, and life duration are considered, there are three promising technologies deployed in EVs batteries. These are lithium-ion, lead-acid, and nickel-metal hydride technologies. Lithium-ion batteries have the advantages of high energy density and no memory effect that makes them the most prospective. Two major criteria for estimation of battery's EoL are calendar aging and cycle aging. Charging and discharging rate, Depth of Discharge (DoD), State of Charge (SoC), End of Charge Voltage (EoCV), ambient and operational temperatures, total energy withdrawn and the number of charging and discharging cycles determine the cycle aging. Among these, the number of charging and discharging cycles and total processed energy are the most significant, so these should be modeled adequately [19]. In this paper, charging and discharging costs per each hour are taken into account.

Small EVs, such as Nissan Leaf with 30 kWh battery capacity, may use different charging modes as given in Table I [20].

Faster charging results in faster degradation of batteries.

However, ultra-fast chargers are often used for powerful vehicles. Wireless charging is also a developing technology. EVs may swap empty batteries in EVs battery swapping stations that charge them later in optimal time periods [21].

There are also other popular small EVs of similar battery capacities ($\pm\,20\,\%$) as given in Table II [22].

TABLE I. CHARGING MODES FOR BATTERIES OF SMALL EVs.

Charging Point (Nominal power)	Max. power	Charging power (kW)	Charging time (hours)
Standard 3.3 kW on-board charger			
Wall Plug (2.3 kW)	230 V/1 × 10 A	2.3	14.5
1-phase 16 A (3.7 kW)	230 V/1 × 14 A	3.3	10
1-phase 32 A (7.4 kW)	230 V/1 × 14 A	3.3	10
3-phase 16 A (11 kW)	230 V/1 × 14 A	3.3	10
3-phase 32 A (22 kW)	230 V/1 × 14 A	3.3	10
Wall Plug (2.3 kW)	230 V/1 × 10 A	2.3	14.5
Optional 6.6 kW on-board charger			
Wall Plug (2.3 kW)	230 V/1 ×10 A	2.3	14.5
1-phase 16 A (3.7 kW)	230 V/1 × 16 A	3.7	9
1-phase 32 A (7.4 kW)	230 V/1 × 29 A	6.6	5
3-phase 16 A (11 kW)	230 V/1 × 16 A	3.7	9
3-phase 32 A (22 kW)	230 V/1 × 29 A	6.6	5
Fast charging			
CHAdeMO (50 kW DC)	47 kW	45	0.5

TABLE II. BATTERY CAPACITIES OF SOME SMALL EVs.

Vehicle	Year	Battery capacity (kWh)
Nissan Leaf	2016	30
BMWi3	2017	33
Ford Focus Electric	2017	33.5
Volkswagen e-Golf	2017	35.8
Renault Kangoo Maxi ZE 33	2017	32.6
Kia Soul EV	2018	30
Mazda MX-30	2019	30
Volkswagen e-Up!	2019	32.3
Mini Cooper SE	2020	32.6
Honda e	2020	28.5
Seat Mii Electric	2020	32.3

Main components of the microgrid (MG) analyzed in this paper (Fig. 1) are non-deferrable loads of the company, photovoltaic generators, wind generators, EVs fleet and their charging station with available V2G technology. These components are controlled by the management system and connected to the main grid at the point of common coupling (PCC).

Bidirectional flow of electricity is provided for storage devices and EVs charging station. In this paper, other storage devices than EVs batteries are not considered in the optimization procedure to minimize the costs.

The non-deferrable loads curve of one company [12] is given in Fig. 2. The daily curve represents power $P_L(i)$ per each hour $i = 1, 2, ..., 24$. Maximum power is demanded in the starting working hours of the company. Although deferrable loads are desirable, they are not considered in this scenario.

Electricity buying prices $BP(i)$ at SEEPEX market [2] for Tuesday, July 27, 2021, per each hour $i = 1, 2, ..., 24$, are given in Fig. 3. The same procedure, as given in this paper

for the prices and electricity demands per hour, may be conducted done for shorter time intervals if needed.
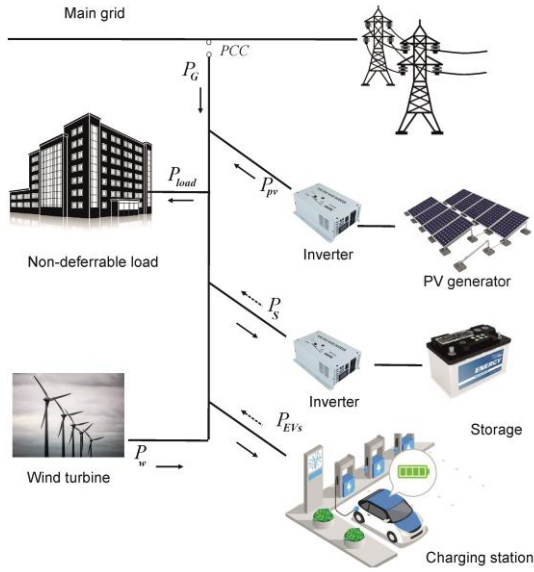

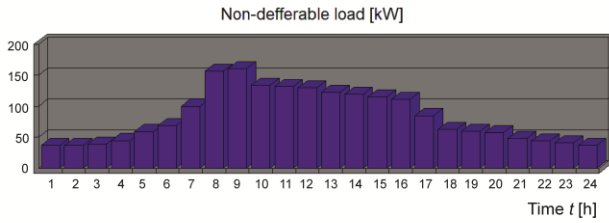Fig. 1. Microgrid structure scheme.

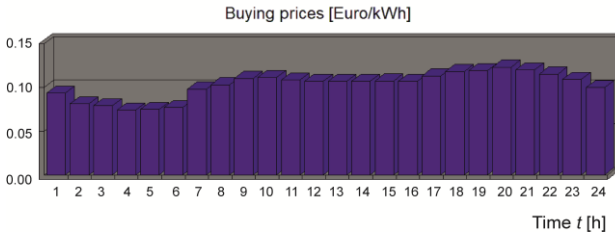Fig. 2. Non-deferrable load curve of the company [12].

Fig. 3. Electricity market buying prices for Tuesday, July 27, 2021.

It is important to note that electricity prices in October 2021 were twice as great as in July 2021 due to increased electricity demand in the global market as a consequence of industry recovery in many countries after the Covid-19 crisis. In December 2021, electricity prices were higher than in October 2021 for additional 20 %. That makes optimization of electricity costs even more significant. The sales prices $SP(i)$ for the given microgrid scenario are estimated to be 75 % of the buying prices $BP(i)$, for $i = 1, 2, ..., 24$.

The energy productions from photovoltaic panels and wind generators of the same peak power 33 kW are given as estimated curves for the 24-hour interval, based on data for solar irradiation and for wind energy potential in the region of Banat, Serbia [23]–[25]. Daily curve of $P_{PV}(i)$, for $i = 1, 2, ..., 24$, is given in Fig. 4, and $P_W(i)$, for $i = 1, 2, ..., 24$, is shown in Fig. 5.

The company has $n_{EV} = 5$ small EVs in its fleet, each with battery capacity $E_{EV} = 30$ kWh. Such an EV has a range distance from 120 km to 250 km with totally charged battery. This depends on weather conditions, route conditions, speed and style of driving. If the range distance is estimated to be 166.67 km, it means that for 55 km of driving its battery loses about 33 % of the full capacity. Each vehicle is available for driving for 6 hours of the company's working time (e.g., from 10 am in the morning to 4 pm in the afternoon) and meanwhile it drives 55 km distance in total. If EVs are fully charged at the beginning of driving hours, after that period SoC decreases to 67 %, which means on average 5.5 % per each hour. From 4 pm in the afternoon to 10 am next morning, i.e., for the next 18 hours, all EVs are available for V2G service at the station.

If the charging power is assumed to be constant during charging/discharging, $P_{CH} = 3.3$ kW, then EV's battery SoC increases for 11 % per hour in the case that EV is charging, or decreases for 11 % if discharging. The same efficiency of charging and discharging is assumed in the calculations, although some difference exists. During 24 hours, each EV is charged for minimum 3 hours to get back the electricity of 9.9 kWh (i.e., 33 % of 30 kWh), or it is charged for additional hours if discharging in other hours is cost effective. The power $P_{EV}(i)$, for $i = 1, 2, ..., 24$, is positive if the vehicles are charging, and for the fleet $P_{EV}(i) = n_{EV} P_{CH}$, or negative if discharging, so that $P_{EV}(i) = -n_{EV} P_{CH}$. The sign of that power corresponds to the decision variable $x(i)$ which is determined in the optimization procedure.
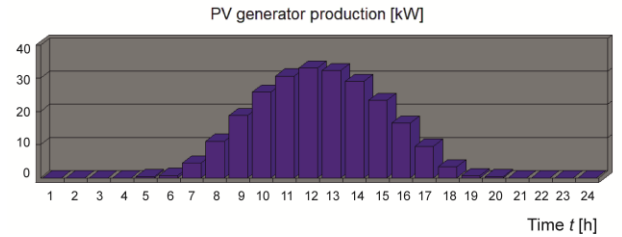

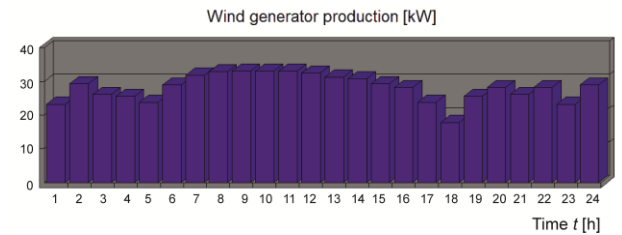Fig. 4. PV generator production as a function of time intervals.

Fig. 5. Wind generator production as a function of time intervals.

SoC(i) is the state of charge at the beginning of i-th time interval $\Delta T = 1h$, and it changes during 24 hours according to the following equation

$$SoC(i) = SoC(i-1) + x(i-1) \times P_{CH} \Delta T / E_{EV}. \qquad (1)$$

There is a constraint for SoC(i), for $i = 1, 2, ..., 24$, so that

$$SoC_{min} \le SoC(i) \le SoC_{max}, \qquad (2)$$

for $SoC_{min} = 20$ % and $SoC_{max} = 100$ %. Optimization is carried out so that the battery of each EV is left at 100 %

SoC at the beginning of next driving time period at 10 am.

$x(i)$ is the decision variable that has to be determined in the optimization procedure. It has discrete values and is equal to 1 if the vehicle is charging, -1 if the vehicle is discharging, and zero if neither charging nor discharging. To define the costs function, two additional variables $x_B(i)$ and $x_s(i)$ are introduced so that

$$x(i) = x_B(i) - x_s(i). \tag{3}$$

$x_B(i)$ is equal to 1 if the microgrid is buying electricity, equal to 0 if the microgrid is not buying electricity, whereas $x_S(i)$ is equal to 1 if the microgrid is selling electricity, equal to 0 if the microgrid is not selling electricity. After the optimization procedure, the results are given for $x(i)$.

Power $P_G(i)$, for $i = 1, 2, ..., 24$, is the total microgrid demand from the main grid in the i-th hour

$$P_G(i) = P_L(i) - P_{PV}(i) - P_W(i) + P_{EV}(i), \tag{4}$$

and it satisfies the constraint

$$P_G(i) \le P_{Gmax}, \tag{5}$$

for P_{Gmax} is the maximum power that can be dispatched from the main grid.

III. MULTI-CRITERIA OPTIMIZATION

There are three terms in the costs function given by (6) to be minimized in the optimization procedure, each of them multiplied by the corresponding weight coefficient

$$F = \min \left\{ \alpha_1 \sum_{i=1}^{24} \left[BP(i) P_L(i) - SP(i) P_{PV}(i) - SP(i) P_W(i) + \right. \right.$$
$$+ n_{EV} P_{CH} \left(BP(i) x_B(i) - SP(i) x_S(i) \right) + $$
$$+ \alpha_2 n_{EV} C_{BD} P_{CH} \sum_{i=1}^{24} Abs \left[x_B(i) - x_S(i) \right] + $$
$$+ \alpha_3 C_{AV} \sum_{i=1}^{24} \sum_{j=1}^{24} Abs \left[P_L(i) + n_{EV} P_{CH} x(i) - P_{PV}(i) - P_W(i) - \right.$$
$$\left. \left. - P_L(j) - n_{EV} P_{CH} x(j) + P_{PV}(j) + P_W(j) \right] \right\}. \tag{6}$$

Costs of the total microgrid electricity demand are multiplied by the weight coefficient α_1.

Total costs of EVs batteries degradation are multiplied by the weight coefficient α_2. These costs depend proportionally to the charging power P_{CH} and the cost C_{BD} per each hour of charging or discharging, per each vehicle in the fleet. The average value of the small EV battery is about 5000 EUR and it is expected to last about 10 years before EoL is reached after about 3000 charging cycles. Battery degradation due to calendar aging is about 50 % of battery costs and other 50 % are due to charging cycles. However, in the first five years of using EVs, the costs of battery degradation due to aging are more dominant than the costs

due to charging. The cost of charging/discharging is estimated to be $C_{BD} = 0.1$ EUR/kW per hour in this paper. These costs are increasing if the charging/discharging occurs in subsequent hours for approximately 5 % in every next hour.

There are costs related to differences of the demanded power per each hour to the average power P_{AV} of that day. These costs are multiplied by the weight coefficient α_3. C_{AV} is the average electricity price for the same day and it is calculated as

$$C_{AV} = \frac{1}{24} \sum_{i=1}^{24} SP(i). \tag{7}$$

Flattening of the microgrid total demand curve is done by valley filling and peak load shaving, and it results in lowering of these costs.

IV. RESULTS OF OPTIMIZATION

In Scenario 1, the microgrid has PV generator of the peak power 33 kW with electricity production as shown in Fig. 4. For the minimization of the function (6), its weight coefficients are chosen as $\alpha_1 = 0.3$, $\alpha_2 = 0.3$, and $\alpha_3 = 0.4$ so that the optimized charging/discharging schedule for EVs is obtained as given in Fig. 6. The total daily demand of that microgrid after optimization is presented in Fig. 7.

In Scenario 2, the microgrid has a wind generator of the same peak power 33 kW with electricity production as given in Fig. 5. For weight coefficients $\alpha_1 = 0.3$, $\alpha_2 = 0.3$, and $\alpha_3 = 0.4$, the charging/discharging schedule for EVs is obtained as given in Fig. 8. The total daily demand of that microgrid after optimization is presented in Fig. 9.

In Scenario 3, the microgrid has wind generator of the same peak power 33 kW, but weight coefficients are $\alpha_1 = 0.5$, $\alpha_2 = 0.5$, and $\alpha_3 = 0$ so that charging/discharging schedule is obtained as presented in Fig. 10. Total daily number of charging/discharging hours is 5 in this case. It shows that costs are minimized just from the microgrid's and EVs fleet owner point of view. Total demand of the microgrid after the optimization is given in Fig. 11.

In Scenario 4, the microgrid has the same wind generator, but the weight coefficients are $\alpha_1 = 0$, $\alpha_2 = 0$, and $\alpha_3 = 1$ so that the electricity costs are optimized from the perspective of the main grid by the flattening of the total demand curve. Charging/discharging schedule is obtained as given in Fig. 12. Total demand after the optimization is presented in Fig. 13. However, better flattening cannot be obtained without greater number of EVs in a fleet. If PV and wind generators are compared, PV is better for reducing costs due to its production curve that has maximum values in working hours, which is convenient for non-deferrable load demand. Wind generator has more flattened daily production curve for the same peak power as PV, but it requires greater investments.

The procedure for obtaining optimized schedule for EVs fleet charging in a microgrid of one company, so to provide compromise between all the parts involved, presents the novelty of this paper. This gives possibility for the smart control of charging that contributes to the energy efficiency
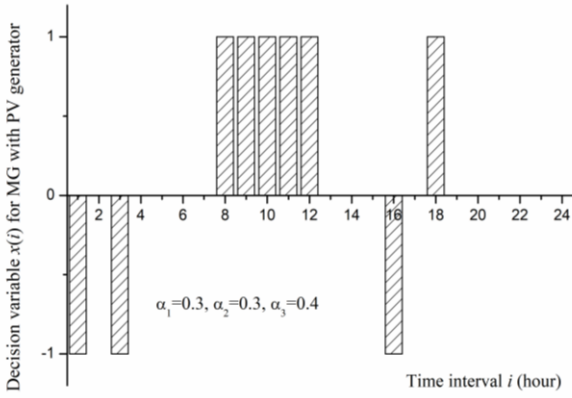
of a microgrid and to environmental protection.

Fig. 6. Decision variable $x(i)$ for charging/discharging of EVs for microgrid with PV generator, for weight coefficients $\alpha_1 = 0.3$, $\alpha_2 = 0.3$, and $\alpha_3 = 0.4$.
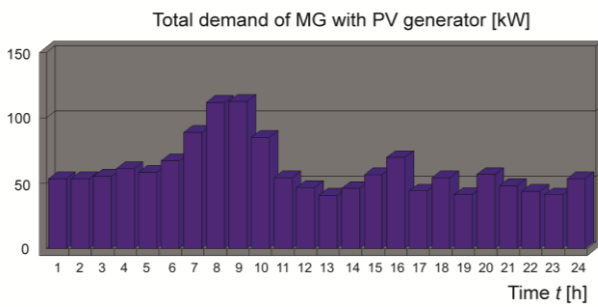

Fig. 7. Total daily demand of the microgrid with PV generator for weight coefficients $\alpha_1 = 0.3$, $\alpha_2 = 0.3$, $\alpha_3 = 0.4$, after the optimization.
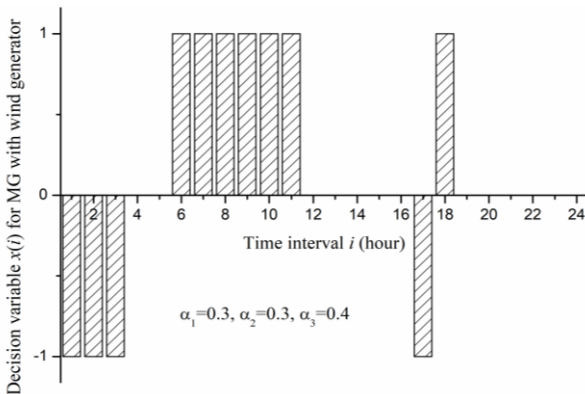

Fig. 8. Decision variable $x(i)$ for charging/discharging of EVs for microgrid with wind generator, for weight coefficients $\alpha_1 = 0.3$, $\alpha_2 = 0.3$, and $\alpha_3 = 0.4$.
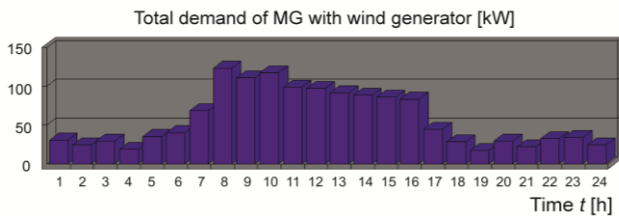

Fig. 9. Total daily demand of the microgrid with wind generator, for weight coefficients $\alpha_1 = 0.3$, $\alpha_2 = 0.3$, and $\alpha_3 = 0.4$, after the optimization.

The large increase in electricity prices in recent years has especially encouraged contributions in this area. In recently published papers [16], [17], the attention is given to the optimization of electric vehicle charging in relation to renewable energy share and to various charging technologies [26].
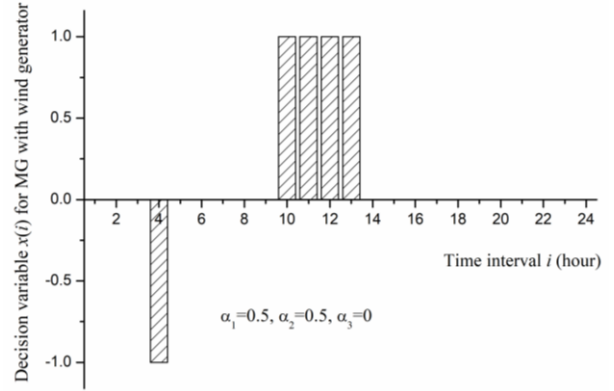

Fig. 10. Decision variable $x(i)$ for charging/discharging of EVs for microgrid with wind generator, for weight coefficients $\alpha_1 = 0.5$, $\alpha_2 = 0.5$, and $\alpha_3 = 0$.
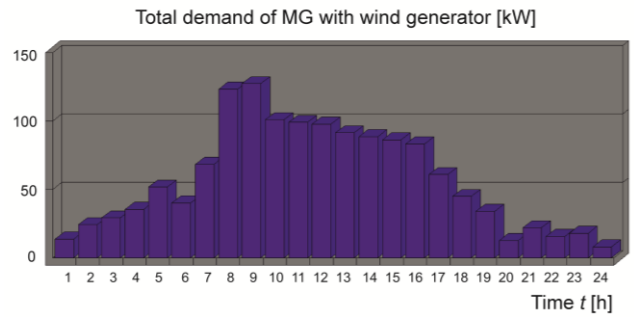

Fig. 11. Total daily demand of the microgrid with wind generator, for weight coefficients $\alpha_1 = 0.5$, $\alpha_2 = 0.5$, and $\alpha_3 = 0$, after the optimization.
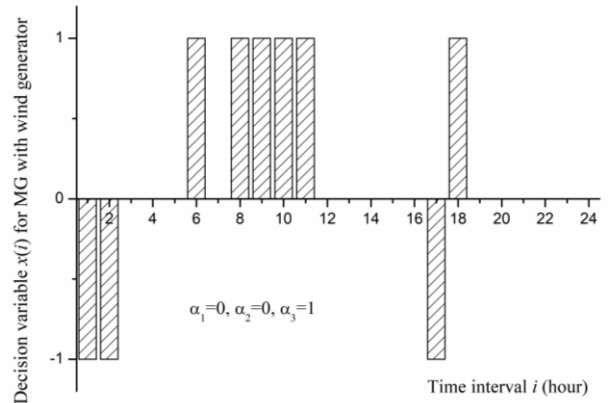

Fig. 12. Decision variable $x(i)$ for charging/discharging of EVs for microgrid with wind generator, for weight coefficients $\alpha_1 = 0$, $\alpha_2 = 0$, and $\alpha_3 = 1$.
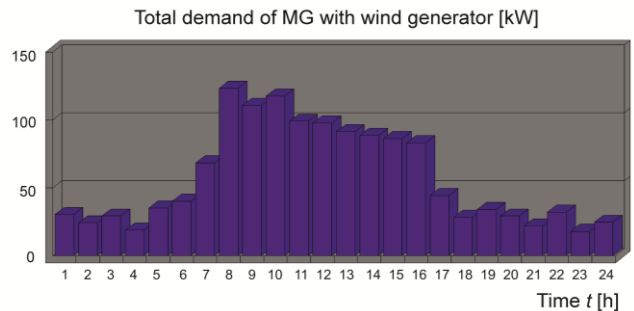

Fig. 13. Total daily demand of the microgrid with wind generator, for weight coefficients $\alpha_1 = 0$, $\alpha_2 = 0$, and $\alpha_3 = 1$, after the optimization.

V. CONCLUSIONS

In this paper, the optimization of electricity costs for one company's microgrid with photovoltaic or wind generator,

the fleet of small EVs, and the charging station with available V2G service is presented. The vehicles have driving hours known in advance when they are not available for charging or discharging at the station. The optimization is done based on the day-ahead prices per hour taken from the electricity market, estimated curves of production by renewable energy sources and daily demand curve of non-deferrable loads of that company.

The multi-criteria costs function is a linear combination of the three functions and it is optimized for different values of their weight coefficients. Optimization of electricity costs is done in LINGO program. Results obtained in this paper showed that optimal EVs charging/discharging schedules can take into account benefits of all participants in the electricity market.

In the future work, it is planned to include the effects of the ambient temperature on EVs range [27] and their electricity consumption. It is also planned to take into consideration the costs of green-house gasses emissions (CO_2, NO_x, SO_2, and other) as well as operation and maintenance costs of different types of dispatchable generators (diesel generators, microturbines, fuel cells) in a microgrid.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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