A method for the Assessment of Multi-Objective Optimal Charging of Plug-in Electric Vehicles at Power System Level

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Abstract: Nowadays, plug-in electric vehicles (PEVs) have gained popularity because of their operational and environmental advantages. As a result, power systems must deal with new operation challenges from their integration. In this article, a method for the assessment of the effects of multi-objective optimal charging of PEVs at power system level is proposed. The proposed multi-objective optimization method takes into consideration the forecasts of power system load, Renewable Energy Sources (RES) and electricity price. Moreover, it is enhanced by the detailed modeling of the daily EV activity taking into consideration the characteristics of the area they are having activity, the type of the activity, the charging preferences of the driver as well as the technical characteristics of the EV. Moreover, Vehicle to Grid (V2G) operation can be modeled by the proposed method. Real-world data were used and the method was applied to the power system of Crete. The results obtained from the study of indicative application scenarios are presented and finally prove the efficiency of the proposed method.

Key-Words: Electric Vehicles; Energy Management; Optimization; Vehicle to Grid; Virtual Electricity Price; Renewable Energy Sources.

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1 Introduction

Nowadays, automotive industry and researchers have focused their attention on Plug-in Electric Vehicles (PEVs) and Electric Vehicles (EVs) because of the lack of fossil fuels, the rise in oil prices and environmental concerns. In addition, EVs offer a lot of advantages such as low gas emissions and low operational costs. EVs may also help to improve grid reliability, operation security and the increase of the penetration of Renewable Energy Sources (RES). EVs can help RES as under suitable control EVs total power can be used to alleviate large power generation deviations from RES and fill the “valleys” of system load while “shave” the peak loads [1].

Although PEVs feature many advantages in several aspects of power system operation, they can also be the source of power system operation problems. These problems become more evident if they are not suitably controlled and their penetration to the power system increases significantly. Distribution network is the part of the power system that will provide charging power to the PEVs or absorb the power injected by them (V2G operation) and therefore the first that will face overloading problems, voltage instability, protection coordination etc [1]. Hence, it is deemed important to adopt smart charging and power and energy management techniques to alleviate these problems or even change them to opportunity for power system operation improvement and in this way, enable their further integration to the electric power system. For instance, their use as a large smart distributed energy storage devices will help the integration of more RES [2],[3].

Regarding the PEV and distribution network cooperation, a lot of research has been done in PEV optimal charging control that will reduce the distribution load demand peaks, reduce voltage instability, reduce distribution network active and reactive power losses and alleviate network congestion [4], [5]. Moreover, PEVs will be able to offer ancillary services to the network. Depending on charging conditions and equipment PEVs may be able to inject power to the grid (V2G), provide frequency support and reactive power regulation providing that they employ suitable charging converters [6], [7]. In [8], power and energy management techniques like peak load shaving and valley filling are applied to PEVs via suitable smart charging. In [9], the financial impact for of EV charging is assessed at distribution network level. A charging cost minimization strategy is compared with one aiming to peak load shaving at distribution network level. In [10], it is shown that EV charging system using solar PVs can reduce the charging cost in the range of 50–100%. In [11], a method that minimizes PEVs' charging cost and at the same time ensures the normal operation of the distribution grid is proposed. In [12], a method that optimally maintains the frequency fluctuations between the acceptable limits under a large penetration of PEVs is proposed. In this work, frequency support is optimally provided taking into consideration the flexibility of the PEVs. In [13], another charging method that minimizes the total charging cost of the PEVs at parking lot level is proposed. In [14], the goal is to minimize the charging cost in real time considering all constraints at EV and distribution network levels and with the minimum dependence on the forecasting of some critical inputs of the charging optimization algorithm. In [15], a particle swarm based optimization method is exploited to optimally charge or discharge PEVs. Parameters like electric network power losses, daily load smoothness and EV owners' charging preferences were taken under consideration.

In [16] research on charging price estimation during valley filling taking into account the RES power generation has been done. In [17], a power management algorithm is applied to a system comprising RES, Energy Storage Systems, and EVs. It aims to provide virtual inertia supporting the frequency of the system. In [18], a stochastic linear programming model for EV charging is proposed for various operation scenarios. In [19], a method that solves a multiple vehicle routing problem with time constraints is proposed and compared with various algorithms. In [20], a simulation method of an electricity market that depends on prosumers and electric vehicles and reduces the electricity cost is proposed.

In this article, a method for the efficient multi-objective optimal charging of PEVs is proposed. The main targets of the method are to minimize the charging cost of the PEV and at the same time reduce the variations of the net load (the load remaining after subtracting RES power generation) of the power system. The proposed method was applied to the power system of Crete and evaluated for different operation scenarios. The efficiency of the method is proved by simulation results and their statistical analysis.

The method proposed in this article comprises a number of features listed in the following that can be jointly included in other research works very rarely.

1. A realistic model of EV activity, based on real world data, is developed to simulate the daily schedule of the EV. The developed model considers several parameters associated with the EV type, driver behavior and the characteristics of the area the EV is travelling. In this way, the charging time periods and the energy needs of the EV are estimated.
2. A simple and easy to apply charging optimization method at EV level is proposed. It is based on the estimation of a virtual electricity price which is defined in a way to incorporate the real electricity price and the net load of the power system. In this way a multi-target optimal charging problem is solved taking into account all associated technical and operational constraints of the EV charging system and battery.
3. The proposed method can be easily applied as it does not employ time consuming computations and does not require sophisticated hardware. The inputs required by the proposed method are only the forecasts of electricity price, RES production and power system load. The above inputs are available by power system operator.
4. The proposed multi-target optimal charging method is integrated with the detailed modeling of EV activity to provide an accurate assessment of the impacts of their charging to the power system load.

The article is structured as it follows. The formulation of EV activity model, the inputs and all data used by the model are described in Section 2. Moreover, the formulation of PEV optimal charging problem is provided in paragraph 2.3. In Section 3 the method is applied to the power system of Crete and detailed simulation results obtained for several operation scenarios are presented. The results are discussed, and the efficiency of the proposed method is highlighted. Finally, the major conclusions drawn by this study are provided in the concluding section of the paper.

2 Formulation of the Method

The purpose of this work is to jointly minimize the charging cost of EVs plugged into the grid and the variation of the net load of the power system to alleviate any possible repercussion from RES integration. The input data and the implementation of the proposed method were based on the exploitation of real-world data as well as realistic probability density function where it was necessary to simulate the stochastic behavior of system components.

It is noted that it is essential to create realistic daily driving schedules of the EVs as they affect both charging load throughout the day and consequently the total electrical power system load.

2.1 General Inputs of the Model

2.1.1 Input Daily Time Series

The daily forecasts of photovoltaic power production, wind power production and electricity price are inputs of the developed model. For application purposes, real time series of the above quantities recorded in Crete power system were used.

2.1.2 EV Types

The selection of the EV types was based mainly on their purchase cost. Four different EV models with generally affordable cost were chosen as low and medium cost EVs are expected to dominate the market. Their characteristics e.g. battery capacity, maximum/minimum rate of charging in the Results Section.

2.2 EV Activity Model

The basic data which are necessary to produce the daily schedule of an EV are stored in a data structure with several fields of the general form: *EV.field*. The *EV* structure consists of vectors and variables stored in its fields and are presented next.

2.2.1 Variables

Single value parameters of the simulated system are stored in the respective fields of the EV structure which are called next as variables. The most significant of them are described next in this paragraph.

$EV.SoC_0$ denotes the initial state of charge (SoC) of the EV at the begging of the simulation. It takes values from a normal distribution, with μ=90 and σ=3.5.

$EV.SoC_{max}$ and $EV.SoC_{min}$ refer to the maximum and minimum SoC of the EV battery, respectively, and depend on the type of battery.

$EV.P_{max}$ and $EV.P_{min}$ are the maximum and the minimum charge power of the EV battery.

The specific energy consumption variable, *EV.Spec_Cons*, comprises the typical energy consumption per 100km of travel of an EV type.

2.2.2 Vectors

Multiple value quantities are stored in the respective fields of the EV structure, which are called next as vectors. The most significant of them are described next in this paragraph.

(EV.$Tr\_Destination$) defines the type of the type of EV travel destination travel. Three destination types are considered: “*home*”, “*shop-social*” and “*work*”. The EV starts its daily schedule from home and the algorithm randomly selects the next destination according to a predefined probability distribution in day time. Travel destination highly depends on the starting time of the travel.

$EV.T_{Dep}$ vector comprises the starting time of the next trip of the EV (EV departures). The first element of the vector is defined randomly using the normal distribution, with μ=7.5 and σ=1.5. This ensures that most people start their daily schedule from home around 7:30 am. The most common starting time for social activities and shops is at 11:00 am to 18:00 pm and for home is at 3:00 pm.

Let us assume that *j* denotes the number of the *j*th EV departure then the *j*th element of $EV.T_{Dep}$ vector is estimated by the following equation:

$$EV.T_{Dep}(j) = EV.Arr\ (j) + EV.\Delta T_{tr}(j) + EV.\Delta T_{ch}(j) \quad (1)$$

$EV.\Delta T_{tr}$ vector comprises the durations of the EV trips in a day. It is obtained by using a normal distribution with characteristics depending on the size of the city the travels take place.

$EV.Arr$ vector comprises the arrival times of the EV in a day. According to the calculation of $EV.T_{Dep}(j)$ the *j*th element of $EV.Arr$ is calculated according to the following equation.

$$EV.T_{Arr}(j) = EV.T_{Dep}(j) + EV.\Delta T_{tr}(j) \quad (2)$$

$EV.Vel$ vector comprises the travelling speeds of the EV during its trips. It is randomly obtained using the normal distribution, with μ=35 and σ=7. The selection of the distribution was based on the assumption that the travelling speed inside a city usually ranges between 15 and 55 km/h with an average value of 35 km/h.

$EV.\Delta S_{tr}$ vector comprises the distances covered by the EV during its trips in a day. Knowing the EV travelling speed and the duration of the *j*th travel of the EV then the *j*th element of $EV.\Delta S_{tr}$ is estimated as in the following:

$$EV.\Delta S_{tr}(j) = EV.Vel(j) \times\ EV.\Delta T_{tr}(j) \quad (3)$$

The time $EV.\Delta T_{ch}$ vector comprises the durations of the idle periods the EV (charging or parking). Its elements are selected randomly by using suitable probability density distributions depending on the activity of the driver while the EV is parked e.g. "*home*", "*shop - social*" or "*work*".

$EV.Cons$ vector comprises the energy consumption during the trips of the EV in a day. Knowing the travelled distance $EV.\Delta S_{tr}$ and the specific consumption of the EV $EV.Spec\_Cons$ then the *j*th element of the vector is calculated as in the following.

$$EV.Cons(j) = EV.\Delta S_{tr}(j) \times EV.Spec\_Cons \quad (4)$$

The specific energy consumption of the EVs used in this work is provided in the Results section.

$EV.E_{arr}$ vector comprises the energy stored in the battery of the EV when it arrives at its destination. Knowing the stored energy at the beginning of the *j*th travel and the energy consumed during it $EV.Cons$ then the *j*th element of $EV.E_{arr}$ is calculated as in the following.

$$EV.E_{arr}(j) = EV.E_{dep}(j) - EV.Cons(j) \quad (5)$$

$EV.E_{dep}$ vector comprises the energy stored in the battery at the beginning of a trip.

In this work, $EV.E_{arr}$ is also used by the EV driver to decide if the EV batteries will be charged or not. Specifically, it was assumed that the possibility of charging increases linearly with the decrease of battery SoC. An indicative SoC – probability of charging characteristic used in this work, is shown in the Results section.

2.3 PEV optimal charging

First, a virtual electricity price is estimated in order to be used for the optimal charging scheduling of the PEVs. The idea behind the formulation of virtual electricity price is to combine the information from the forecast of the real electricity price and the forecast of the net electric power system load in a single variable.

Let us assume that the optimization horizon is defined by the arrival and the departure of the EV from the parking lot $[T_{0,i}\ T_{f,i}]$ and the electricity price forecast in of the *i*th PEV is normalized as in the following,

$$\underline{\widehat{EP}}(t) = \frac{\widehat{EP}(t) - \widehat{EP}_{min}}{\widehat{EP}_{max} - \widehat{EP}_{min}} \quad (6)$$

With,

$$\widehat{EP}_{max} = \max\left(\widehat{EP}(t)\right), \widehat{EP}_{min} = \min\left(\widehat{EP}(t)\right) \quad \forall\, t \in [T_{0,i}\ T_{f,i}] \quad (7)$$

Where, $\underline{\widehat{EP}}(t)$ (in p.u.) is the normalized forecasted electricity price, $\widehat{EP}(t)$ (in €/MWh) is the forecasted electricity price, $\widehat{EP}_{min}$ (in €/MWh) is the minimum electricity price and $\widehat{EP}_{max}$(in €/MWh) is the maximum electricity price in the optimization period $[T_{0,i}\ T_{f,i}]$.

Let us assume that RES power generation forecast in the optimization horizon $[T_{0,i}\ T_{f,i}]$ of the *i*th PEV is $\hat{P}_{RES}(t)$ and the respective forecast of power system load is $\hat{P}$. Then the forecast of the net load of the electric power system is,

$$\hat{P}_{net} = \hat{P} \quad - \hat{P}_{RES}(t) \quad (8)$$

Then the forecasted net load of the power system is normalized as in the following,

$$\underline{\hat{P}}_{net}(t) = \frac{\hat{P}_{net}(t) - \hat{P}_{net,min}}{\hat{P}_{net,max} - \hat{P}_{net,min}} \quad (9)$$

with,

$$\hat{P}_{net,max} = \max\left(\hat{P}_{net}(t)\right), \hat{P}_{net,min} = \min\left(\hat{P}_{net}(t)\right)$$

$$\forall\, t \in [T_{0,i}\ T_{f,i}] \quad (10)$$

Where, $\hat{P}_{RES}(t)$ is the forecasted RES power generation, $\underline{\hat{P}}_{net}(t)$ (in p.u.) is the normalized forecasted net load of the power system, $\hat{P}_{net,\min(\max)}$ is the minimum(maximum) value of the forecasted net power system load in the optimization period.

Forecasted electricity price and RES power generation were normalized as described above in order to be integrated in a single variable called next as virtual electricity price.

Then the virtual electricity price (in p.u.) can be defined as,

$$EP'(t) = a \cdot \underline{\widehat{EP}}(t) + (1 - a) \cdot \underline{\hat{P}}_{net}(t) \quad (11)$$

Where, a is a parameter varying between [0-1] defining the weight of the electricity price in the calculation of virtual electricity price. The remaining part of the virtual electricity price corresponds to the net load of the electric power system. α can be set by the operator of the system.

The optimal PEV charging problem solved in this work is defined in (12)-(17) where the "*virtual charging cost*" of the EVs is minimized. In this way, the charging power is appropriately estimated to jointly minimize the real charging cost and the variations of the net load of the electric power system taking into account the technical constraints of the EV battery and its charging system.

$$\min_{P_i^*} \sum_{t=T_{0,i}:\Delta t:T_{f,i}} P_i^*(t) \cdot EP'(t) \cdot \Delta t \qquad (12)$$

Subject to,

$$P_i^*(t) \leq P_{i,max}(t) \quad \forall\, t \in [T_{0,i}, T_{f,i}] \qquad (13)$$

$$P_i^*(t) \geq P_{i,min}(t) \quad \forall\, t \in [T_{0,i}, T_{f,i}] \qquad (14)$$

$$E_i\ (T_{Arr,i}) + \sum_{T_{0,i}:\Delta t:t} P_i^*(t) \cdot \Delta t\ \geq E_{i,min}$$

$$\forall\ \ t \in [\ T_{0,i}, T_{f,i}] \quad (15)$$

$$E_i\ (T_{0,i}) + \sum_{T_{0,i}:\Delta t:t} P_i^*(t) \cdot \Delta t \leq E_{i,max}$$

$$\forall\ \ t \in [\ T_{0,i}, T_{f,i}] \quad (16)$$

$$E_i\ (T_{0,i}) + \sum_{T_{0,i}:\Delta t:T_{f,i}} P_i^*(t) \cdot \Delta t = E_i\ (T_{f,i}) \qquad (17)$$

Where, i denotes the ith EV, $P_i^*(t)$ is the optimal active power the EV exchanges with the electricity grid (load convention), Δt is the used time interval (12 min in this study), and E_i is the energy stored in the battery of the ith EV.

It should be noted that there are no particular numerical stability problems to be addressed in this method. Instability could occur if the proposed optimal PEV charging method in not able to find a solution. However, this will not happen due to the scale of the problem as it is of small scale, but only when the required charging energy cannot be met by the available charging power and charging duration. This is solved by a preliminary check of the above and if the charging targets cannot be met then they are suitably re-calculated and dumb charging is applied as it is shown in Fig. 1.

2.4 Tour Generation Algorithm

The daily schedule and the optimal charging process of each EV are synopsized next and shown in Fig. 1.

- All EVs depart from '*home*' at time obtained from the respective probability density distribution.
- The next destination as well the duration of the trip are generated using respective probability density distributions.
- The arrival time of the EV is obtained using the duration of the trip.
- When the EV arrives to the parking the charging decision is made according to the SoC of its battery.
- The duration of PEV charging is obtained by using suitable probability density distributions according to the type of the activity of the EV driver is having during the charging period.
- The proposed optimal charging method to the PEV or dumb charging is applied if this is decided by the driver or the parking duration and the available maximum charging power are not enough to achieve the desired SoC target.

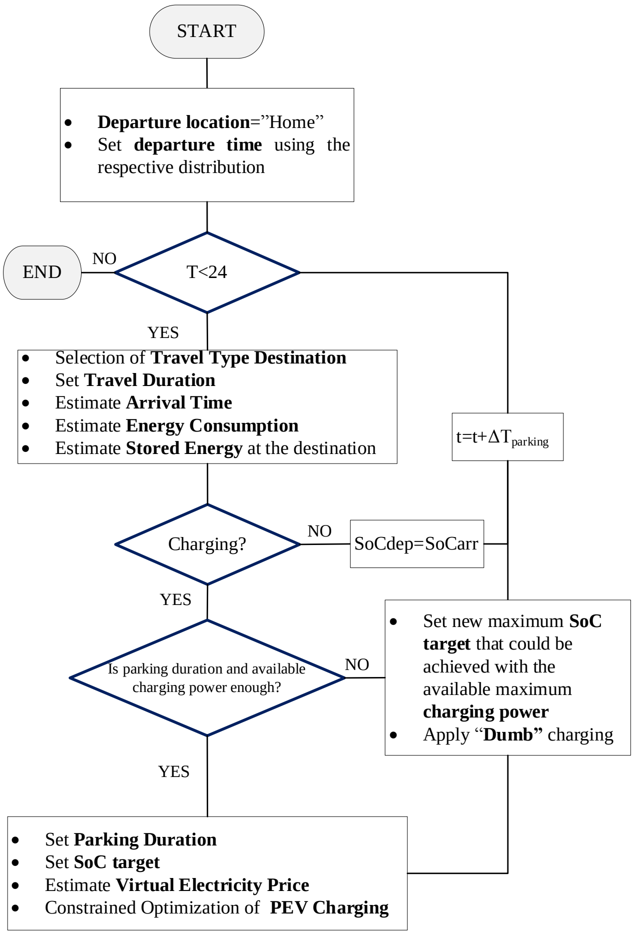

Fig. 1 Algorithm of the EV daily schedule estimation and charging optimization.

3 Results

The proposed method was used to estimate the impact of PEV charging to the load of the electric power system of Crete.

According to the National Energy and Climate Plan target the EV penetration rate should reach 30% of vehicle's number in 2030. In the following, we chose to apply an aggressive scenario where the number of EVs is considered to correspond to the 40% of the number of total vehicles in Crete by 2030. In addition, the total fleet of vehicles in Crete is estimated to amount approximately to 500,000 in 2030 [21]. The above lead to of the assumption that the number of EVs in Crete in 2030 will approximate 200,000. This total number of EVs was dispatched to the four bigger Cretan cities, namely, Heraklion, Chania, Rethimno and Agios Nikolaos according to their populations. Hence, the EV activity and charging load were calculated for each city separately according to their local characteristics and sizes.

In Fig. 2, the probability distributions used for the reproduction of the initial SoC, the first departure time and the travelling speed of the EVs are shown. In Fig. 3, the distribution of the probability of specific EV travel destination types with regard to the daytime are shown.

Normal distribution has been used to simulate the travel duration in the major cities of Crete. More specifically, normal distributions with μ=15, 20, 13, 9 and σ=3.5, 5, 2.7, 2.2 were used to reproduce travel duration in Chania, Heraklion, Rethimnon and Agios Nikolaos, respectively. The respective distributions are shown in Fig. 4.

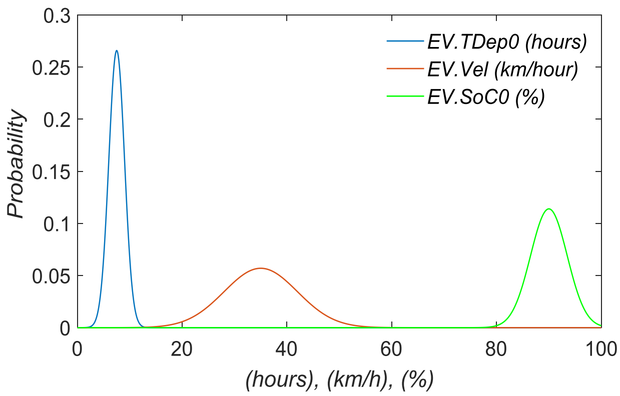

Fig. 2 Probability distributions of the initial departure time, travelling speed and initial SoC.

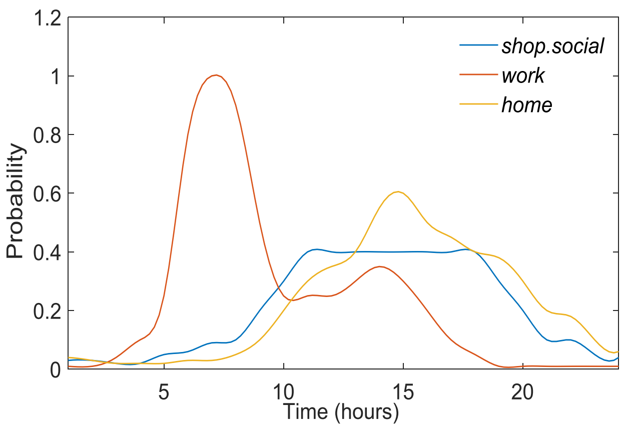

Fig. 3 Probability of the EV travel destination types over the day.

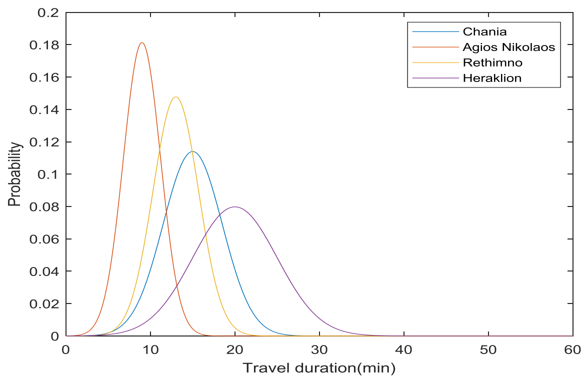

Fig. 4 EV travel duration probability distributions.

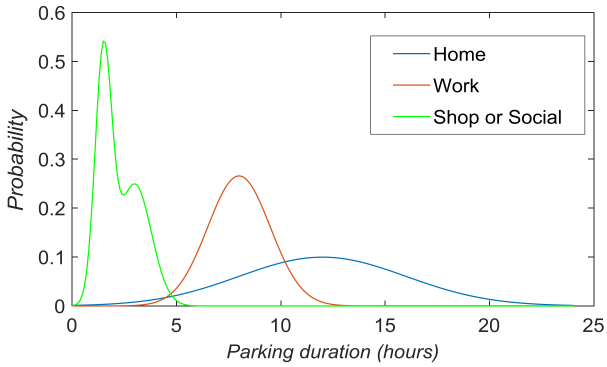

Fig. 5 Parking duration probability distributions for different EV's driver activities while parking.

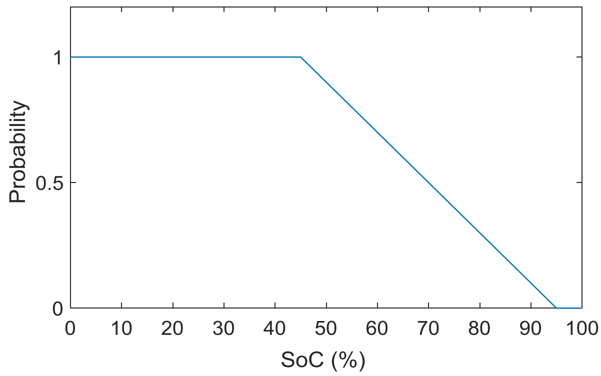

Fig. 6 Probability of charging according to the state of charge of PEV's battery.

The probability distributions used to estimate parking duration while staying home, being at work, shopping or having social activities are shown in Fig. 5. Finally, the probability of the EV to charge its battery with regard to its SoC before plugging into the charger is shown in Fig. 6.

Next, three application scenarios of the proposed method are presented.

In Scenario 1 (SC1), the optimal charging of the PEVs is done using a virtual electricity price formed only by the normalized net electric load of Crete.

In Scenario 2 (SC2), the optimal charging of the PEVs is done using a virtual electricity price formed only by the normalized electricity price.

In Scenario 3 (SC3), the optimal charging of the PEVs is done using a virtual electricity price formed by the normalized net electric load of Crete and the normalized electricity price with a weight of 50%.

It was also considered that the 75% of the PEVs will apply the proposed smart charging method. The remaining 25% will apply dumb charging, absorbing a constant amount of power during the charging period.

Moreover, the scenario SC3 was divided in three sub-scenarios to examine different acceptance rates of V2G and V1G (optimal charging without injecting power to the network). More specifically, it was considered in sub-scenarios SC3.a, SC3.b and SC3.c that 70%, 60% and 40% of the PEVs applying smart charging will use V2G, respectively. The remaining will use V1G. All the examined scenarios are tabulated in Table 1.

In Fig. 7, the time series used for the electric load of the power system of Crete, the wind power production, the PV power production and their sum, are shown. In Fig. 8, the used electricity price time series is shown.

Table 1 Examined operation scenarios.

Method Application Scenarios					
	SC1	**SC2**	**SC3**		
			SC3(a) Low V2G	**SC3(b) Medium V2G**	**SC3© High V2G**
a	0	1	0.5	0.5	0.5
Smart Charging *(% of PEV population)*	75	75	75	75	75
Dumb Charging *(% of PEV population)*	25	25	25	25	25
V2G *(% of PEV population)*	45	45	30	45	52.5
V1G *(% of PEV population)*	30	30	45	30	22.5

Table 2 PEVs' Parameters

EV Model	1	2	3	4
P_{max} (kW)	4.6	3.7	11	7.2
E_{max} (kWh)	17.6	16	35	36.8
Specific Cons. (kWh/100km)	25. 5	25.8	25	26

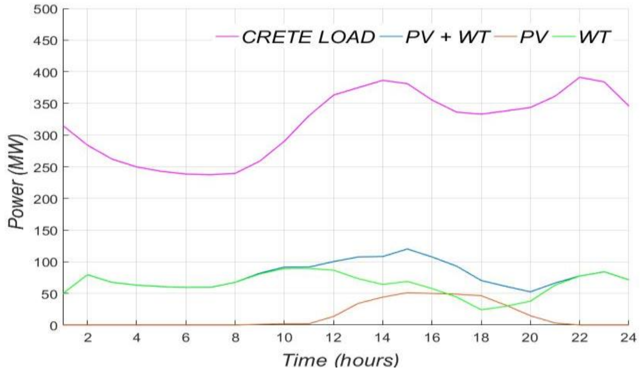

Fig. 7 Crete load, Wind and PV power production time series.

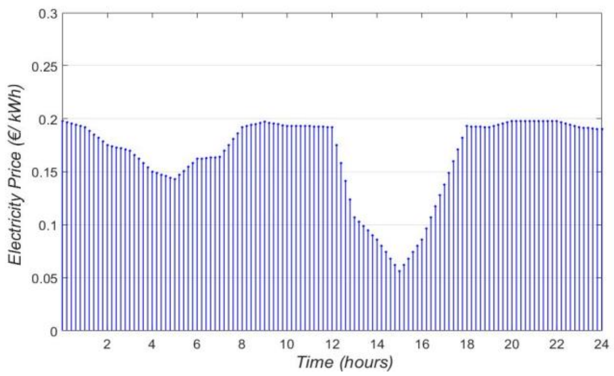

Fig. 8 Electricity price.

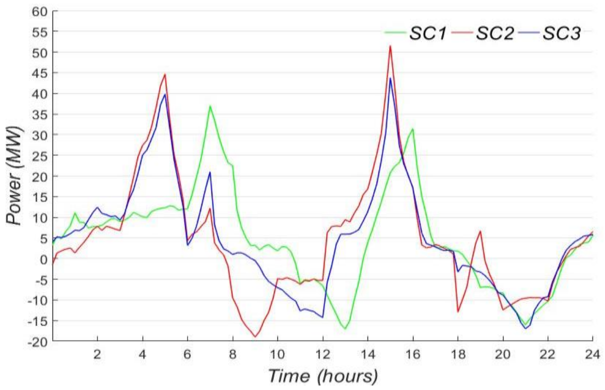

Fig. 9 Total power that PEVs exchange with the network.

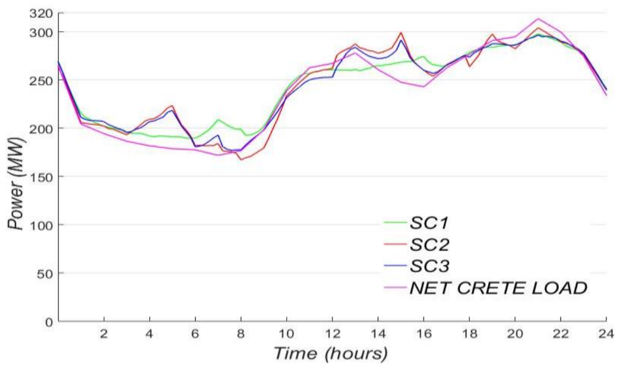

Fig. 10 Crete net load and net load with PEVs' total power for SC1, SC2 and SC3.

In Fig. 9, the total power of the PEVs is depicted for scenarios SC1-SC3. In SC1, PEVs inject power to the grid when the net load of the system features peaks i.e. 14:30 am and 22:00 am) while they absorb power when the net load of the system features low value i.e. 05:00 am - 07:00 am and 17:00 pm. In SC2, PEVs absorb more power, when the electricity price is low (05:00 am and 15:00 pm) and inject power to the grid when the electricity price is high. In SC3, PEVs absorb more power when the electricity price and at the same time the net load demand are low (05:00 am and 15:00 pm) and inject power to the grid when the electricity price and the net load demand are high (10:00 am - 13:00 pm and 18:00 pm – 21:00 pm).

In Fig. 10 the net load of Crete with the load of the EVs added is depicted for SC1-SC3. In particular, SC1 helps the network to feature smaller net load variations with peak load shaving and valley filling applied at the appropriate time periods. Hence, the major objective to balance the load curve is achieved. In SC2, only the electricity price is taken into consideration and not the net load of the power system while both factors are jointly taken into consideration in SC3.

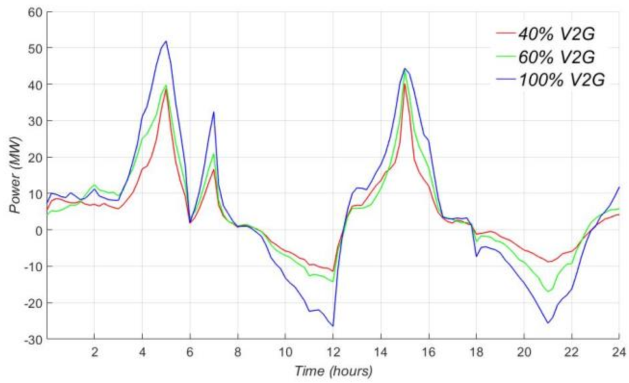

Fig. 11 PEVs' total power for different V2G acceptance rates.

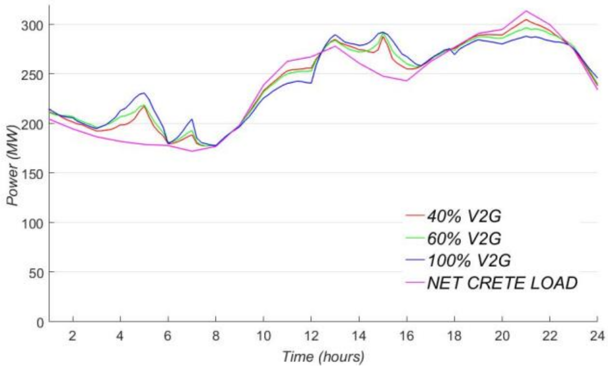

Fig. 12 Net load with PEVs' total power for different V2G acceptance rates.

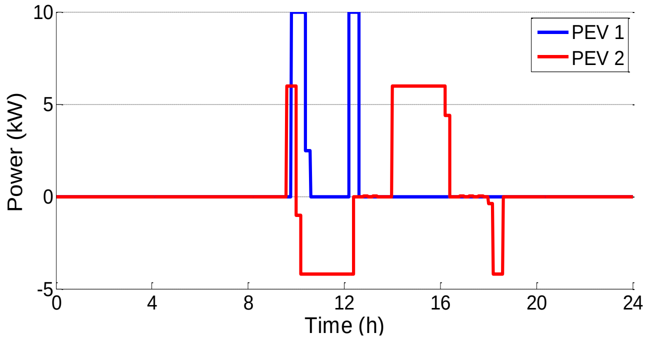

Fig. 13 Charging power of two indicative PEVs.

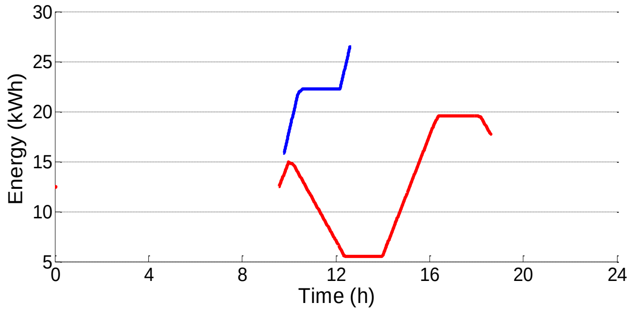

Fig. 14 Stored energy of two indicative PEVs.

In Fig. 11 and Fig. 12 the total electric power of the PEVs is depicted for different V2G acceptance rate scenarios (SC3.a-SC3.c). It is observed that the bigger the V2G penetration is, the better balance of the load is achieved and the lower the charging cost.

In Fig. 13, the optimal charging power trajectories of two indicative PEVs are shown. PEV1 uses V1G while PEV2 uses V2G. Obviously, the two PEVs adjust optimally their charging power according to the formed virtual electricity price. The two trajectories were taken under the SC3 operation scenario. The respective trajectories of the stored electric energy of the two PEVs are shown in Fig. 14.

The daily operation cost of the electric power system of Crete and the charging cost of the PEVs for SC1-SC3 are tabulated in Table 3. The obtained costs confirm the above remarks.

Furthermore, the standard deviation of the sum of net load of Crete power system with the total PEV load is given in Table 4. It is noted that the standard deviation of the net load of Crete power system is 44.24MW. The obtained results confirm that the proposed method decreases the deviation of the net load of the power system with the biggest reduction obtained in SC1 where only the net load is used for the definition of the virtual electricity price (α=1). Moreover, the bigger the V2G the lower the obtained standard deviation of the sum of the net load of the power system and the PEV load.

Finally, t-test was applied to the results obtained for total PEV load and virtual electricity price. The total load of the PEVs will behave in an opposite way to the virtual electricity price i.e. when virtual electricity price is increasing then PEV load is decreasing and vice versa. Hence, the transformation and normalization of the equations (18) (19) was applied to the two variables to ensure the above remark and zero mean value. The t-test was successful for all examined operation scenarios.

$$EP_t'(t) = \frac{mean\left(EP'\ (t)\right) - EP'\ (t)}{EP_{max}'} \quad (18)$$

$$P_{PEV,t}(t) = \frac{P_{PEV}(t) - mean\left(P_{PEV}(t)\right)}{P_{PEV,max}} \quad (19)$$

Where, EP_t' and $P_{PEV,t}$ denote the transformed virtual electricity price and total PEV load used to apply the t-test, respectively.

Table 3 Operation Cost

PEV Charging Cost ($x10^6$ €)			Power System Operation Cost ($x10^6$ €)		
SC1	SC2	SC3	SC1	SC2	SC3
0.01455	0.00918	0.01159	0.9737	0.9684	0.9708

Table 4 Standard deviation of the net load and PEV load of Crete electric power system

	SC1	SC2	SC3(a)	SC3(b)	SC3(c)
σ(MW)	36.42	41.55	40.21	38.43	37.13

4 Conclusion

A method that simulates accurately the daily activity schedule of EVs and optimizes their charging according to it and taking into consideration multiple objectives is proposed in this article. The method can be easily applied while it provides to the user a powerful tool to analyze in detail the effects of PEVs' charging on the power system taking into account a multitude of parameters. The proposed method was applied to the power system off Crete under several different application scenarios. The obtained simulation results prove that a significant reduction in PEVs' charging cost in conjunction with the reduction of power system load variability is possible. Specifically, the method can help the power system to feature smaller load variations applying peak shaving and valley filling while the charging cost of the PEVs is reduced at the same time.

A future expansion of this work could be the application of the proposed method at PEV aggregator level and the modelling of the electric power generation and transmission systems. Moreover, some peripheral applications of artificial intelligence could be exploited. More specifically, the forecast of the next day PEV activity level, electricity price, RES production and charging decision based on the state of charge of PEV battery, driver's anxiety, electricity price level, V2G application etc. could be exploited, provided that the required training data are available.

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Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Aikaterini-Agapi Karandinou wrote the original draft of the manuscript, developed the software, and contributed to visualization, modelling and simulation.
Fotios D. Kanellos carried out the conceptualization and supervision, revised and edited the manuscript, contributed to the software, modelling and simulation.

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