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# A Dynamic Real-Time Optimization Algorithm for the Revenue Assessment of a Vehicle-To-Grid System in Presence of Wear Cost Model

Majid Mehrasa, Reza Razi, Mehrdad Gholami, Khaled Hajar, Antoine Labonne, Ahmad Hably, Seddik Bacha

**Abstract** This paper presents a linear programming optimization algorithm with changeable weighting factors for reaching maximum revenue in the peak-value duration of the PV power and electricity price in a smart Vehicle-to-Grid (V2G) system. In order to render an accurate revenue assessment, the EV battery wear model is also taken into consideration through the parameters including the equivalent daily discount, estimated cycle life, the battery capital cost and battery salvation value. Moreover, a linear objective function is proposed by exerting the forecasted PV power profile to constitute the dynamic weighting factors for the EV battery power variables. The comparative simulation results in MATLAB/Simulink verify that the proposed dynamic optimization algorithm can reach its maximum revenue in three times i.e., the peak-value duration of the PV power, the peak-value duration of electricity price and the end of the simulation. In addition, the results affected by the EV battery wear model are presented.

## 1 Introduction

Nowadays, Vehicle-to-Grid system has been paid attention due to the technological needs of various structures of power

systems including microgrids [1-2] and smart grids [3]. The smart charging/discharging strategies designed for Electric Vehicles (EVs) as a vital part of V2G systems have faced different kinds of technical and control design challenges [4-5]. In order to attain reliable and cost-effective smart grids in presence of smart charged EVs, these challenges must be taken into account to the extent possible. One of these challenges is associated with the battery degradation [6-7]. A battery aging management system was proposed by [8] to regulate the battery capacity degradation for EVs by noticing the driving range, recharge time, drivability, maximum battery current, and the depth of discharge. Ref [9] concentrated on an auction-based energy commerce for reaching a specified optimized energy sharing to minimize the final payment of the present EVs by considering their practical battery condition. A model-free deep reinforcement learning was proposed in [10] to accurately estimate the battery degradation cost while the control challenge was shaped using Markov Decision Process (MDP) as well as the charging/discharging technique was designed based on a noisy network based deep reinforcement learning method. A vehicle-to-grid (V2G) system was optimized in [11] through a multi-objective function with variables and specifications including the peak demand, load variations, the battery degradation cost, EV charging/discharging cost, the driving distance of EV, the driving periods of EV, and the charging/discharging levels and also locations. The disparate vehicle-to-building (V2B) applications were discussed in [12] wherein the battery capacity faded due to the bidirectional power flow and also the extra discharging cycles with V2B were taken into account leading to the battery degradation integration into energy management development.

Apart from the importance of battery lifespan consideration for EVs [13], selecting an appropriate optimization method has also a key role at providing a suitable charging/discharging strategy for a V2G system [14-15].

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The linear programming algorithm that is taken into account as a solver for optimization problem and global optimal solutions [16-17], have been applied to many V2G systems in disparate conditions [18]. In an on-demand EV fleet, a binary linear programming has combined with deep reinforcement learning to provide an optimal solution for a Markov decision process aiming to the EV fleet operator welfare maximization [19]. In Ref [20], a bi-level optimization algorithm was redrafted as an equivalent single-level linear program for an optimized planning process of a EV charging station to reach optimal configuration of the renewable energy resources (RCS), the maximized total profits of RCS owner, and the planned charging intentions of EV users. A single mixed integer linear programming algorithm acted as a model predictive energy management system in [21] for the EV fleet charging process from PV panels to provide the grid stability, employ a single EV charger for charging numerous EVs, and prevent the grid overload. It was also aimed in [22] to divide a mixed integer programming algorithm into two linear programming problems reaching an effective charging method for multiple EVs.

In spite of the related discussions regarding the EVs-based and battery-based systems [23-25], in this paper, a linear programming optimization algorithm with changeable weighting factors is presented for a smart Vehicle-to-Grid (V2G) system to reach maximum revenue in the peak-value duration of the PV power and electricity price. The paper is organized as follows. The introduction is given in Section I. Section II focuses on the wear model of EV battery. In section III, the proposed dynamic optimization algorithm is discussed. Simulation results and conclusions are written in Sections IV and V, respectively.

## 2 Wear Model of EV Battery

The estimation process of the lithium-ion battery actual lifespan can be executed using two major factors including:

- 1) *Calendar life* that determines how many years the lithium-ion battery can be expected to be retained.
- 2) *Cycle life* that indicates the number of charge–discharge cycles wherein the lithium-ion battery is able to possess a persistent function before its exploitable capacity reaches 80% of its initial rated capacity.

However, the calendar life can somewhat confine the actual lifetime, but this life is not taken into account in the battery degradation formulation. It is worth mentioning that if the cycle life is higher than the calendar life, the V2G/G2V cycles can be increased to provide more revenue for the EV owner. The following components will affect the battery wear for both V2G and G2V applications [6]:

- *Temperature*: When the resistance of the electrode film in the lithium-ion batteries is raised, the charging capacity is mitigated with an accelerated ramp. In order to hamper the resistance increment, the ambient temperature, as well as the charge and

discharge currents, must be placed within acceptable ranges.

- *Charge and Discharge Currents*: High charge and discharge currents will speed up the lithium-ion battery degradation.
- *Depth of Discharge (DOD)*: The DOD is equalized to (1-SOC) meaning that as DOD increases, the SOC decreases.
- *Cycle Numbers*: High cycle number along with high charge-discharge current can make maximum degree of battery degradation.

Since it is assumed that the temperature is attempted to remain at standard level and the charge and discharge currents are kept below the moderate value, only DOD effect is employed to attain the *Daily Wear Cost (DWC)* [6]. The relation (1) is used to calculate DWC wherein the  $\lambda_{EDD}$  and  $\gamma_{ECL}$  are respectively the Equivalent Daily Discount (EDD) and Estimated Cycle Life (ECL).

$$DWC = \frac{\lambda_{EDD} (BCC(1 + \lambda_{EDD})^{\gamma_{ECL}} - BSV)}{(1 + \lambda_{EDD})^{\gamma_{ECL}} - 1} \text{ US\$ / day} \quad (1)$$

In addition, the *BCC* and *BSV* are respectively the Battery Capital Cost and Battery Salvation Value while the cycle life is ended. The ECL is achieved through (2). It is assumed that the EVs with initial energy ( $E_0$ ) possess the average daily amounts of the consumed energy in the driving and discharging modes respectively as  $E_{DRV}$  and  $E_{DIS}$ .

$$\begin{cases} \gamma_{ECL} = \frac{0.2E_0}{\phi} \quad (\text{days}) \\ \phi = K_{es} ((1+k)E_{DRV} + 2E_{DIS}) \quad (\text{kW.h / day}) \end{cases} \quad (2)$$

In (2), the coefficient  $k$  is deliberated for when the higher capacity loss occurs in the driving state. The  $K_{es}$  is named as the discharge coefficient that can be 0.00015 (kW.h/kW.h) with an acceptable approximation. Fig. 1 depicts the estimated cycle life based on the factors  $E_{DRV}$  and  $E_{DIS}$  while coefficient  $k$  is diminished. The three-dimension curves in Fig. 1 verify that the  $\gamma_{ECL}$  can reach its maximum value when both factors  $E_{DRV}$  and  $E_{DIS}$  approach to their minimum values.

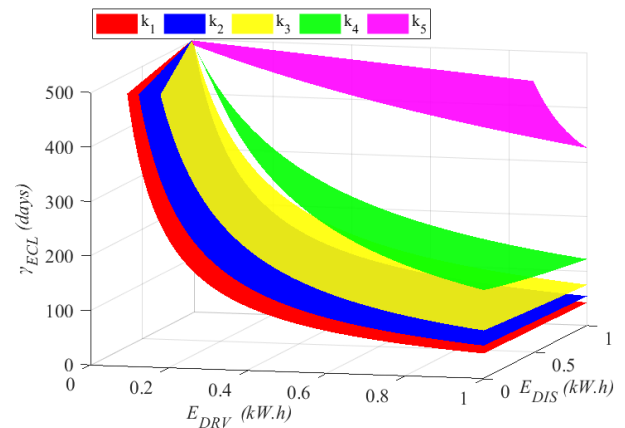
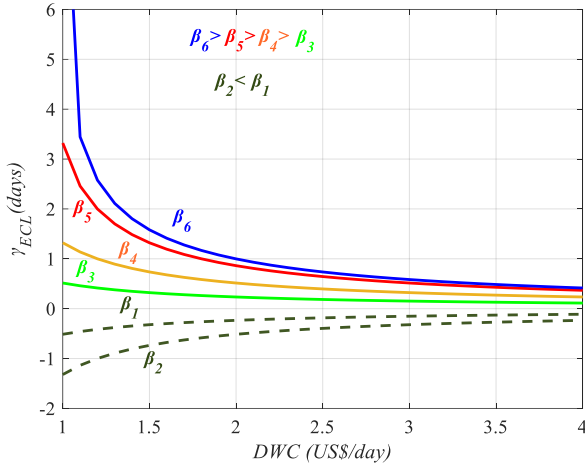


Fig. 1 The estimated cycle life based on the factors  $E_{DRV}$  and  $E_{DIS}$  while

coefficient  $k$  is mitigated.



**Fig. 2** The estimated cycle life based on the daily wear cost while  $\beta$  is increased or decreased.

Noticing the inequalities  $k_1 > k_2 > k_3 > k_4 > k_5$  as the variation trend of  $k$  in Fig. 1, it can be found that the estimated cycle life increment can be intensified through the decrement of the coefficient  $k$ . It can be also investigated how the wear cost can impact on the cycle life. To this end, the relation (1) is rewritten to obtain the ECL as a function of DWC.

$$\gamma_{ECL} = \frac{\ln \left[ \frac{DWC - \lambda_{EDD} BSV}{DWC - \lambda_{EDD} BCC} \right]}{\ln(1 + \lambda_{EDD})} \quad (3)$$

Where  $\ln(\cdot)$  is the natural logarithm ( $\ln(\cdot) = \log_e(\cdot)$ ,  $e = 2.718281828459$ ). In order to reach authentic relation for (3), the equivalent daily discount must comply with the conditions (4).

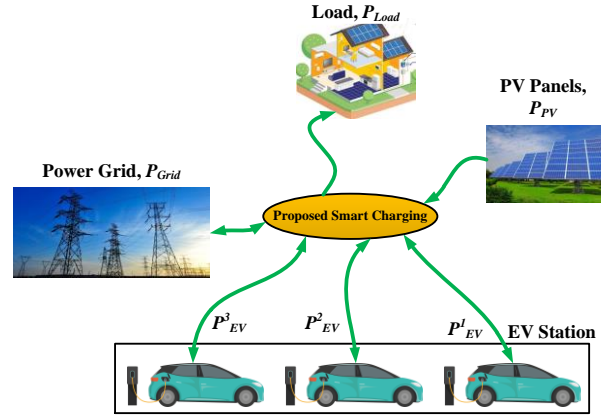
$$\left\{ \begin{array}{l} \lambda_{EDD} \neq \left\{ -1, \frac{DWC}{BSV}, \frac{DWC}{BCC} \right\} \\ \left\{ \begin{array}{l} \frac{DWC}{BSV} > \lambda_{EDD} \\ \frac{DWC}{BCC} > \lambda_{EDD} \end{array} \right\} \text{ or } \left\{ \begin{array}{l} \frac{DWC}{BSV} < \lambda_{EDD} \\ \frac{DWC}{BCC} < \lambda_{EDD} \end{array} \right\} \\ \lambda_{EDD} > -1 \end{array} \right. \quad (4)$$

Assuming  $\beta = BCC/BSV$ , the estimated cycle life is plotted in Fig. 2 based on the daily wear cost while  $\beta$  is increased or decreased accordingly. In this figure, while  $\beta_1(\beta_2) \ll \ll \ll 1$  (meaning that  $BCC \ll \ll \ll BSV$ ), the estimated cycle life will be equalized to negative which is an unacceptable outcome. But, when  $\beta \gg \gg \gg 1$  that happens for  $\{\beta_3 < \beta_4 < \beta_5 < \beta_6\}$ , the estimated cycle life can be significantly increased as well.

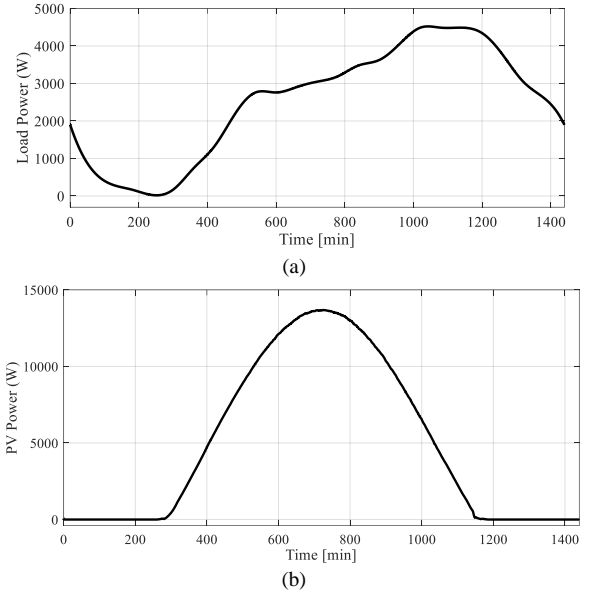
### 3 Proposed Dynamic Real-Time Optimization Algorithm

The Vehicle-to-Grid (V2G) system under study is shown in Fig. 3. There are three types of electricity sources (ESs) in this system including 1) The PV panels as the ESs that only generate power, 2) The variable load as an ES that only consumes power, and 3) The power grid and EVs as other

ESs that can function in both generation and consumption modes.



**Fig. 3** The V2G system including EV station, power grid, load, and PV panels.



**Fig. 4** The power profiles for (a) Variable load, and (b) PV panels.

It is realized from the categorized ESs that the flexible power exchange can be provided by both power grid and EVs. The relation between the flexible power generation units and other ESs is first written as follows,

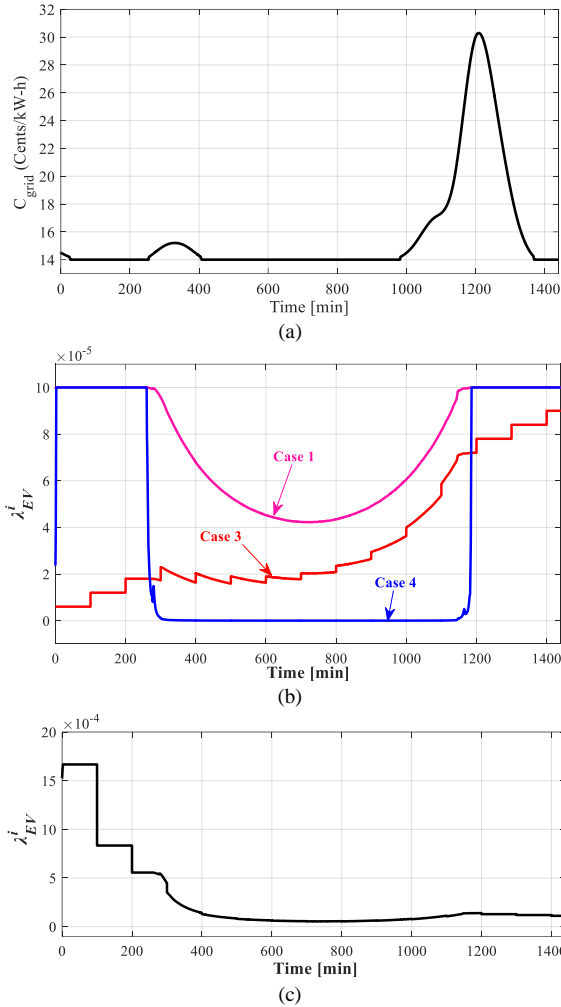
$$P_{Grid} + \sum_{i=1}^3 P_{EV}^i = P_{Load} - P_{PV} \quad (5)$$

The relation (5) is regarded as one of the optimization constraints. The forecasted profiles shown in Fig. 4(a), and (b) are employed respectively for load ( $P_{Load}$ ), and PV ( $P_{PV}$ ). The grid power is demonstrated by  $P_{Grid}$  and the  $i^{th}$  EV has the power  $P_{EV}^i$ . Since there is a flexible power feature for the grid and EVs, the objective function can be fortified by assigning dynamic coefficients to the related optimization variables. For this reason, a dynamic price profile ( $C_{grid}(t)$ ) for the grid power is aimed in the proposed objective function (6) as depicted in Fig. 5(a).

$$\text{Min} \sum_t \Delta t \times \left( C_{grid}(t) \times P_{grid}(t) + \lambda_{EV}^1 \times P_{EV}^1(t_0 + \Delta t) + \lambda_{EV}^2 \times P_{EV}^2(t_0 + \Delta t) + \lambda_{EV}^3 \times P_{EV}^3(t_0 + \Delta t) \right) \quad (6)$$

The set of  $\{\lambda_{EV}^1, \lambda_{EV}^2, \lambda_{EV}^3\}$  are the dynamic coefficients of EV battery power. The V2G system in Fig. 3 is persistently encouraged to max out the utilization of PV power during the smart charging process. Noticing this aim, the dynamic coefficients (7) are proposed for the EV battery power.

$$\begin{cases} \lambda_{EV}^1 = \frac{\alpha_{EV1}^1}{\alpha_{EV1}^2 + \alpha_{EV1}^3 P_{PV}} \\ \lambda_{EV}^2 = \frac{\alpha_{EV2}^1}{\alpha_{EV2}^2 + \alpha_{EV2}^3 P_{PV}} \\ \lambda_{EV}^3 = \frac{\alpha_{EV3}^1}{\alpha_{EV3}^2 + \alpha_{EV3}^3 P_{PV}} \end{cases} \quad (7)$$



**Fig. 5** The dynamic coefficients for the optimization variables including (a) The grid power, (b) The EVs power for cases 1, 3 and 4, and (c) The EVs power for case 2.

Supposing  $i=1,2,3$ , four cases are defined to obtain the dynamic coefficients ( $\lambda_{EV}^i$ ). These cases that are given as follows, are exerted to the relation of the dynamic coefficient in (7) leading to the results depicted in Figs. 5(b) and (c).

- **Case1:**  $\alpha_{EV1}^1=1$ ,  $\alpha_{EV1}^2=10000$ , and  $\alpha_{EV1}^3=1$ .
- **Case2:**  $\alpha_{EV1}^1=1$ ,  $\alpha_{EV1}^2=\uparrow$ (increasing), and  $\alpha_{EV1}^3=1$ .
- **Case3:**  $\alpha_{EV1}^1=\uparrow$ (increasing),  $\alpha_{EV1}^2=10000$ ,  $\alpha_{EV1}^3=1$ .
- **Case4:**  $\alpha_{EV1}^1=1$ ,  $\alpha_{EV1}^2=10000$ ,  $\alpha_{EV1}^3=\uparrow$ (increasing).

In the case 1, all the parameters  $\alpha_{EV1}^1$ ,  $\alpha_{EV1}^2$ , and  $\alpha_{EV1}^3$  are assumed to be constant. The importance of the parameter  $\alpha_{EV1}^2$  is specified when the PV power reaches zero. Consequently, in this condition, the dynamic coefficients  $\lambda_{EV}^i$  are equalized to  $1/\alpha_{EV1}^2$ . The dynamic coefficient in case 1 during the simulation interval is seen in Fig. 5(b). By noticing the PV panel power profile in Fig. 4(b), it can be realized that the coefficient in case 1 is completely inverted in comparison with the PV power profile. Based on Fig. 5(b), the EV battery power dynamic coefficients for the case 3 is more fluctuated compared to other coefficients. It may lead somewhat to the fluctuated optimal responses for the EV power as the solutions of the proposed linear optimization problem. However, as can be understood from Fig. 5(b), the case 3 provides smaller coefficients during the optimization run time compared to the coefficients achieved from the first case. When the PV power is placed within its peak value, the case 4 will enforce the dynamic coefficients  $\lambda_{EV}^i$  to reach its smallest values to the extent possible in comparison with other cases as depicted in Fig. 5(b). According to this figure, an irregular inverse curve compared to the PV power profile is indeed obtained for the dynamic coefficients of EV battery power in the fourth case. On the other hand, the dynamic coefficients  $\lambda_{EV}^i$  for the case 2 is approximately kept at its smaller values that is not suitable for the variable profile of the PV power.

## 4 Simulation Results

The V2G system shown in Fig. 3 is simulated in MATLAB/Simulink environment. The EVs parameters are given in Table I. The first part concentrates on comparing the revenue achieved from the constant weighting factors with the revenue due to the proposed dynamic weighting factors. In next part, the effects of the EV battery wear cost model is taken into consideration as well for assessing the revenue obtained from the dynamic weighting factors-based optimization algorithm.

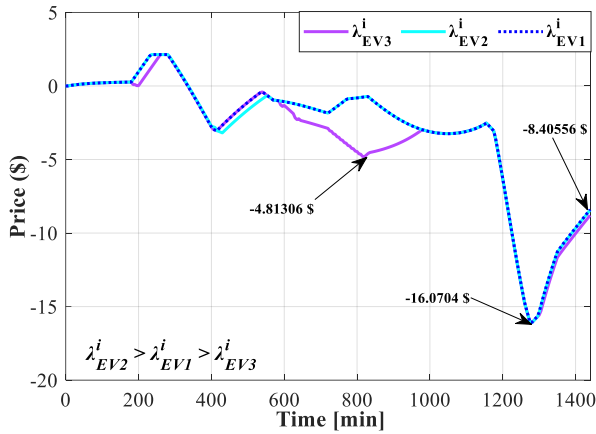
**Table 1** The V2G system parameters

The EVs	EV1	EV2	EV3
Max and Min SOC	20%, 90%	20%, 90%	20%, 90%
Nominal EV Energy	55 kWh	48.2 kWh	55kWh
Max and Min $P_{EV}^i$	-8.5/8.5 kW	-25/25 kW	-15/15 kW
Arrival Time	09:15	11:00	03:30
Departure Time	21:15	23:30	23:00

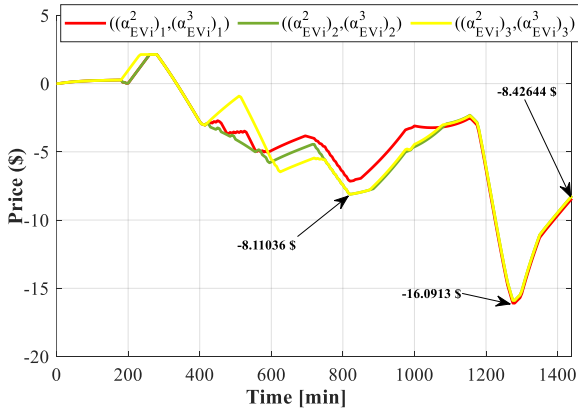
Fig. 6 illustrates the revenue obtained by using various values of the constant weighting factors in the proposed objective function. As it can be understood from this figure, when the constant weighting factors  $\lambda_{EV}^i$  are chosen as small as possible, more revenue in the peak-value duration of the PV power can be obtained. However, this decreasing trend does not impact the revenue in both the peak-value duration of electricity price and the end of the simulation. It is worth mentioning that the extent of this decrement is restricted because of the charging/discharging cycle numbers as will



be discussed in the final version of the paper. In Fig. 7, the revenue achieved from various values of the coefficients involved with the dynamic weighting factors are exhibited. The inequalities and equalities that are exerted for attaining these results are  $(\alpha^2_{EV1})_2 > (\alpha^2_{EV1})_1 > (\alpha^2_{EV1})_3$  and  $(\alpha^3_{EV1})_2 = (\alpha^3_{EV1})_3 > (\alpha^3_{EV1})_1$ . Noticing the logical relations, the small and big values for respectively  $\alpha^2_{EV1}$  and  $\alpha^3_{EV1}$ , can lead to higher revenue within the peak-value duration of the PV power as depicted in Fig. 7. By paying attention to both Fig. 6 and Fig. 7, it can be realized that using the dynamic weighting factors provides at least around two times more revenue in comparison with when the constant ones are employed. The accurate comparison can be carried out when the wear cost model of the EV battery is also considered.



**Fig. 6** The revenue achieved from various values of the constant weighting factors.

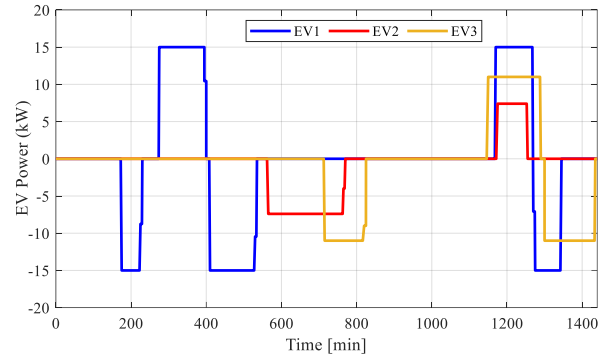


**Fig. 7** The revenue achieved from various values of the coefficients involved with the dynamic weighting factors.

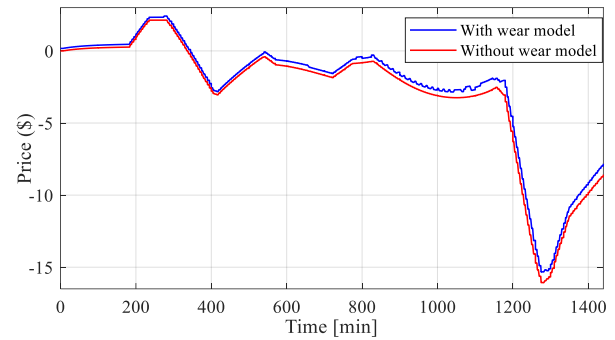
#### 4.1 Revenue Assessment in Presence of Wear Cost Model

In this sub-section, the revenue achieved from the proposed smart charging with dynamic weighting factors in presence of wear cost model is assessed. The battery and EV specifications are extracted from references [6] and [26]. The cost per  $kW \cdot h$  due to wear model is calculated through the relation  $(K_{esDWC})/\phi$ . Fig. 8 presents the optimal power of EVs while the dynamic weighting factors in (7) are used for the objective function (6). The revenues of these results for the EVs power when the wear model is/is not considered are illustrated in Fig. 9. As it can be understood from Fig. 8,

the aims of proposed smart charging strategy are obtained. However, when the wear cost model is taken into account, the revenue is decreased as depicted in Fig. 9.



**Fig. 8** Optimal power of EVs while the dynamic weighting factors are used.



**Fig. 9** Revenue in the states of with/without wear model.

## 5 Conclusions

A dynamic optimization algorithm with changeable weighting factors has been proposed in this paper to attain its maximum revenue in three times i.e., the peak-value duration of the PV power, the peak-value duration of electricity price and the end of the simulation. The EV battery wear model has also exerted to the revenue achieved from optimization algorithm using the parameters including the equivalent daily discount, estimated cycle life, the battery capital cost and battery salvation value. The proposed dynamic optimization algorithm has consisted of a linear objective function with a changing pre-defined electricity price and the dynamic weighting factors for the EV power variables formed based on the forecasted PV power profile. Simulation results without considering the wear cost model have shown the high ability of proposed algorithm at reaching the specified aims. The results along with considering the EV battery wear model will be presented in the final version of the paper.

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