JCAMECH

Vol. 51, No. 2, December 2020, pp 275-280
DOI: 10.22059/jcamech.2019.262776.305

Energy cost minimization in an electric vehicle solar charging station via dynamic programming

Mohammad Reza Hajidavalloo [a], Farzad Ayatolah Zadeh Shirazi [a], Mahammad Mahjoob [a]*

[a] *School of Mechanical Engineering, University of Tehran, Teehran, Iran*

ARTICLE INFO

Article history:
Received: 25 July 2018
Accepted: 15 October 2019

Keywords:
Dynamic programming
Solar charging station
Electric vehicles
Cost minimization

ABSTRACT

With growing numbers of Electric Vehicles (EVs), the coordinated charging is necessary to prevent large peaks and power losses for the grid and to minimize charging costs of EVs. This paper proposes an optimal charging schedule based on Dynamic Programming (DP) to minimize the overall cost of charging EVs for consumers in a solar Charging Station (CS). The large state space that makes the use of general DP inefficient is handled by using modified DP. Also, due to the stochastic behavior of the PV production, four different cases are considered. Simulation results demonstrated a significant decrease in the total CS purchased power cost, indicating reduced costs for consumers.

1. Introduction

The number EVs is growing as they are green, environmentally friendly and alternatives for the conventional vehicles. Using renewable energies for their charging can make them even greener. The number of EVs sold in the US in 2018 is predicted to be 400,000 [1] becoming double from the last year. However, this growth has some effects on the load shape of the grid system. Uncontrolled charging can cause large peaks, overstressing of distribution circuits and finally the occurrence of high prices for consumers [2]. Therefore, researchers have proposed different algorithms with various objectives to control the charging of electric vehicles.

Vehicle-to-Grid (V2G) technology gives the ability to address the aforementioned problems with services such as frequency regulation and spinning reserves. It is shown in [3] that an EV can respond to regulation signals in less than 4 seconds. Though this work showed the V2G capability for one EV, the large fleet of EVs participation in V2G is studied in [4] and [5] as well as meeting their charging demands. These works used unidirectional V2G technology i.e. the EVs do not discharge electricity into gird. The discharging capability of EVs which is called bidirectional V2G is considered in [6]. The main objective of all these works is to maximize the aggregators' profit. This comes from either the markup price that passed through the electricity price for charging EVs or the services that the aggregator provides for the grid system such as frequency regulation and spinning reserves.

The charging algorithm with the objective of minimizing the consumers' cost as well as fulfilling the charging needs was considered in [7]. In this work, the author proposed two different algorithms. The first algorithm solved the optimization problem by knowing the charging needs in advance and the second algorithm solved the problem in a more practical manner with less information about charging demands and arrival time.

The integration of renewable energies in a charging station is studied in [8] and [9]. In [8] the randomness of PV power production and the charging energy demand of the vehicles was studied and the problem solved using Dynamic Programming (DP). The curse of dimensionality which is common in DP problems with a large number of states and control inputs was handled in this paper. In [8], the vehicles were classified based on their charging needs to premium, conservative and green which the latter is friendly to the environment and reduces the charging stations costs with their capability to discharge energy to the grid.

In [10] the coordinated charging with the goal of minimizing the power losses of the grid was considered. This was compared to uncoordinated charging to illustrate the benefits of optimal charging of PHEVs. The uncertainties of household loads were taken into account by implementation of stochastic programming by two techniques: Quadratic Programming, and Dynamic Programming Successive Approximation (DPSA).

The problem of charging a Plug-in EV (PEV) in a smart home is presented in [11] using Stochastic DP (SDP). The smart home is equipped with an EV and PV array. The stochastic behavior in using the EV, and forecast models for PV power supply and home load demand are considered and the optimal charging schedule has proposed to reduce the electricity price of the smart home. In [12] the authors aimed to minimize the mean time that EVs wait for charging in a charging station equipped with renewable energy. The uncertainty of EV arrival

* Corresponding Author. . fshirazi@ut.ac.ir

as well as the intermittency of renewable energy is considered in the paper and a Markov Decision Process framework is proposed to tackle the problem. To offer guidelines for charging service providers managing set of charging stations, Luo et al. [13] proposed SDP and greedy algorithms to study the energy management problem under intermittency of renewable energy and fluctuation of electricity price. These algorithms make a balance between different objectives: the profit of charging provider, customer's satisfaction and impact reduction on grid power. In [14] a Genetic algorithm (GA) is presented which propose a reliable optimal load pattern for EV charging. In this investigation the developed algorithm took account for the transformer's load, limit of thermal line and parking availability to improve the flexibility of the system. In [15] an optimization method based on approximate dynamic programming is proposed to manage fleets of EVs connected to the gird to meet the owners' preferences. Instead of conventional open-loop methods which are widely used in papers, a feedback-based method with continuous state and action space is used to minimize the energy costs for EV owners. Maigha et al. [16] used a moving horizon optimization method to reduce the over-loading in distribution line resulted from charging of EVs with static and dynamic frameworks representing day-ahead and real-time scheduling. A decentralized charging scheme is proposed in [17] with bidirectional energy flow formulated as a mixed discrete programming problem. The objective is to provide load shifting service by scheduling the charging and discharging sequences in an optimal way. In [18] Wang et al. investigated the charging energy management of PHEVs with bidirectional V2G capability via DP. To overcome the computational challenge of DP, a new strategy is proposed and its optimality has been proved. Minimizing the energy cost for PHEV owner and shaving the peak load are the objectives of this method.

In this paper, an optimal charging schedule is proposed based on DP to minimize the overall cost of charging EVs for customers in a solar Charging Station (CS). The objective of minimizing the overall customers' charging cost has been considered in the literature with various algorithms as can be found in [2], [7] and [9]. In this work, a well-defined optimal control problem to completely meet the charging demands of each EV attending at the CS is presented. A modified version of DP for solving the problem is investigated, which is the main contribution of this paper. The large state-space causing inefficient use of DP has been handled by implementing a successive algorithm. Due to the stochastic behavior of the PV production, the simulations are done in four different weather conditions representing four different months. Controlled and uncontrolled charging in different scenarios are studied and the results illustrate the significant reduction in charging cost for customers as well as meeting their charging demands.

2. System Model

2.1 Photovoltaic Panel

The 50 kW PV panels are assumed to be used in the charging station. The output power of the PV panels is modeled using [19] and is given by:

$$P_{pv} = \left[P_{pv,STC} \times \frac{G_T}{1000} \times \left[1 - \gamma \times (T_j - 25)\right]\right] \times N_{PVs} \times N_{PVp} \qquad (1)$$

Where, the cell temperature is calculated as follows:

$$T_j = T_{amb} + \frac{G_T}{800} \times (NOCT - 20) \qquad (2)$$

And T_{amb} is the ambient air temperature. The panel parameters are shown in the table below:

Table 1: Panel parameters

Parameter	Description	Value
$P_{pv,STC}$	Rated power at MPPT	165 W
G_T	Irradiance level at STC	$800 \frac{W}{m^2}$
γ	Power temperature coefficient at MPP	0.043%
N_{PVs}	Number of modules in series	50
N_{PVp}	Number of modules in parallel	6
$NOCT$	Nominal Operating Cell Temperature	45.5°C

To estimate the value of PV power output, the solar radiation and temperature data are derived from Indiana state climate office [20] which is available with a resolution of an hour. Due to the randomness of temperature and radiation in different days and seasons, it is difficult to obtain a certain value for PV power output in each hour. To get more accurate values, instead of using historical data for a whole year the monthly data are used and simulations are carried out with those specific weather conditions [8]. As it can be seen from Fig. 1 the PV power output for four different months in four different seasons are presented and the variation between months is significant.

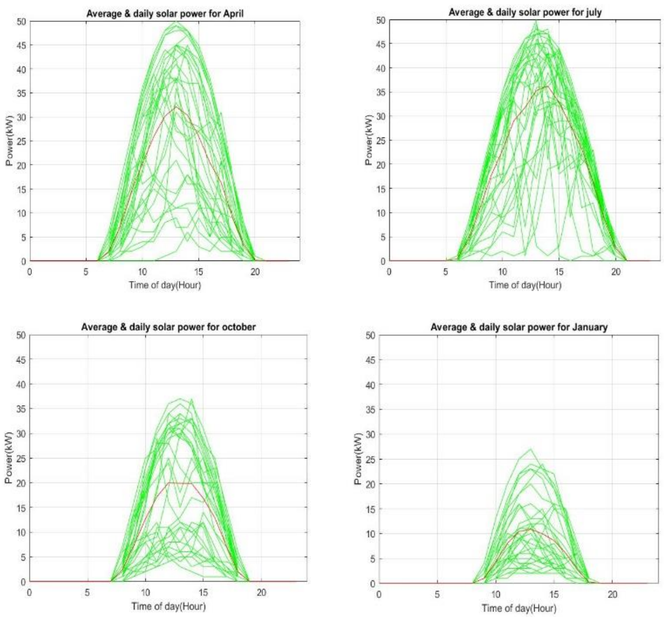


Fig.1. PV power distribution for four different months

2.1 Problem Formulation

An EV charging station (EVCS) with PV panels is considered in a workplace, where the CS is used mainly during the day. The charging station has a capacity of 50 vehicles in total and it consists of level 2 standard charging sockets. The charging rate of each EV is under control of the CS and ranges from a minimum to a maximum value. The CS is connected to the grid which can extract or inject power into it.

For optimizing the total electricity cost of CS consumers as well as meeting the charging demand of each EV, a careful and well-defined optimal control problem is proposed. Solving this problem controls the charging/idle sequence of the EVs attended in the CS and offers the utility a great benefit in performance with delaying the charging schedules form peak hours to off-peak hours. In this model, the CS receives the information of arrival time, initial State of charge (SoC) and departure time from each EV acting as constraints, as well as electricity price of the open market to manage the charging/idle sequences. In addition, an uncontrolled charging scheme is compared with this optimal scheduling to highlight the advantages for both the consumers and grid.

2.1.1. Optimal control to minimize power consumption costs

In this section, an optimal constrained control problem is designed with the objective of minimizing overall consumers' charging costs. By this algorithm, a charging/idle schedule for each EV is found. The cost function is defined as

$$J = \sum_{k=0}^{N-1} c(k)\Delta t[A_1(k)p_1(k) + A_2(k)p_2(k) + \cdots + A_n(k)p_n(k)] \quad (3)$$

$$\min_{p_1, p_2, p_3, \dots p_n} J \quad (4)$$

$$P_{grid}(k) = P_{charge}(k) - E\{P_{pv}(k)\} \quad (5)$$

$$P_{charge}(k) = p_1(k) + p_2(k) + \cdots p_n(k) \quad (6)$$

In (3) $c(k)$ is the electricity price in time step k, Δt is the time step, A_i is the variable indicating the plugging state of the EV i to CS [11], p_i is the charging power of vehicle i and N is the time horizon of the problem. Since the electricity market operates on an hourly basis, the cost function is discretized with Δt =1 h time step. This cost function holds for minimizing the total charging costs of the consumers by finding proper charging sequence for each vehicle i.e. $p_1, p_2, \dots, p_n$ during the specified time horizon. The value P_{grid} represents the power purchased from the grid or sold to the grid, indicating the difference between the charging demand and the PV power production. Expectation values are used since the PV power production is stochastic due to weather conditions.

2.2. Constraints

The optimal control problem is subjected to the following constraints which are necessary to make the approach more practical. Each EV owner in the charging station declares its arrival time and departure time to the CS. For each vehicle, the availability time is between these two times. For each vehicle, the variable A_i indicates the availability and is defined as follows:

$$A_i(k) = \begin{cases} 1 & for \quad k_{plug\ in,i} < k < k_{plug\ out,i} \\ 0 & otherwise \end{cases} \quad i = 1, 2, 3, \dots, n \quad (7)$$

where, i is the vehicle index. For a time when the i^{th} EV is connected to the station, A_i is equal to 1, otherwise is zero. When an EV is connected to the station, the SoC of each EV can be updated, and for each vehicle, the dynamics of the battery are expressed in terms of the following equation:

$$E_i(k+1) = E_i(k) + A_i(k)\Delta t(p_i(k) - \eta|p_i(k)|) \quad i = 1, 2, 3, .., n \quad (8)$$

where $E_i(k)$ is the energy stored in the battery of the i^{th} EV in time step k and η is the charging efficiency. This equation shows that when an EV is connected to the CS, how the vehicle's battery energy varies; energy can increase or remain without change due to the optimal charge scheduling.

As mentioned before EV owners notify the SoC of the battery when entering the charging station. The initial battery energy in the i^{th} EV when connected to the station is specified as:

$$E_i(k_{plug\ in}) = E_i^{k_{plug\ in}} \quad i = 1, 2, 3, \dots, n \quad (9)$$

The battery energy of the i^{th} EV at the end of charging period is also given by:

$$E_i(k_{plug\ out}) = E_i^{k_{plug\ out}} \quad i = 1,2,3, \dots n \quad (10)$$

In this paper, it is considered that every EV leaving the CS has a sufficient SoC of 0.9 at the end of charging period.

For each vehicle, the charging rate has a maximum and minimum value. Equation (8) shows this constraint indicating the power output of the charger can take the values between:

$$0 \le p_i(k) \le p_i^{max} \quad i = 1, 2, 3, \dots, n \quad (11)$$

In this paper, it is assumed the power electronics are designed just for unidirectional power flow and EVs are unable to discharge their battery.

Another constraint is related to the range of battery energy. The controller must keep the battery energy of EV i in this limit

$$E_i^{min} < E_i(k) < E_i^{max} \quad i = 1, 2, 3, \dots, n \quad (12)$$

The last constraint is addressed through the power consumption of all EVs in time step k, which is considered due to the limited transformer delivery capacity [6] in the area that the CS exists. This value is taken as half as the value in [7] to strongly represent the effect of the constraint.

$$p_1(k) + p_2(k) + \cdots p_n(k) < P_{max} \quad (13)$$

2.3. Dynamic programming

In this paper, DP method [21] is used to solve the optimal control problem. In DP the original optimal problem is turned to subproblems which can be solved backward using Bellman principle of optimality. The principle of optimality can be expressed by the cost-to-go function. In this case, the optimal cost to go from time step k to time step N is given by:

$$J_k^*(E_1, E_2, .. E_n) = \min_{p_1, p_2, .. p_n} \{c(k)\Delta t[A_1(k)p_1(k) + A_2(k)p_2(k) + \cdots + A_n(k)p_n(k)] + J_{k+1}^*(E_1, E_2, .. E_n)\} \quad k = 0,1, \dots N-1 \tag{14}$$

In words, the above equation states that the optimal cost from time step k to N can be computed by finding the best solution for current time step (k) adding to the optimal cost from time step $k+1$ to N.

The main advantage of general DP is providing global optimality in the problem. One of the general DP drawbacks is the curse of dimensionality and occurs when the number of states and control inputs arises. In this case, the number of computations increases with an exponential order respect to number of states. In this paper, one state is considered for each vehicle, and due to the large number of states, which are quantized with a proper value, the computation quickly becomes exhaustive and inefficient. Here DPSA [22] is used to solve the dynamic programming for each state, maintaining the other states constants. By this method, the number of computations significantly decreases although the global optimality may be lost.

2.4. Uncontrolled Charging

In uncontrolled charging, the vehicles start charging as soon as they plug into the CS. The charging power for each vehicle takes its maximum value while the vehicle is connected. If the charging energy demand for each vehicle is not a multiple of the p_{max}, the vehicle is charged with this amount as much as possible in each hour and for the remaining time the vehicle is charged with a lower power. This is shown in the following equations [8]:

$$\Delta k_{ch,i} = min\left\{\frac{E_i^{k_{plug\ in}} - E_i^{k_{plug\ out}}}{p_i^{max}}, k_{plug\ out,i} - k_{plug\ in,i}\right\} \tag{15}$$

$$p_i(k) = \begin{cases} p_i^{max} & k_{plug\ in,i} \le k < k_{plug\ in,i} + \Delta k_{ch,i} \\ E_i^{k_{plug\ out}} - p_i^{max}(\Delta k_{ch,i} - 1) & k = k_{plug\ in,i} + \Delta k_{ch,i} \\ 0 & otherwise \end{cases} \tag{16}$$

which $\Delta k_{ch,i}$ is the charging time for i^{th} EV. Also, in this case, the constraint (9) is imposed i.e. the total charging power of the CS should not exceed the P_{max} value.

3. Simulations

In this paper, a case study of a charging station located at a workplace is considered. The capacity of the charging station is 50 EVs. The information of the arrival and departure of electric vehicles to the charging station at [8] is adopted for simulations. In this reference, arrival and departure times are generated using probability distribution functions. The probability distributions are empirically derived from information at the Ohio State University's charging station.

For this case study, a parking time duration of EVs is shown in Fig. 2 that matches the aforementioned distributions. The optimal and uncontrolled charge scheduling is applied using this parking time of EVs although other distributions and parking patterns are valid for implementing the optimal control procedure.

In this paper, it is assumed that all EVs are Nissan Leaf, although the optimal control problem is applicable for other types of EVs or plug-in hybrid EVs (PHEVs). This type of EV has a battery capacity of $E_i^{max} = 30$ kWh. The initial energy for each electric vehicle is considered as a random variable in the range (0.3-0.9) E_i^{max}. The final battery energy for each EV is considered to be $0.9E_i^{max}$ so that EVs will be sufficiently charged when leaving the charging station [7]. The maximum charging power is considered to be 6 kW in simulations which represents the use of level 2 standard chargers. Level 2 chargers are often placed at destinations so that drivers can charge their car while at work or shopping. The charging standard used here is SAE J1772, which the line voltage is 240 V and the current has a value up to 25 ampere which results in maximum charging power of 6 kW [23].

One of the important parameters in the simulation is the price of electricity. Electricity prices generally reflect the cost to build, finance, maintain, and operate power plants and the electricity grid. In this paper, to determine the price per unit of energy, the locational marginal electricity price obtained from PJM is used. It should be noted that the power grid market usually operates on an hourly or half hour basis, therefore, the time horizon should be discretized into smaller intervals. In this paper, the step of discretization is considered to be $\Delta t = 1h$.

In this paper, the average electricity prices for four different months are considered exact to months that weather data were used and simulations are done using these prices for one day in these months. This data has been taken from PJM regional transmission organization website [24] in July and October 2017 and January and April 2018. The relative high prices in January are due to the high electric heating demand indicating the cold winter of that region.

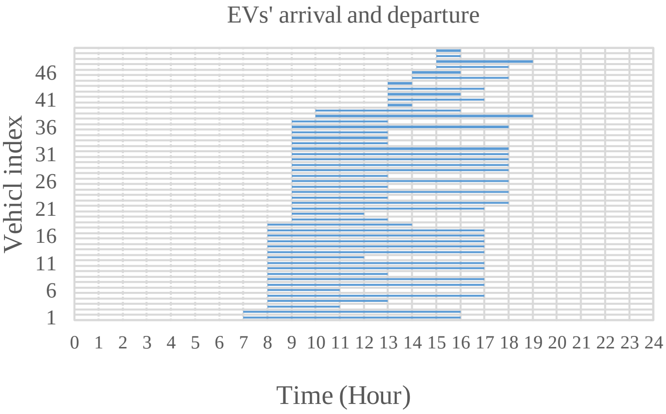


Fig.2. EVs parking time duration at workplace

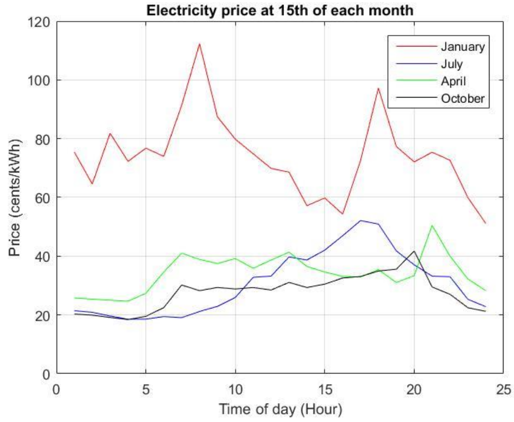
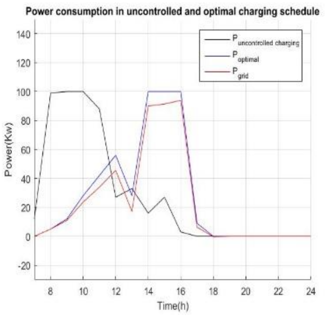


Fig.3 Average electricity price of aforementioned months

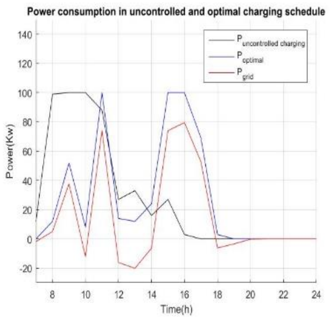
4. Results and Discussion

In this section, the performance of both charge scheduling schemes is evaluated. The charging cost for each case is calculated and the potential benefit of optimized charging by adopting DP is compared in a day at four different months. Four different months is selected to determine the effect of the weather condition on the performance of the CS and showing how the proposed scheme can reduce the charging cost of the consumers. The simulations are run for 8 A.M.-10 P.M. resembling the actual workplace.

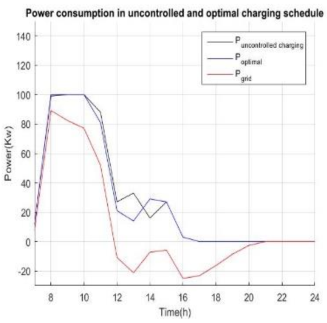
In Fig. 4, the simulation results in four different months are presented. The total charging power with optimized scheduling and uncontrolled scheduling is obtained for each time step. The optimal control algorithm tends to charge the vehicles when the electricity price is the lowest. In these figures at 8-10 a.m. the total power consumption of uncontrolled charging reaches its maximum value as predicted, since in these hours the arrival of the EVs is in the highest point. However, the optimal control algorithm takes the electricity price into account and schedules the charging optimally to obtain minimized cost.



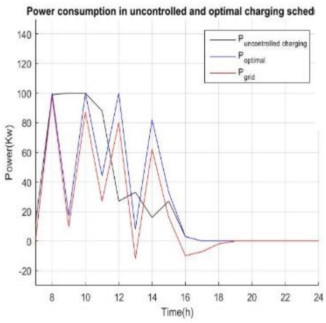
a. January



b. April



c. July



d. October

Fig.4 total power consumption in optimal and uncontrolled charging

After 10 a.m. the power consumption in an uncontrolled charging scheme decreases showing both the less arrival and fulfilling the charging demand of the EVs. In contrast, the optimal control algorithm keeps the charging amount according to both electricity price and meeting the charging demand of each EV, resulting in different charging plan in each scenario. In controlled charging, in addition to cost benefits for consumers, the grid also takes the advantage of lower demand from CS in peak times; since high load on grid shows itself in higher electricity prices. In uncontrolled charging, however, this issue is not considered.

The value P_{grid} represents the power purchased or sold from the grid, indicating the difference between the charging demand and the PV power production. In early morning due to the low solar radiation, the PV power cannot cover all the charging demands in all cases. However in afternoon the high PV power exceeds the charging demand of the EVs and gives the opportunity for the CS to sell the excess power to the grid.

In Fig. 5 the optimal and uncontrolled charging is shown for two sample vehicle. The horizontal-axis is the parking time the charging station. These results are shown for two sample EVs, one for a long stay in the station and the other is for a short stay at the station.

In Fig. 6 EV's battery energy variation in optimal control charging is shown for the two vehicles mentioned above. For each EV, the algorithm works properly and meets the charging need and reaches the SoC of the battery to 90% i.e. 27kWh for each vehicle as it is assumed the vehicles are identical.

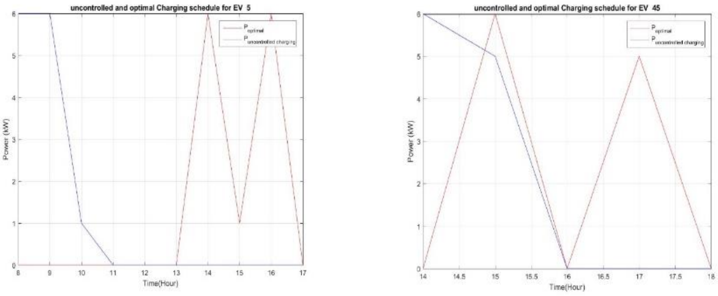


Fig. 5. Optimal and uncontrolled charging for two sample vehicle

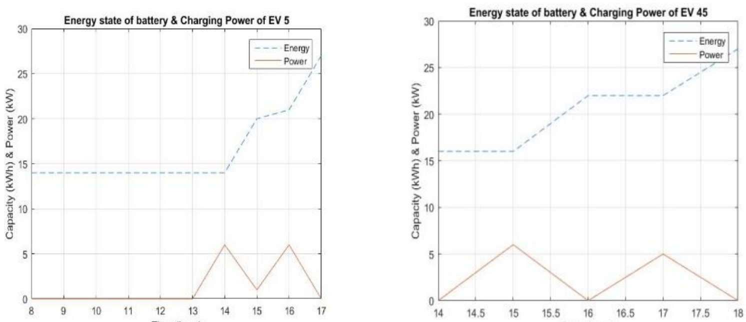


Fig. 6. Energy state of the EV battery in optimal control charging

The DPSA algorithm for this problem works in this way: for each state in the problem (where the state is the battery energy of each vehicle) other states is held constant and the dynamic program runs for that state to find the optimal control input (where the control input is charging power of each vehicle) corresponding to that state. After that, the second state is taking into account and the other states (including the first optimized state) are held constant. The proof of DPSA algorithm convergence to the global optimum is presented in [21]. In our problem if constraint (12) was not present, the problem became similar to the cases with convergence proof. However, the implementation of the general DP algorithm, may not be done practically because of the "curse of dimensionality" described before.

The overall CS charging cost for each case is shown in Table 2. As it can be seen the charging cost with optimal control are significantly lower than the uncontrolled charging, showing that notable cost savings can be brought for consumers. In January, when the average electricity price is generally much more than in other months, the reduction in cost is more significant.

An important issue arises from the implementation of the algorithm. In reality, some of the information we assumed in the simulation such as the arrival and departure time of the EVs, the type of the EV and in some cases the initial SoC of the EVs is unknown in advance. However, the developed algorithm can be easily implemented in a real-time manner as it is a future work to be done.

Table 2. The overall CS charging cost for each case in a day in below months

Month / Method	January	April	July	October
CS total purchased power in optimal scheduling (US$)	264.6$	86.4$	22.18 $	99.4$
CS total purchased power in uncontrolled charging (US$)	382.2$	104.5 $	28.7$	105.9$
Percentage of cost reduction	30.7%	17.3%	23.0%	6.1%

5. Conclusions

This paper presented an optimal control problem for minimizing the EVs overall charging cost from consumers' perspective. Instead of using general DP, DPSA was used to tackle the optimal control problem since the defined large state space leads to a challenging implementation of the general DP. Due to the stochastic behavior of the PV power production, four different cases accounting for four different weather conditions were considered and the simulations were carried out for one day in these weather conditions. Also, uncontrolled charging of EVs was introduced to compare the potential cost savings of using the optimal charging. The simulation results showed a significant reduction in the overall CS power purchased cost which means the customers pay less for their charging. It was found that with optimal charging the total power purchased of the CS can be reduced to 30%, 17%, 23% and 6% in a typical day in January, April, July and October, respectively. In optimal charging, the charging tasks are sensitive to electricity prices, and the optimal controller shifts the charging load to low demand hours. Therefore, the grid takes the advantage of less demand on peak times, which results in a smooth load shape and more reliability.

References

[1] "The U.S. electric vehicle industry - Statistics and facts", https://www.statista.com/statistics/801263/us-plug-in-electric-vehicle-sales/, Accessed April 2018.

[2] Wu X., Hu X., Yin X., Moura S. J., 2016, Stochastic optimal energy management of smart home with PEV energy storage, IEEE Transactions on Smart Grid 9 (3), 2065-2075.

[3] Kempton W., Udo V., Huber K., Komara K., Letendre S., Baker S., Brunner D., Pearre N., 2008, A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system, Univ. Delaware, Newark, DE,

[4] Sortomme E., El-Sharkawi M. A, 2011, Optimal charging strategies for unidirectional vehicle-to-grid, IEEE Transactions on Smart Grid 2 (1), 131-138.

[5] Han S., Han S., Sezaki K., 2010, Development of an optimal vehicle-to-grid aggregator for frequency regulation, IEEE Transactions on Smart Grid 1 (1), 65-72.

[6] Sortomme E., El-Sharkawi M. A, 2012, Optimal scheduling of vehicle-to-grid energy and ancillary services, IEEE Transactions on Smart Grid 3 (1), 351-359

[7] Jin C., Tang J., Ghosh P., 2013, Optimizing electric vehicle charging: a customer's perspective, IEEE Transactions on Vehicular Technology 62 (7), 2919-2927.

[8] Tulpule P. J., Marano V., Yurkovich S., Rizzoni G., 2013, Economic and environmental impacts of a PV powered workplace parking garage charging station, Applied Energy 108, 323-332.

[9] Tushar W., Yuen C., Huang S., Smith D. B., Poor H. V., 2016, Cost minimization of charging stations with photovoltaics: an approach with EV classification, IEEE Transactions on Intelligent Transportation Systems 17 (1), 156-169.

[10] Clement-Nyns K., Haesen E., Driesen J., 2010, The impact of charging plug-in hybrid Electric vehicles on a residential distribution grid, in IEEE Transactions on Power Systems 25 (1), 1371-1380.

[11] Wu X., Hu X., Yin X., Moura S. J, Pickert V., 2016, Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array, Journal of Power Sources 333, 203-212.

[12] Zhang T., Chen W., Han Z., Cao Z., 2014, Charging Scheduling of Electric Vehicles With Local Renewable Energy Under Uncertain Electric Vehicle Arrival and Grid Power Price, IEEE Transactions on Vehicular Technology, 63 (6), 2600-2612.

[13] Luo C., Huang Y., Gupta V., 2018, Stochastic Dynamic Pricing for EV Charging Stations With Renewable Integration and Energy Storage, IEEE Transactions on Smart Grid, 9 (2), 1494-1505.

[14] Alonso, M., Amaris, H., Germain, J.G., Galan, J.M., 2014**,** Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms. Energies, *7*, 2449-2475.

[15] Korkas C. D., Baldi S., Yuan S., Kosmatopoulos E. B. 2018, "An Adaptive Learning-Based Approach for Nearly Optimal Dynamic Charging of Electric Vehicle Fleets," IEEE Transactions on Intelligent Transportation Systems, 19 (7), 2066-2075.

[16] Maigha, Crow M. L., 2017, "Cost-Constrained Dynamic Optimal Electric Vehicle Charging," IEEE Transactions on Sustainable Energy, 8 (2), 716-724.

[17] Xing H., Fu M., Lin Z., Mou Y., 2016, "Decentralized Optimal Scheduling for Charging and Discharging of Plug-In Electric Vehicles in Smart Grids," IEEE Transactions on Power Systems, 31 (5), 4118-4127.

[18] Wang X., Liang Q., 2017, "Energy Management Strategy for Plug-In Hybrid Electric Vehicles via Bidirectional Vehicle-to-Grid," IEEE Systems Journal, 11 (3), 1789-1798.

[19] Riffonneau Y., Bacha S., Barruel F., Ploix S., 2011, Optimal power flow management for grid connected pv systems with batteries, IEEE Transactions on Sustainable Energy 2 (3), 309-320.

[20] "Indiana state climate office", https://iclimate.org/, Accessed March 2018.

[21] Bertsekas D. P., Bertsekas D. P., Bertsekas D. P., 1995, Dynamic programming and optimal control. Athena Scientific Belmont 1 (2).

[22] Larson R. E., Korsak A.J., 1970, A dynamic programming successive approximations technique with convergence proofs, Automatica 6, 245-252.

[23] Kempton W., Tomić J., 2005, Vehicle-to-grid power fundamentals: Calculating capacity and net revenue, Journal of Power Sources, 144 (1), 268-279.

[24] PJM, "Real-time energy market", http://www.pjm.com/markets-and-operations/energy/real-time/monthlylmp.aspx, Accessed April 2018.