Contemporary Engineering Sciences, Vol. 7, 2014, no. 22, 1131 - 1137
HIKARI Ltd, www.m-hikari.com
http://dx.doi.org/10.12988/ces.2014.49141

EV Charging Control for Energy Cost Optimization Using Model Predictive Control

Chang-Jin Boo

Department of Electrical Energy Engineering
Jeju International University
Jeju-si, 690-714, Korea

Kwang Y. Lee

Department of Electrical and Computer Engineering
Baylor University, One Bear Place 97356
Waco, TX 76798-7356, USA

Ho-Chan Kim*

Department of Electrical Engineering, Jeju National University
102 Jejudaehakno, Jeju-si, 690-756, Korea
*Corresponding Author

Abstract

The electric vehicle (EV) charging control algorithm for energy cost optimization is proposed in this paper. A model predictive control (MPC) with linear programming (LP) is used for optimal control, and the time-of-use (TOU) price is included to calculate the energy costs. Simulation results show that the reductions of energy cost and peak power can be achieved using the proposed algorithms.

Keywords: EV charging control, Model predictive control, Linear programming, Optimization

1. Introduction

The development of EV is an important direction of modern automobile vehicles. However, the restriction of the EV's rapid growth is mainly due to the lack of the EV charging facilities [1]. With continued development in EV charging facilities, EV loads are expected to increase dramatically in the near future and this will bring negative impacts on the stability of power grids. EV loads are seldom controlled in the current practice of power system planning, which results in risks in power system operation and management.

The electricity pricing policy provides guides for power demand and consumption mode of customers. Customers will respond to variable electricity prices, deciding whether they prefer charging or discharging and actively adjusting charging rate and time. In countries with a mature electricity market environment, research has been focused in this area. For instances, Cao et al. used the time-of-use (TOU) price to find optimal charging loads, which minimizes the charging cost in a regulated market [1]. Deliami et al. proposed a two-stage control strategy to maximize the profit of the charging station and minimize the peak load of the distribution transformer [2].

Electricity market in Korea may be a typical example of the regulated market, where electricity prices are fixed by the government and remain unchanged for a relatively long period of time. At present, the electricity pricing mechanism in Korea mainly includes the stepwise power tariff and the TOU price. With such a transparency, the EVs in Korea will play a significant role in balancing power supply and demand.

Based on the state-of-charge (SOC), this paper focuses on the application of the model predictive control (MPC) to electric vehicle that is charged on the TOU rates. An MPC approach with the linear programming (LP) is selected to model and simulate the EV systems. An MPC strategy is selected, because its periodic re-optimization characteristic provides stability during external disturbances [3]. By using the proposed method, EVs are able to adjust charging power and reduce the cost of costumers in load demand.

2. Efficient EV Charging Control

An EV is an automobile which is driven by an electric motor that uses electrical energy stored in a battery pack. The battery pack of an EV is the major component that determines the range and recharging times, and it tends to be heavy and expensive. The capacity of the battery pack varies depending on the type and size of the vehicle. There is a 16.4 kWh capacity battery for KIA Ray, but only 10.7 kWh of the full capacity (65%) is available for consumption. The Nissan Leaf, KIA Soul and Tesla Roadster have 24 kWh, 27kWh and 53 kWh capacity battery packs, respectively.

2.1. Energy cost function for EV charging

Since the purpose is to ensure EV charging with minimal energy consumption, the cost function must reflect its performance in a mathematical formulation. Thus, the proposed cost function minimizes energy consumption, subject to constraints on the SOC, which should be higher or equal to the lower limit of the comfort range. This formulation being linear, allows the use of the LP method for solving the optimization problem. In this paper, we used the following energy cost function to represent the daytime electricity expense.

$$\min J = \sum_{k=1}^{N} \left\{ \sum_{i=1}^{M} u_i(k) \cdot p_i(k) \right\} \cdot c(k) \tag{1}$$

where the variable $u_i(k)$ is the charging function which needs to be solved by the optimization algorithm over a control horizon (H), $p_i(k)$ is the power consumption at the time *k*, *M* is the number of charging stations, and $c(k)$ accounts for the TOU electricity rates in the *k*-th switching interval. If a control horizon (H) of a 9-hour daytime is divided into 15 min switching intervals, then, $N = 36$ is the total number of time steps per daytime.

In this paper, a practical rate plan in Table 1 is applied, where the time period is divided into on-peak, mid-peak and off-peak.

Table 1. Summary of TOU electricity rates in electric vehicle

Energy charge (KRW/kWh)			
Time period	Summer	Spring/fall	Winter
Off-peak	52.5	53.5	69.9
Mid-peak	110.7	64.3	101.0
On-peak	163.7	68.2	138.8

The SOC is defined as the remaining capacity of a battery and it is affected by its operating conditions such as load current and temperature. If the rated capacity is used, the SOC at time *t* can be expressed as

$$SOC_i(t) = SOC_{i,init} + \frac{1}{Q_r} \int_{t_0}^{t} P_i(t)dt \tag{2}$$

where $SOC_{i,init}$ represents the initial SOC of an EV battery at time t_0 and Q_r is the rated capacity of the EV battery. Therefore, in this paper, the time duration T_i in minutes of the charging process can be derives as [4]

$$T_i = \frac{(SOC_{i,tar} - SOC_{i,init}) \cdot E_i}{\varepsilon P_{c,i}} \times 60 \qquad (3)$$

where $SOC_{i,tar}$ represents the target SOC of the EV battery, E_i is the battery capacity in kWh, $P_{c,i}$ is the charging station level in kW, and ε is the charging efficiency.

Eq. 1 is an optimization problem. Additional inequality constraints can also be directly imposed on the charging to regulate the charging time within a range. This implies that constraints need to be added to the cost function:

$$SOC_i(k) \le SOC_{i,tar} \qquad (4)$$

There still exists potential to reduce the peak load, and then save money on a TOU pricing, by wisely pre-designing the charging set-point schedules. However, performing an efficient strategy requires significant amount of knowledge and efforts from charging station operators.

The MPC algorithm will be compared with the conventional on/off charging algorithm of the EV system. The on/off control algorithm is based on the revised switching levels, and it is defined as

$$u_i(k) = \begin{cases} 1 & \text{when } SOC_i(k) \le SOC_{i,tar} \\ 0 & \text{when } SOC_i(k) \ge SOC_{i,tar} \end{cases} \qquad (5)$$

2.2. MPC Control Algorithm using Linear Programming

The MPC control strategy can be explained further with Fig. 1, which shows the result of a hypothetical controller that controls the SOC levels of EV. The control model in Fig. 1 uses 15 min switching intervals, and a control horizon (H) of 9 h. The process of the MPC controller in Fig. 1 can be described as follows [5]: At the current time (11 h) the controller samples the SOC levels of EV, applies all the constraints, and predicts the future statuses of the EV system that will optimize cost over the next 7 h. It shows that the current time is 11 h which means that the inputs and output prior to 11 h are historical and the inputs and output after 11 h are the future predicted values. Note that the MPC sampling intervals are chosen to coincide with the switching intervals of the EV systems.

However, once the predicted inputs are calculated only the first predicted input is implemented and the rest of the predicted inputs are discarded. After the first predicted input is implemented the entire optimization process is repeated. This means that the EV system is switched on for 15 min, and when the 15 min interval lapses the level of the reservoir is sampled again, the constraints are re-applied and the future statuses of the SOC are computed over the next 7 h.

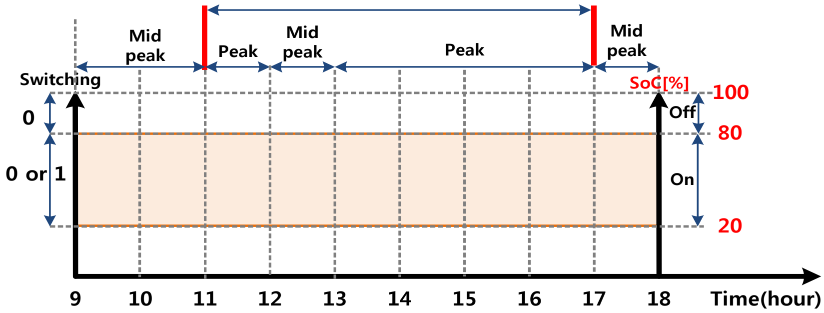


Fig. 1. Control horizon switching strategy.

3. Simulation Results

In order to verify the effectiveness of optimized charging model presented in this paper, we consider the multi-EV and multi-station case for performance comparison. The number of EVs and the number of charging stations are 4 and 2, respectively in Fig. 2. It is assumed that the initial SOCs of 4 EVs at 9 o'clock are 0.2, 0.3, 0.31, 0.41 and the target SOC of all vehicles is set to 0.8 at 18 o'clock. The total battery capacity of all vehicles and the power level of charging stations have 24 kWh and 6.6 kW, respectively. The charging efficiency ε is considered as 0.9.

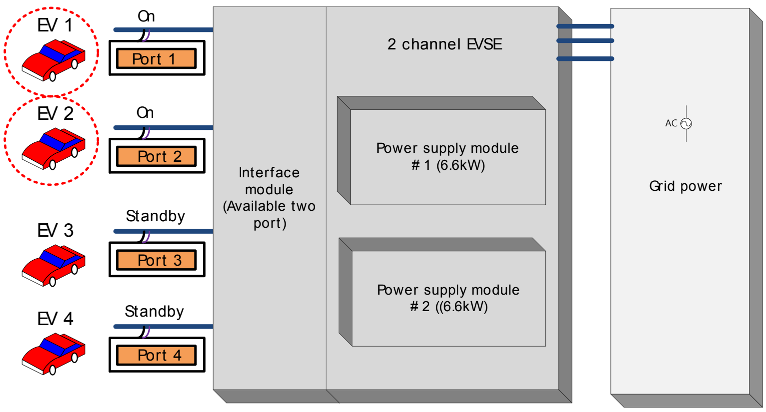


Fig. 2. Charging station and EV configuration.

This paper simulates and compares the following two control algorithms.

(1) On/off control algorithm ($u_i(k) = 0$ or 1, $\quad k = 1, \cdots, N$).

(2) MPC control algorithm with LP ($0 \le u_i(k) \le 1, \quad k = 1, \cdots, N$).

Fig. 3 and Fig. 4 show the simulation results of the two control algorithms. In Fig. 3, we see that the SOCs in four electric vehicles are operated in the upper bound of the defined SOC region ($SOC_{1,tar} = 0.8$ and $SOC_{2,tar} = 0.8$). If the SOC of an EV charged by the station reach the target SOC, then the charging station connects with another EV. Furthermore, the proposed MPC with LP method is more effective than on/off method, because the two electric vehicles are charged in off-peak and mid-peak periods. Fig. 4 shows that when MPC with LP method is used, the loads are moved out of the on-peak periods and the energy level of power with MPC control method at peak period is lower than the On/off control method. This is caused by the moving control horizon (H) of the MPC control method, which means that after each implemented control step the MPC algorithm is optimizing more into the next cycle. Fig. 4 shows that MPC control method result in a TOU saving of 4.7% for on/off per day. This shows that the MPC with LP control method is better than the on/off control algorithm.

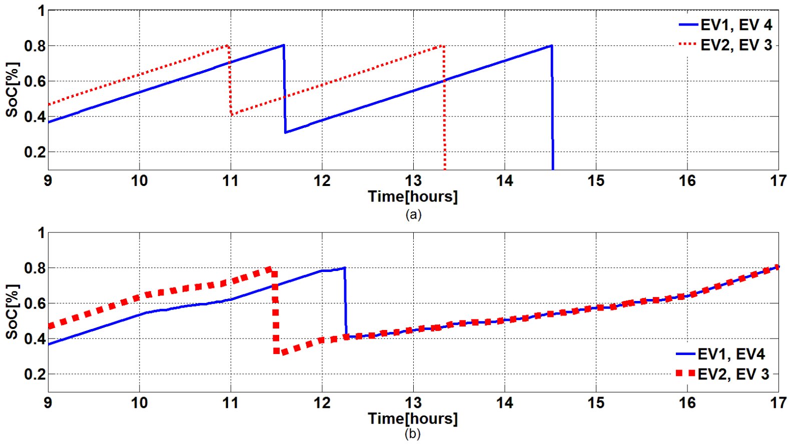
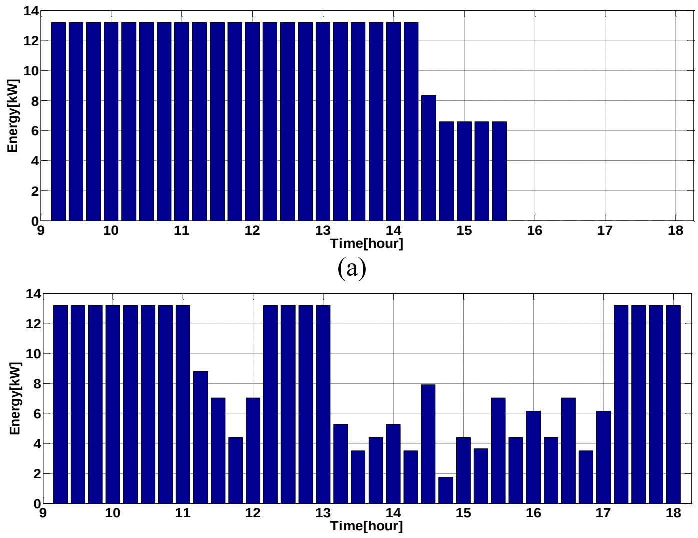


Fig. 3. Comparisons of SOCs in two charging stations: (a) On/off, (b) MPC with LP



(a)

(b)

Fig. 4. Energy costs for EV charging: (a) On/off, (b) MPC with LP.

4. Conclusion

This paper proposed the MPC control algorithm with LP for saving energy cost and reducing peak demand. In the MPC algorithm, the optimization problem with constraints is transformed into an LP algorithm and solved in each time step. Future works include the applications of the MPC controller for various types of electric vehicles.

Acknowledgements. This work was supported in part by the Inter-ER Cooperation Projects through Korea Institute for Advancement of Technology (KIAT), and in part by the Power Generation and Electricity Delivery through the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea Government Ministry of Knowledge and Economy.

References

[1] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang and J. Li, An optimized EV charging model considering TOU price and SOC curve, *IEEE Trans. on Smart Grid*, **3** (2012), 388-393.

[2] S. Deliami, A. S. Masoum, P. S. Moses and M. A. S. Masoum, Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile, *IEEE Trans. on Smart Grid*, **2** (2011), 456-467.

[3] I. Hazyuk, C. Ghiaus and D. Penhouet, Optimal temperature control of intermittently heated buildings using model predictive control: Part I - Building modeling, *Building and Environment*, **51** (2012), 379-387.

[4] L. Chen, C. Y. Chung, Y. Nie and R. Yu, Modeling and optimization of electric vehicle charging load in a parking lot. In: *5th IEEE PES Asia-Pacific Power and Energy Engineering Conference*, 0271. IEEE PES, Hong Kong (2013).

[5] C. J. Boo, J. H. Kim, H. C. Kim, M. J. Kang and K. Y. Lee, Energy efficient temperature control for peak power reduction in building cooling systems. *International Journal of Control and Automation*. **6** (2013) 105-114.

Received: August 9, 2014