Energy Management of Smart Home by Model Predictive Control Based on EV State Prediction
Yuuki Ogata and Toru Namerikawa

Abstract—The purpose of this paper is to minimize the total electricity cost while considering comfort in the home. We propose home energy management (HEMS) method by model predictive control (MPC) based on EV state prediction. If charging and discharging can be planned based on electric vehicle (EV) usage prediction, it can minimize the charging with an external charging station because it can be charged in advance at home. We introduce a model considering the passage of time in order to predict the use of EV. Finally, we confirm the validity of this research through numerical simulations.

I. INTRODUCTION

Technology enabling the efficient use of energy is gaining attention against the backdrop of such social problems as global warming from excess CO₂, the depletion of energy resources, and an increase in power demand owing to the development of cities and advanced information utilization. Studies on energy management (EMS) systems for the efficient use of energy have been undertaken. Previous studies, the problem of determining the size of battery storage used in grid-connected photovoltaic (PV) systems are discussed [1]. Also [2] proposed a method that uses model predictive control (MPC) to predict PV power generation, plan for the electricity demand in a building using the predicted value, and apply it online to correct the prediction error. [3] and [4] identified a low-dimensional data-driven model and a high-dimensional physics-based model for the same system at different spatial granularities and temporal seasons using experimental data collected from an entire floor of an office building. [5] illustrated the power grid value with the first experimental demonstration of frequency regulation from commercial building heating ventilation and air conditioning (HVAC) systems. [6] investigated an HVAC system in a data center equipped with a previously developed super-multipoint temperature sensing system.

To solve this problem, in recent years, an electric vehicle (EV) is one of the measures of transportation. Since EV’s battery capacity is large, there is a possibility that it can be used as a movable storage battery. In a recent study, [7] discussed the problem of battery scheduling based on EV state prediction. And also [8] proposed optimization of EV and home energy scheduling to minimize the total electricity cost considering the indoor temperature.

In this paper, we propose the home energy management system (HEMS) method by model predictive control (MPC) based on EV state prediction. [7] was researching to use EV as a storage battery to perform home energy scheduling, but it was not considered about the comfort related to the indoor temperature. In [8], there was a strong assumption that EV can be charged only at home, so it was thought that there was controversy in the constraints of the overall system model and state of charge (SOC) of the battery. If charging and discharging can be planned based on EV state prediction, it can be possible to minimize charging at an external charging station (CS). We introduce a model considering the passage of time to predict the EV state, and use the statistic model predictive control method to control the total electricity cost considering the indoor temperature.

II. ENERGY MANAGEMENT OF SMART HOME WITH EV

As an advantage of EV, it can be mentioned that it is good for the global environment and economically superior. On the other hand, there are also disadvantages.

First, it takes much time to charge. If it is a gasoline-powered car, refueling time is only about 5 minutes, but EV takes about 30 to 40 minutes at the shortest to charge. According to [9], even at Nissan Reef which was just released in October 2017, rapid charging takes 40 minutes. Therefore, it is necessary to adjust the lifestyle to EV, which is considered to be one of the reasons why the penetration rate of EV is sluggish.

Second, the number of charging stations is still small. As of July 2017, there are 28500 charging spots for EV in Japan and there are 7108 charging spots corresponding to rapid charging [10]. It is said that there are over 30000 gasoline stations in Japan, so this difference is obvious and hinders the spread of EV. However, if the EV increases and quickly charges all over the wide area at the same time, conventional power supply facilities cannot deal with it and fear of large blackouts also arises. Therefore, it is necessary
to greatly increase power supply facilities and large-sized storage batteries. However, it is difficult to make an appropriate investment at a prior stage when we do not know when there is a demand.

In this paper, we will incorporate EV state prediction to solve these two problems. If charging and discharging can be done systematically based on EV state prediction, it can minimize the charging with an external charging station because it can be pre-charged at home.

III. PROBLEM SETTING

A. System Model

Fig. 1 shows the whole system model. Energy scheduling decisions are made for each time \( k \), and energy usage is allocated among components such as HVAC and EV, how much energy should be taken from the grid based on the electricity cost and electricity demand. In this paper, we assume that EV can be charged with an external charging station. Parameters are shown in Table I.

<table>
<thead>
<tr>
<th>TABLE I</th>
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<tbody>
<tr>
<td><strong>DEFINITION OF NOTATIONS</strong></td>
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<tr>
<td>Notation</td>
</tr>
<tr>
<td>( \gamma ) [( \text{[C]} )]</td>
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<td>( \delta ) [( \text{[C]} )]</td>
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<tr>
<td>( \eta ) [-]</td>
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<tr>
<td>( \Phi ) [( \text{kW/m}^2 )]</td>
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<tr>
<td>( \sigma ) [-]</td>
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<td>( a_k ) [-]</td>
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<tr>
<td>( b_k ) [-]</td>
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<tr>
<td>( C ) [( \text{kWh/\text{C}} )]</td>
</tr>
<tr>
<td>( E^{\text{cap}} ) [( \text{kWh} )]</td>
</tr>
<tr>
<td>( e ) [( \text{JPY/kWh} )]</td>
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<tr>
<td>( e^{\text{sell}} ) [( \text{JPY/kWh} )]</td>
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<tr>
<td>( k ) [-]</td>
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<tr>
<td>( N ) [-]</td>
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<tr>
<td>( p_k ) [-]</td>
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<tr>
<td>( P_{\text{cap}} ) [( \text{kW} )]</td>
</tr>
<tr>
<td>( P_{\text{grid}} ) [( \text{kW} )]</td>
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<tr>
<td>( P_{\text{hvac,in}} ) [( \text{kW} )]</td>
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<tr>
<td>( P_{\text{hvac,out}} ) [( \text{kW} )]</td>
</tr>
<tr>
<td>( q_k ) [-]</td>
</tr>
<tr>
<td>( R ) [( \text{[C/kW]} )]</td>
</tr>
<tr>
<td>( S ) [( \text{[m}^2 )]</td>
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<tr>
<td>( \text{SOC}_k ) [-]</td>
</tr>
<tr>
<td>( T_k ) [( \text{[C]} )]</td>
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<tr>
<td>( T_{\text{ext}} ) [( \text{[C]} )]</td>
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<tr>
<td>( T_{\text{ext}} ) [( \text{[C]} )]</td>
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<tr>
<td>( T_0 ) [( \text{[h]} )]</td>
</tr>
<tr>
<td>( t_{\text{D}} ) [( \text{[h]} )]</td>
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<tr>
<td>( t_{\text{A}} ) [( \text{[h]} )]</td>
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</tbody>
</table>

B. Power Grid

First, the power purchased from the grid \( P_{\text{grid}} \) is given as follows:

\[
P_{\text{grid}} = P_{\text{hvac}} + P_{\text{ev}} - P_{\text{solar}}
\]

where \( P_k \) is power supplied. The constraint of power purchased from the grid is given as follows:

\[
0 \leq P_{\text{grid}} \leq P_{\text{max}}
\]

C. House Thermal Dynamic Model [8]

In this section, we formulate the dynamics of indoor temperature and HVAC load of the house to express the HVAC and EV scheduling problem.

First, the continuous model equation of the room temperature \( T \) is given as follows:

\[
C \frac{dT}{dt} = \frac{1}{R} (T_{\text{ext}} - T) + \sigma P_{\text{hvac,out}} + S \Phi_{\text{solar}}
\]

\[
\sigma = \begin{cases} 
-1 & \text{Summer} \\
1 & \text{Winter} 
\end{cases}
\]

where the first term is about an outside air temperature, the second term is about the power used for air conditioning, and the third term is about thermal energy by solar radiation.

Next, we rewrite (3) to the state space model by using the backward subtraction method.

\[
T_{k+1} = AT_k + BP_{\text{hvac,out}} + Dd_k
\]
\[ A = 1 - \frac{1}{CR} T_s \]  
\[ B = \frac{\sigma}{C} T_s \]  
\[ D = \begin{bmatrix} 1 \\ CR \end{bmatrix} T_s \left( \begin{array}{c} S \\ C \end{array} \right) T_s \]  
\[ d_k = \begin{bmatrix} \Phi_0 \\ k \end{bmatrix} T \]  

Here, the system state is indoor temperature \( T \), and input is HVAC output power \( P^{hvac,out} \).

The output power \( P^{hvac,out} \) is given as follows:

\[ P^{hvac,out} = \gamma P^{hvac} \]  

where \( \gamma \) indicates the coefficient of performance (COP) of the HVAC system.

Temperature constraint in the rooms of each house is given as follows:

\[ a_k |T_k - T_{ref}| \leq \delta \]  

where \( a_k \) is state of the house, “1” for occupied, “0” otherwise and \( \delta \) is Max. acceptable temperature deviation.

Since the power that can be supplied to the HVAC system will not take a negative value, it can be given as follows.

\[ 0 \leq P^{hvac} \leq P^{hvac,max} \]  

D. SOC Dynamics

It is necessary to model running patterns for EV and to define the battery capacity and driving efficiency. The usage pattern of EV can be given by departure time, arrival time and power consumption amount. In this paper, \( t_D \) is departure time and \( t_A \) arrival time.

SOC dynamics is expressed as follows:

\[ SOC_{k+1} = \begin{cases} SOC_k + b_k \frac{P_{ev}}{E^{cap}} & \text{if } P_{ev} \geq 0 \\ SOC_k + b_k \frac{P_{ev}}{E^{cap}} & \text{if } P_{ev} < 0 \end{cases} \]  

where \( b_k \) is state of EV, “1” at home, “0” otherwise, \( E^{cap} \) is capacity of the battery. They are applied when they are being charged and discharged. When \( k = t_D \), the constraints are given as follows:

\[ SOC_{t_A} = SOC_k - SOC_{cons} \]  
\[ P_{t_A}^{ev} = -SOC_{t_A} E^{cap} \]  

where \( SOC_{cons} \) represents the amount of SOC consumed by the EV’s driving. When EV is used, the difference between SOC at departure time and arrival time is indicated by (14). When \( SOC_{t_A} < 0 \), it is necessary to charge with an external charging station, so we will use (15) to represent purchasing power.

In addition, we guarantee the following constraint that the ratio of SOC does not increase when EV is used.

\[ SOC_{t_A} \leq SOC_k \leq SOC_{t_D} \text{ if } k \in [t_D, t_A] \]  

Since EV needs to maintain the capacity of the battery within a certain range, the constraint is given as follows.

\[ SOC_{min} \leq SOC_k \leq SOC_{max} \]  

When the EV arrives at home, the constraint is given as follows if the battery is connected to the home charger at once.

\[ P_{ev,min} \leq P_{k}^{ev} \leq P_{ev,max} \]  

Here, \( P_{ev,min} \) and \( P_{ev,max} \) indicate the lower and upper limits of charge and discharge.

The battery SOC algorithm is summarized below.

**Algorithm 1 Battery SOC Algorithm**

1: if \( b_k = 1 \) then
2: if \( P_k^{ev} \geq 0 \) then
3: \( SOC_{k+1} = SOC_k + \frac{\eta P_k^{ev}}{E^{cap}} \) \( \quad \) else
4: \( SOC_{k+1} = SOC_k + \frac{P_k^{ev}}{E^{cap}} \) \( \quad \) end if
5: \( SOC_{k+1} = SOC_k + \frac{P_k^{ev}}{E^{cap}} \) \( \quad \) end if
6: end if
7: else if \( k = t_D \) then
8: \( SOC_{t_A} = SOC_k - SOC_{cons} \) \( \quad \) end if
9: if \( SOC_{t_A} < 0 \) then
10: \( P_{t_A}^{ev} = -SOC_{t_A} E^{cap} \) \( \quad \) end if
11: \( SOC_{t_A} = 0 \) \( \quad \) end if
13: end if

IV. EV STATE PREDICTION

In this section, we will discuss EV state prediction. The departure time, arrival time and power consumption are important factors to predict the EV state. When EV is used, we will go out from departure time to arrival time and stay in the house between arrival time and next departure time. In this paper, we assume that power consumption is proportional to going out time for simplicity.

\[ 1 - q_k \]

Fig. 3. State transition diagram for stochastic plug-in/out state \( b_k \)
In this paper, we introduce a Markov model with reference to [7] in order to predict the use of EV. Since EV takes only two states of plugging-out and plugging-in, expressing it with a Markov model results in a simple structure like Fig. 3. In Fig. 3, "0" is out (Plugging-out), "1" is parking (Plugging-in), and \( q_k \) is the probability of departing while parking at time \( k \). Also, Fig. 4 shows the distribution of time at departure and arrival time in Chengdu, China. According to Fig. 4, the probability that EV departs and arrives in everyday life is different in the time zone, so it seems that it is not appropriate to equalize the state transition probability of Markov model. Therefore, we adopt a Markov model considering the passage of time and the state transition probability changes according to the time zone.

Here we make the following assumptions.

**Assumptions**

- Ev goes out between departure time and arrival time, and park at home from arrival time to the next departure time.
- Power consumption is proportional to the time EV goes out.

**V. OBJECT FUNCTION**

The evaluation function used in this paper consists of three parts. First, the term of the comfort evaluation function is expressed as follows:

\[
J_1 = \sum_{j=1}^{H_p} \omega a_{k+j} (T_{k+j} - T_{e_{cfj}})^2 \quad (19)
\]

where \( \omega \) is a weight, \( a_k \) represents the occupancy situation of the house, and \( a_k = 1 \) means that the house is occupied. In the case of \( a_k = 0 \), since the house is not occupied, the indoor temperature evaluation function is not taken into account.

Next, the term of the evaluation function related to power is expressed by follows:

\[
J_2 = \begin{cases} 
\sum_{j=1}^{H_p} \varepsilon_{k+j}^p P_{k+j}^{grid} + e^{cs} P_{t_a}^{cs} & \text{if } P_{k}^{grid} \geq 0 \\
\sum_{j=1}^{H_p} \varepsilon_{k+j}^{sell} P_{k+j}^{grid} + e^{cs} P_{t_a}^{cs} & \text{if } P_{k}^{grid} < 0 
\end{cases} \quad (20)
\]

where \( \varepsilon_k \), \( \varepsilon_{k}^{sell} \) represent the electricity price and the power selling price at time \( k \), and \( e^{cs} \) represents the price in charging station(CS). When \( P_{k}^{grid} \geq 0 \), it means purchasing electricity, so the usual electricity price is applied. When \( P_{k}^{grid} \leq 0 \), it means selling electricity, so the selling price is applied. That is the \( J_2 \) is switched by the value of \( P_{k}^{grid} \).

Finally, the term of the evaluation function for SOC is expressed as follows:

\[
J_3 = \sum_{j=1}^{H_p} \mu b_{k+j} (SOC_{k+j} - SOC_{max})^2 \quad (21)
\]

where \( b_k \) represents the state of EV, and \( b_k = 1 \) means that the EV is connected to the house. If \( b_k = 0 \), which means that the EV is not connected to the house, the evaluation function is not taken into account. \( \mu \) is a weight.

From (19), (20), (21), the evaluation function for minimizing cost can be expressed as follows.

\[
\min_{P_{grid}^{grid}, P_{pv}^{pv}, P_{ev}} J = J_1 + J_2 + J_3 \quad (22)
\]

s.t. (1) - (2), (5), (10) - (18)

**VI. SIMULATION**

A. Setting

In this simulation, one house with EV is assumed and the operation period of HVAC is one day. The setpoint room temperature is 24 °C, and the constraint is set to be controlled within ±2 °C. Since \( P_{hvac}^{hvac} \) does not take a negative value, it is defined as 0 to 8 [kWh]. The capacity constraint of SOC is 0 to 1, the upper limit of \( P_{ev}^{ev} \) is 4 [kWh], and the upper limit of \( P_{grid}^{grid} \) is 12 [kWh]. When EV is charged by charging station, \( e^{cs} \) is 900 [JPY / kWh] (it is calculated by [11]). For simulation, we will show 2 ways.

- **Case 1** When EV is used at 09: 00-18: 00
- **Case 2** When EV is used at 15: 00-22: 00

Case 1 is the case that assumed the action of the majority people like Fig. 4, and Case 2 is the case that assumed the action of the minority people.

In the simulation we apply model predictive control (MPC), and also verified its effectiveness. Here, we compare with the case where we did not predict the EV state as the conventional method. Detailed parameters are as follows.
TABLE II

MODEL PARAMETERS

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma )</td>
<td>COP of HV AC.</td>
</tr>
<tr>
<td>( \delta )</td>
<td>Max. acceptable temp. deviation.</td>
</tr>
<tr>
<td>( \eta )</td>
<td>Charging and discharging efficiency.</td>
</tr>
<tr>
<td>( C )</td>
<td>Total thermal capacitance.</td>
</tr>
<tr>
<td>( E^{cap} )</td>
<td>Capacity of Battery.</td>
</tr>
<tr>
<td>( H_p )</td>
<td>Prediction horizon.</td>
</tr>
<tr>
<td>( \omega )</td>
<td>The weight of indoor temp.</td>
</tr>
<tr>
<td>( R )</td>
<td>Thermal resistance.</td>
</tr>
<tr>
<td>( S )</td>
<td>Window area.</td>
</tr>
<tr>
<td>( T_{ref} )</td>
<td>Desired indoor temp.</td>
</tr>
<tr>
<td>( T_s )</td>
<td>Sampling time.</td>
</tr>
</tbody>
</table>

For the time using EV, \( p_{EV}^{t_e} = 0 \) because the EV cannot be charged and discharged to the home. There is also no SOC data for the time using EV, because the calculation has not been updated. Both methods can satisfy the constraints regarding the room temperature.

The value of the evaluation function \( J \) calculated by (22) and the electric charge are shown below.

As for the value of the evaluation function \( J \), the result was that the value of the proposed method was smaller. This is because home energy management and EV battery management become efficient as a result of EV state prediction. Also, since we charged external charge in the conventional method and it has purchased electricity of 2.04 [kW], the electricity cost increased.

TABLE III

SIMULATION RESULT (CASE 1) \([\times 10^3]\)

<table>
<thead>
<tr>
<th>Evaluation Func. ( J )</th>
<th>Elect. Price [JPY]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>4.992</td>
</tr>
<tr>
<td>Proposed</td>
<td>3.050</td>
</tr>
</tbody>
</table>

The results are shown below.
The value of the evaluation function $J$ calculated by (22) and the electric charge are shown below.

**TABLE IV**

<table>
<thead>
<tr>
<th>Simulation Result (Case 2) [$\times 10^3$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>----------------------</td>
</tr>
<tr>
<td>Conventional</td>
</tr>
<tr>
<td>Proposed</td>
</tr>
</tbody>
</table>

Although not as large as the (Case 1), the value of the evaluation function $J$ has decreased in the proposed method. Also, since we charged external charge in the conventional method and it has purchased electricity of $15,000$ [kW], the electricity cost increased.

**VII. CONCLUSION**

In this paper, we proposed home energy management (HEMS) method by model predictive control (MPC) based on EV state prediction. In order to realize systematically control of the battery, we considered control of charging and discharging that took EV state prediction and minimized the electricity cost. For future studies, the author would like to consider multiple house models to assume the real situation.

**REFERENCES**


