

Distributed Real-Time Stochastic Optimization based ESS Management Strategy for residential customers

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Abstract— In this paper, we propose an energy storage system (ESS) management strategy using the distributed real-time stochastic optimization to solve the prediction error by the forecasting system for added spending reduction of residential customers. Firstly, the optimization problem concerning photovoltaic (PV), ESS and flexible load is reformulated for the real-time scale problem by utilizing the stochastic optimization technique. After that, the optimization problem is designed for the distributed real-time stochastic optimization problem through the decomposition technique in the real-time scale. The result of simulation shows variation of the time-averaged delayed backlog and time-averaged electricity power cost by the portion of unsatisfied flexible load and control of backlog value.

Keywords— ESS management strategy, Distributed real-time stochastic optimization, prediction error, cost minimization

I. INTRODUCTION

PV is one of the issue about the future energy resource. In the future power grid, the customers fulfil a demand through the renewable generator (i.e. PV) on their own. However, ESS is utilized in the home area for using PV because amount of generating PV is intermittent. The utilization of PV and ESS is expected to increase in the home area. [1], [2]

The real-time price is utilized for demand management in the power grid. Home Energy Management System (HEMS) which is being researched in order to reduce the electricity fee of customers by using real-time price and flexible load in the home area, can be benefitted for cost side by positively utilizing real-time price.

Various methods have been proposed for EMS to deal with PV and ESS. Optimal home energy management system proposes a method to reduce the demand side cost by utilizing different load profiles, local renewable and storage. An intelligent HEM algorithm reduces the demand side cost by handling the household load. In addition, an optimal residential load commitment framework reduces the demand side cost by managing the charge / discharge of the storage system using the operating status of appliances. The real-time scheduling of residential appliances reduces the demand side cost by utilizing electric water heater (EWH), air-conditioner, electric vehicle, PV and storage system. However, the first of method does not utilize the advantages of PV and ESS because the method of predicting PV generation was not applied. The other methods

do not take advantage of the demand response because do not predict the variation of demand. [3]-[6]

Several studies have been conducted to predict PV production or demand. Joint optimization scheduling respond to predicted demand by using EV and storage system for cost minimization. Optimized distributed energy resource (DER) operation method provides the demand and load prediction model by utilizing independent DER and load profile and reduces cost by using coordinated game mechanism. However, since the prediction system of PV and demand may cause an error, the prediction system needs a solution to the occurrence of prediction error. [7], [8]

An aggregator coordinating a group of distributed storage units uses a modified Lyapunov optimization framework to solve the prediction on a real-time scale, but does not consider the characteristics of various loads in the home area. Distributed real-time power balancing method is similar to cost reduction in power grid by using stochastic optimization technique but the cost of customers is not considered. [9], [10] Therefore, a cost minimization method needs the considering characteristics of the variable appliance in order to minimize the cost by the prediction error in the home area.

In this paper, we propose ESS management strategy based on distributed real-time stochastic optimization technique for cost minimization of customers in home area. The optimization problem is designed by modeling PV, ESS and load for ESS management strategy. This optimal problem is reformulated into a real-time optimization problem based on the Lyapunov optimization technique which is one of the stochastic optimization techniques. Then, the cost minimization of customer reformulates distributed real-time stochastic optimization problem by utilizing the decentralization technique. The remainder of this paper is organized as follows. In section 2, we refer to the related work. In section 3, we propose the optimization problem. In section 4, we describe the performance analysis. Finally, the section 5 concludes the paper.

II. RELATED WORK

In section 2, we examine the previous paper about handling the stochastic optimization technique and the decomposition technique.

In the past few studies, there propose the methods of cost minimization which is focus on aggregators by handling distributed storage systems in the local area. The aggregator proposes the method of Lagrange dual decomposition for distributed storage system in order to charge / discharge the

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power generated in the local area and determines the charge / discharge about amount of each distributed storage system. In another study, the aggregator proposes the ADMM (Alternating Direction Method of Multipliers) method to supply the power generated from the RG (Renewable Generator) to the demand side. This method decomposes not only the distributed storage system but also the demand and purchase / sales volume from the power grid.

After designing the optimization problem in large scale, SOC is designed by using Lyapunov function and the variation of SOC is proved by utilizing one-slot Lyapunov drift and it reformulates the optimization problem in the real-time scale. However, the previous study focuses on the total of cost minimization for the aggregators and does not consider the customer side. Therefore, it is necessary to study the method of cost minimization considering characteristics of customer's variable appliance in terms of home area. [9] – [11].

III. REAL-TIME DISTRIBUTED OPTIMIZATION PROBLEM

We perform a system modeling on the session 3-A and an optimization problem for cost minimization of the customer in large-scale on session 3-B. Then, in session 3-C, the real-time optimization problem is redesigned by using the stochastic optimization technique and the distributed real-time optimization problem is redesigned by using the decomposition technique in session 3-D.

A. System Modeling

We model the energy imbalance, PV, ESS, and load for formulation of the customer's cost minimization problem. If the PV and demand values is presented by the predicting system on the large scale differ from the actual PV and demand values, the difference between the predicted PV demand value and the actual PV demand value is defined as the prediction error value ($g_{i,t}$). If the actual PV value and the demand value are smaller than the predicted PV value and the demand value of the customer i during the time slot t, this state is the energy surplus. If it is bigger, this state is the energy deficit.

The load of household appliances consists of the base load and flexible load. The base load must be satisfied when the customer requests it and the flexible load can supply the power after delaying the customer's requirement.

The minimum base load by requesting customer i is $b_{i,\min}$ and the maximum base load is $b_{i,\max}$ and the minimum flexible load is $f_{i,\min}$ and the maximum flexible load is $f_{i,\max}$. If it satisfies $b_{i,\min} \leq b_{i,t} \leq b_{i,\max}$ about the base load requirement of customer i for time slot t and $f_{i,\min} \leq f_{i,t} \leq f_{i,\max}$ about the flexible load requirement, the amount of satisfied load is defined as the following equation (1).

$$b_{i,t} \leq m_{i,t} \leq b_{i,t} + f_{i,t} \quad (1)$$

If the definition of satisfied load is satisfied, the time-averaged upper bound restricting the portion of unsatisfied flexible load to control of flexible load is defined as following equation (2). [10]

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E\left[\frac{b_{i,t} + f_{i,t} - m_{i,t}}{b_{i,t}}\right] \leq \alpha \quad (2)$$

The maximum amount of charge can be purchased from the power grid during the unit time slot, $e_{b,\max}$, and the maximum amount of sales can be sold to the power grid, $e_{s,\max}$. The amount of charge ($e_{b,i,t}$) and discharge ($e_{s,i,t}$) that can be purchased from the power grid during the time slot t in the residential area is defined as equation (3).

$$0 \leq e_{b,i,t} \leq e_{b,i,\max}, \quad 0 \leq e_{s,i,t} \leq e_{s,i,\max} \quad (3)$$

When the ESS maximum discharge amount of customer i is satisfied during the unit time slot, $x_{i,\min} < 0$, and the maximum charge amount is satisfied, $0 < x_{i,\max}$, the charge / discharge amount of customer i during the time slot t is defined as the following equation (4).

$$x_{i,\min} \leq x_{i,t} \leq x_{i,\max} \quad (4)$$

If the charge / discharge amount of customer i satisfies equation (4) and the ESS SOC of customer i which is the condition that it does not exceed the minimum SOC ($s_{i,\min}$) and maximum SOC ($s_{i,\max}$) during the time slot t, the one-slot variation of the ESS SOC with customer i is defined by the following equation (5).

$$s_{i,t+1} = s_{i,t} + x_{i,t} \quad (5)$$

If the charging / discharging amount is satisfied as equation (4), (5) during the time slot t, the time-averaged charge / discharge amount is defined as the following equation (6). [10]

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E[x_{i,t}] = 0 \quad (6)$$

When the maximum PV charge amount of customer i is $a_{i,\max}$, the PV charge amount of customer i during the time slot t is defined as equation (7).

$$0 \leq a_{i,t} \leq a_{i,\max} \quad (7)$$

If the above equations (1) - (7) are satisfied, the power charge / discharge amount of customer i during the time slot t is defined by the following equation (8).

$$\sum_{i=1}^N e_{b,i,t} + \sum_{i=1}^N a_{i,t} = \sum_{i=1}^N e_{s,i,t} + \sum_{i=1}^N m_{i,t} \quad (8)$$

The equations of (1) - (8) are satisfied and $p_{b,t}$ is power price which is purchased from power grid during time slot t and $p_{s,t}$ is power price which is sold by power grid during time slot t . If the $D(x_{i,t})$ is the ESS degradation cost during the time slot t , the total electricity fee of customer i during time slot t is defined as equation (9).

$$w_t = p_{b,t} e_{b,t} - p_{s,t} e_{s,t} + \sum_{i=1}^N D(x_{i,t}) \quad (9)$$

B. Optimization Problem Formulation

We design the ESS charge / discharge problem by using the PV, ESS and load models. If PV, ESS, and Load are satisfied with the equations (1) - (8), the time-averaged total electricity power cost of customer i is defined as follows equation (10).

$$\min_{u_{i,t}} \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E[w_t] \quad (10)$$

s.t. (1) - (8)

We determine the charge / discharge amount of customer i for one day to optimize the objective function of the proposed optimal problem. The monitoring parameters $q_t \in [A_t, B_t, F_t, S_t, J_t, p_{b,t}, p_{s,t}]$ and decision parameters $u_t \in [X_t, M_t, e_{b,t}, e_{s,t}]$ are used to determine the optimum charge / discharge amount. The monitoring parameters consist of PV generation ($A_t \in [a_{i,t}]$), base load requirement ($B_t \in [b_{i,t}]$), flexible load requirement ($F_t \in [f_{i,t}]$), ESS SOC ($S_t \in [s_{i,t}]$) and virtual queue for the unsatisfied load ($J_t \in [J_{i,t}]$) in the residential area. Also, it is composed of price of electricity when purchased from the grid and the price of electricity when sold as a grid. The monitoring parameter is the monitored parameter for cost minimization of customer in residential area. In addition, the decision parameters consist of the ESS charge / discharge amount ($X_t \in [x_{i,t}]$) and the amount of the satisfied load $M_t \in [m_{i,t}]$ in all customers of residential area. In addition, it consists of the amount of power purchased from the power grid and the amount of power sold

by the power grid. The decision parameters are determined according to the monitoring parameters for cost minimization of the customer in the residential area and the virtual queue state for the unsatisfied load defined in 3-C.

C. Real-Time Stochastic Optimization Problem

In this session, we propose a virtual queue for unsatisfied load to handle ESS charge / discharge in the real-time scale and the unsatisfied load is buffered in the proposed virtual queue.

A virtual queue ($J_{i,t}$) is required before time slot by the predefined formula (2). Also, the above queue awaits the flexible load which is non-service load. If the load of customer i satisfies the pre-defined equation (2), the one-time slot variation of $J_{i,t}$ is defined as following equation (11).

$$J_{i,t+1} = \max\{J_{i,t} - \alpha\} + \frac{b_{i,t} + f_{i,t} - m_{i,t}}{f_{i,t}} \quad (11)$$

If the ESS SOC of customer i is satisfied with the equation (5) and the virtual queue is satisfied with the equation (11), the drift-plus-cost function can be obtained by using Lyapunov function and one-slot Lyapunov drift [9]. We can reformulate the real-time problem and are defined with equation (12).

$$\min_{u_{i,t}} \sum_{t=1}^N p_{b,t} e_{b,i,t} - \sum_{t=1}^N p_{s,t} e_{s,i,t} + \sum_{i=1}^N S_{i,t} x_{i,t} - \sum_{i=1}^N \frac{J_{i,t}}{f_{i,t}} m_{i,t} \quad (12)$$

s.t. (1), (3), (4), (8)

D. Distributed Real-Time Stochastic Optimization Problem

In this session, we apply the decomposition technique for designed stochastic optimization problem to perform cost minimization for each customer on real-time scale. Then, it reformulates the distributed optimization problem.

The distributed real-time optimization problem derives the optimal value according to the proposed algorithm 1.

Algorithm 1. Distributed real-time operation algorithm in residential area for each customers

observe the monitoring parameter q_t , virtual queue $J_{i,t}$, and energy state $S_{i,t}$

solve optimization problem and obtain optimal solution u_t^*

$$m_{i,t}^* = \frac{\beta * J_{i,t}}{f_{i,t}} + b_{i,t} + (1 - \alpha) f_{i,t}$$

if $a_{i,t} > m_{i,t}^*$ and $x_{\max} < k_{i,t} + a_{i,t} - m_{i,t}^*$

$$x_{i,t}^* = a_{i,t} - m_{i,t}^* - k_{i,t} + a_{i,t} - m_{i,t}^* - x_{i,\max}$$

$$e_{s,i,t}^* = \sum_{i=1}^N (s_{i,t} + a_{i,t} - m_{i,t} - x_{i,\max})$$

else if $a_{i,t} > m_{i,t}^*$ and $x_{\max} \geq k_{i,t} + a_{i,t} - m_{i,t}^*$

$$x_{i,t}^* = a_{i,t} - m_{i,t}^*$$

$$e_{s,i,t}^* = 0$$

else if $a_{i,t} < m_{i,t}^*$ and $0 > k_{i,t} + a_{i,t} - m_{i,t}^*$

$$-x_{i,t}^* = s_{i,t} + a_{i,t}$$

$$e_{b,i,t}^* = \sum_{i=1}^N (m_{i,t} - a_{i,t} + s_{i,t})$$

else if $a_{i,t} < m_{i,t}^*$ and $0 \leq x_{i,t-1} + a_{i,t} - m_{i,t}^*$

$$-x_{i,t}^* = a_{i,t} - m_{i,t}^*$$

$$e_{b,i,t}^* = 0$$

else

$$x_{i,t}^* = e_{b,i,t} = e_{s,i,t} = 0$$

Use u_i^* to update $J_{i,t}$ and $S_{i,t}$

Repeat at each time

IV. SIMULATION RESULT

In section 4, we describe the simulation environment in session 4-A and the results of performance analysis in session 4-B for the simulation analysis of the proposed approach.

A. Simulation Environment

We monitor ESS SOC, monitoring parameter and backlog of unsatisfied load for the added spending reduction of customer from the prediction error problem and determine the decision parameter. Each customer has one PV and ESS and PV can generate 0 ~ 3kW per unit time slot. ESS capacity is 10kW and maximum charging / discharging amount is | 6kW |. The price of power purchased from the power grid is 6 to 10 cents / kWh and the price of power sold by the power grid is 4 to 5 cents / kWh.

B. Performance Analysis

Figure 1 shows the time-averaged delayed backlog for the customer in the home area. This experiment controls the portion of unsatisfied flexible load. If the price of power purchased from the power grid in the residential area is expensive, it delays the requirement to reduce the unsatisfied flexible load value. Then, the portion of unsatisfied flexible load value rise at a cheap time and the requirement is provided with the lower price. Likewise, if the amount of flexible load can be divided into three cases as shown in figure 1, the delay of 5.5 kW is better way about the additional price than the delay of 4.5 kW.

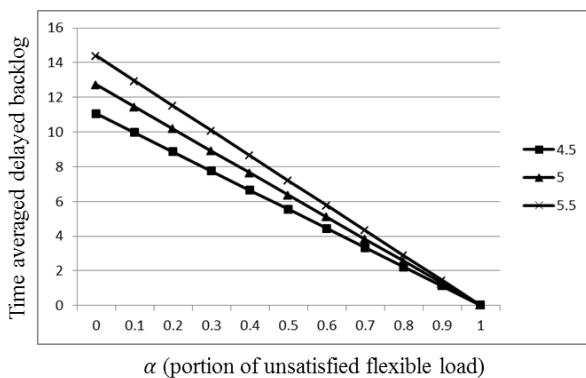


Figure 1. Time-averaged delayed backlog for customer in home area

Figure 2 shows the variation of the time-averaged electricity power cost when controlling the unsatisfied flexible load value. The cases 1 ~ 3 and cases 4 ~ 6 differ the portion of unsatisfied flexible load. The case 1 was set to 4.5, the case 2 was set to 5, the case 3 was set to 5.5 and the case 2 has the same maximum flexible load. Thereafter, the time-averaged electricity power cost variation of customer i can be confirmed by changing the backlog control value. If the power price purchased from the power grid during the unit time is expensive, the flexible load is delayed by decreasing the portion of unsatisfied flexible load value. If the price of power purchased from the power grid for a unit of time is cheap, the large amount of power can be supplied to solve the requirement of the flexible load which has been delayed by setting the backlog control value high.

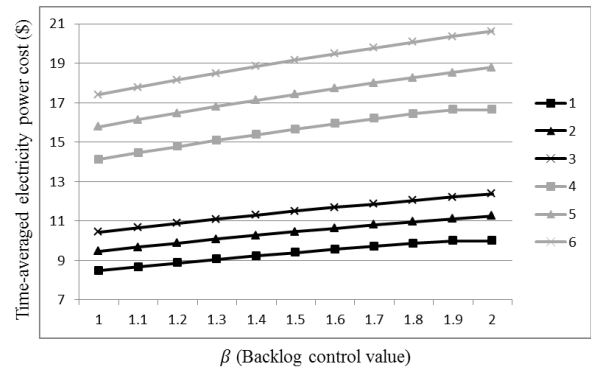


Figure 2. Time-averaged electricity power cost for customer in home area

V. CONCLUSIONS

In this paper, we provided an ESS management strategy using the distributed real-time stochastic optimization to solve the prediction error by the forecasting system for added spending reduction of residential customers. The optimal problem considering PV, ESS and flexible load is designed as a real-time scale problem by using the stochastic optimization technique. The optimization problem designed on the real-time scale is designed as a distributed real-time stochastic optimization problem through decomposition technique. The simulation results show the variation of time-averaged delayed backlog and time-averaged electricity power cost. In the environment about mentioned section 4, the flexible load can be delayed as shown in figure 1 at the power price high time. The cost loss can be minimized to solve the delayed backlog as figure 2 by prediction error.

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References

- [1] D. Gauntlett, and M. Lawrence, "Solar PV Market Forecasts," Navigant Research, Published 3Q, 2013.
- [2] A. Eller and A. Dehamna, "Residential Energy Storage," Navigant Research, Published 2Q, 2016.
- [3] Chen Zhao, Shufeng Dong, Furong Li, and Yonghua Song, "Optimal Home Energy Management System with Mixed Types of Loads", CSEE JOURNAL OF POWER AND ENERGY SYSTEMS, VOL. 1, NO. 4, DECEMBER 2015
- [4] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," IEEE Transactions on Smart Grid, vol. 3, no. 4, pp. 2166–2173, 2012.
- [5] M. Rastegar, M. Fotuhi-Firuzabad, and F. Aminifar, "Load commitment in a smart home," Applied Energy, vol. 96, no. 0, pp. 45–54, 8, 2012.
- [6] Z. Wu, S. Y. Zhou, J. N. Li, and X.-P. Zhang, "Real-time scheduling of residential appliances via conditional risk-at-value," IEEE Transactions on Smart Grid, vol. 5, no. 3, pp. 1282–1291, 2014.
- [7] Mosaddek H. K. Tushar, Chadi Assi and Martin Maier "Distributed Real-Time Electricity Allocation Mechanism for Large Residential Microgrid," IEEE TRANSACTIONS ON SMART GRID, VOL. 6, NO. 3, MAY 2015.
- [8] Trudie Wang, Daniel O'Neill, and Haresh Kamath, "Dynamic Control and Optimization of Distributed Energy Resources in a Microgrid," IEEE TRANSACTIONS ON SMART GRID, VOL. 6, NO. 6, NOVEMBER 2015.
- [9] Sun Sun, MinDong, and Ben Liang, "Real-Time Power Balancing in Electric Grids With Distributed Storage," IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING, VOL. 8, NO. 6, DECEMBER 2014.
- [10] Sun Sun, MinDong, and Ben Liang, "distributed real-time power balancing in renewable-integrated power grids with storage and
- [11] M. Neely, Stochastic Network Optimization with Application to Communication and Queueing System. San Rafael, CA, USA: Morgan & Claypool, 2010.



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