Development of Energy Management System for DC Microgrid for Office Building

-Day Ahead Operation Scheduling Considering Weather Scenarios-

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Abstract—In recent years, distributed generators (DG) with renewable energy (RE) are introduced to electric power systems for saving CO	extsubscript{2} emission. Installation of DGs in user-side leads to the local demand and supply system, called microgrids (MGs). Since the some of DGs work in DC, advantages of DC supply system over the AC might be emphasized. The authors are investigating the merits of DC microgrid (DCMG) using the actual DCMG for an office building. Operation of the DCMG is organized by an energy management system (EMS). This paper proposes an optimal scheduling algorithm implemented in the EMS. Simulation using the actual demand data shows that the proposed scheduling algorithm can save 0.3% CO	extsubscript{2} emission during the simulation terms.

Keywords—DCmicrogrid, Energy Management System, Optimal Scheduling, PV Output Forecast, Scenario Reduction Algorithm

I. INTRODUCTION

In recent years, introductions of distributed generators (DGs) with renewable energy (RE) attract great attention to reduce the environmental loading. Especially in Japan, photovoltaic generation systems (PVs) are introduced to distribution systems due to its advantages: low CO	extsubscript{2} emission, low scale merit, and high installation flexibility.

Due to the low scale merit of PV, it is easy to install PVs in demand area; it leads to a local demand and supply system. Microgrid (MG) would be one of the promising forms of electricity supply in the future. However, the output of PV is fluctuating and intermittent depending on the weather conditions. In order to use a PV as a firm resource in the MG, hybridization with an energy storage system (ESS) is required [1]-[3]. In order to improve the energy efficiency of MG, it is important to operate the components of MG optimally using information technology. Reference [4] developed the loads management in a data center for operation costs minimization. Management of both electric energy and thermal energy in a MG was proposed in [5]. Operation of MG with a battery and an electric vehicle (EV) was considered in [6]. Objectives of the previous works are not unique, however, general objective of MG are follows.

- Monitoring and controlling electric loads, DGs and ESSs to balance demands and supplies by integration control of DGs.
- Estimation and handling of system uncertainties such as PV outputs, loads, or component failures to improve energy efficiency.

On the other hand, some of DGs and ESSs use DC inherently. However, outputs of DGs and/or charge/discharge power of ESSs are converted into AC since the conventional commercial grids use AC. In addition, some of home and office appliances use DC; they also require AC/DC conversion. Since conversions between AC and DC yield conversion losses, number of converters should be reduced; implementation of a DC system would be a solution. A DC system would also bring other advantages such as supply reliability improvement and small-spaces of components [7][8].

The ministry of environment in Japan has started three-year demonstration project on DC microgrid (DCMG) for an office building. An energy management system (EMS), newly
A developed in this project, will monitor the system state and manage the energy flows inside the DCMG. Major functions of the developed EMS are the operation scheduling based on the PV output and demand forecasts, and the real-time control of sources based on the monitored system condition. This paper proposes an optimal scheduling algorithm which is one of the functions of EMS. The proposed algorithm is verified by the computational simulation in which the actual load data and solar radiation data monitored at DCMG site are used.

The other part of this paper is organized as follows. In section II, overviews of DCMG are presented. Section III proposes the optimal scheduling as a linear programming problem. Section IV discusses the effectiveness of the proposed method through computational simulations. Finally, the conclusions and further works are given in section V.

II. OVERVIEWS OF THE DCMG

A. System Configuration

System configuration of the DCMG constructed in this project is shown in Fig. 1. Power resources in the DCMG are the PV, battery, EV and grid-interfacing converter (CONV). These four resources supply the electricity to the DC loads in the office building like LED lightings, refrigerators, computers and etc. The nominal voltage of common DC bus is 380 V, so that new-standard outlets and plugs are developed for this DCMG. DC bus voltage is regulated by one of the CONV, battery and EV. The converters and inverters operate with AC power from the utility grid, however, this DCMG will be able to operate in isolated situation in the future.

Different from the conventional MGs, this DCMG is prohibited to inject the surplus power to the grid. Therefore, if the PV output is larger than demand, surplus power must be absorbed by the battery and/or the EV. If both of the battery and EV cannot absorb surplus power due to some reasons (for example, battery/EV have been fully charged, surplus power is larger than the kW capacities of battery/EV, etc.), PV must be shut off.

B. Functions of EMS

Operation of the DCMG is managed by two algorithms, i.e., day-ahead operation scheduling and real-time operation.

In a day-ahead scheduling, the optimal operation schedules of all components are planned based on the forecasts of PV output and demand and EV driving schedule for every 30-minute interval in the next day. Here, the EV driving plan consists travel distance, departure time and arrival time, and is specified by the users of EV manually.

In the real-time operation, the EMS monitors the state of DCMG and selects the appropriate operation mode. Usually, the battery and EV are operated on their schedule and the converter is controlled to regulate the DC bus voltage (called scheduled operation). If the receiving power through the converter becomes less than the alert level, EMS changes operation mode from the scheduled operation to the converter lock mode, in which the converter output is fixed at the predefined constant value while the battery or EV regulates the DC-bus voltage instead of the converter. If the converter lock mode is activated, the operation schedule defined in a day-ahead scheduling is revised based on the up-to-date system condition and updated PV output forecast (called rescheduling).

III. DAY-AHEAD OPERATION SCHEDULING

A. Proposed Scheduling Method

This paper proposes a detailed algorithm for the day-ahead scheduling. Fig. 2 shows the assumed circuit model for the DCMG.

As described before, the day-ahead scheduling is based on the PV output and demand forecast data. However, the forecast data, especially the PV output forecast data may contain large errors, and as a result, the expected optimal operation might be infeasible and the CO₂ emission cannot be mitigated effectively. That is, the PV forecast data should be treated considering their possible forecast errors. Based on this prospect, this paper proposes an optimization algorithm in which the PV forecast data are recognized as not only as single time-sequential locus, but also a set of loci of PV output and demand forecast data. However, the PV output and demand forecast data. Therefore, the objective function to be minimized is the expected CO₂ emission as follows.

\[
\min f = \sum_j q_j \left( \sum_t E(t) P_{grid}^j(t) \Delta T \right)
\]

where \(E(t)\) is the CO₂ emission rate associated with the grid power at time \(t\) [kg-CO₂/kWh], \(\Delta T\) is a length of time interval [hours] (30 minutes in this study), \(P_{grid}^j(t)\) is purchasing power at time \(t\) in scenario \(j\) [kW], and \(q_j\) is occurrence
probability of scenario $j$.

Considered constraints are described in below.

i. Power Balance

Demand and supply must be balanced in all terms and scenarios.

\[
\eta_{\text{bat}} \cdot P_{\text{bat}}(t) - L_{\text{bat}}(t) + \left[ \eta_{\text{ev}} \cdot P_{\text{ev}}(t) - R_{\text{ev}}^c(t) \right] + \left[ \eta_{\text{bat}} \cdot P_{\text{bat}}(t) - \frac{P_{\text{bat}}(t)}{\eta_{\text{bat}}} - L_{\text{bat}}(t) \right] = \eta_{\text{bat}} \cdot P_{\text{bat}}(t) + L(t)
\]  

where $\eta$ are conversion efficiencies of each converters, $P_{\text{bat}}(t)$ is the receiving grid power in scenario $j$ [kW], $P_{\text{bat}}(t)$ and $P_{\text{bat}}(t)$ are the discharging/charging powers of battery [kW], $P_{\text{ev}}(t)$ is the PV output in scenario $j$ [kW], and $L(t)$ are line losses associated with each components [kW]. Subscripts identify the components and superscripts specify the considered scenario.

ii. Transition of State of Charge (SOC)

Transition of SOCs of the battery and EV are written as follows, respectively.

\[
SOC_{\text{bat}}(t + 1) = SOC_{\text{bat}}(t) + \left[ \mu_{\text{bat}} \cdot P_{\text{bat}}(t) - P_{\text{bat}}(t) \right] \Delta T
\]

\[
SOC_{\text{ev}}(t + 1) = SOC_{\text{ev}}(t) + \left[ \mu_{\text{ev}} \cdot P_{\text{ev}}(t) - P_{\text{ev}}(t) \right] \Delta T
\]

where $SOC_{\text{bat}}(t)$ and $SOC_{\text{ev}}(t)$ are state of charge of the battery and EV at the beginning of $t$-interval [kWh], $\mu_{\text{bat}}$ and $\mu_{\text{ev}}$ are charging efficiencies of the battery and EV.

iii. Daily Operation Constraints of a Battery and EV

If the battery has enough SOC at the beginning of a day, the battery has many opportunities of discharging during a day. On the other hand, further charging is limited. Therefore, initial SOC of the battery affects the flexibility of its operation. From this reason, SOCs of the battery and EV at the end of day are constrained at 50% as follows.

\[
SOC_{\text{bat}}(T^{\text{max}}) = SOC_{\text{bat}}(1) = 0.5 \cdot SOC_{\text{bat}}^{\text{max}}
\]

\[
SOC_{\text{ev}}(T^{\text{max}}) = SOC_{\text{ev}}(1) = 0.5 \cdot SOC_{\text{ev}}^{\text{max}}
\]

where $T^{\text{max}}$ represents the last time, $(T^{\text{max}} + 1)$ is the first time of day after next), $SOC_{\text{bat}}^{\text{max}}$ is maximum kWh capacity of battery [kWh] and $SOC_{\text{ev}}^{\text{max}}$ is maximum kWh capacity of EV [kWh].

iv. Capacity Constraints

\[
0 \leq P_{\text{bat}}(t) \leq P_{\text{bat}}^{\text{max}}
\]

\[
0 \leq P_{\text{ev}}(t) \leq P_{\text{ev}}^{\text{max}}
\]

v. Constraints Associated with EV Travelling

\[
P_{\text{bat}}(t) = P_{\text{ev}}(t) = 0, \text{ if the EV is not connected.}
\]

\[
SOC_{\text{bat}}(T^{\text{run}} + 1) = SOC_{\text{bat}}(T^{\text{run}}) - \eta_{\text{bat}} \cdot D
\]

\[
SOC_{\text{ev}}(T^{\text{run}}) \geq 1.1 \cdot (\eta_{\text{bat}} \cdot D)
\]

where the right hand side of each equation represents the capacity of corresponding component [kW] for each $P$ and $kW$ for each $SOC$.

vi. Approximations of Line Losses

Line loss at the grid line between CONV and DC bus ($L_{\text{grid}}(t)$) can be are written as in

\[
L_{\text{grid}}(t) = \frac{V_{\text{dc}}^2}{2 \eta_{\text{grid}}} - \left[ 2 \eta_{\text{grid}} \cdot P_{\text{grid}}(t) + \frac{V_{\text{dc}}^2}{2 \eta_{\text{grid}}} - 4 \eta_{\text{grid}} \cdot P_{\text{grid}}(t) \right]
\]

where, $V_{\text{dc}}$ is the DC bus voltage [V]. As shown in (17), the line loss is nonlinear function of the passing powers and the DC bus voltage. In order to resolve the considered optimization problem to a linear programming problem, the following approximations are introduced in the proposed algorithm.

- In actual DCMG, the DC bus voltage varies according to the voltage droop characteristics realized by the voltage-regulating component. However, in the proposed formulation, the DC bus voltage is treated as constant at 380V.

- Since the line losses are convex downward, piecewise linear functions are used to represent the line losses as shown in Fig.3. That is,

\[
L_{\text{grid}}^{(i)}(P_{\text{grid}}(t)) \leq L_{\text{grid}}(t)
\]

where $L_{\text{grid}}^{(i)}(P_{\text{grid}}(t))$ corresponds to the $i$-th linear piece [kW], function of passing power $P_{\text{grid}}(t)$.

Same approximations are applied to the other line losses, $L_{\text{bat}}(t), L_{\text{ev}}(t), L_{\text{trans}}(t)$ and $L_{\text{con}}(t)$ [kW].
B. PV Output Scenario Generation

The Japan Meteorological Agency (JMA) \[9\] forecasts the weather condition in the next day in three categories; fine (F), cloudy (C) and rainy (R). The forecasts are made for three-hour intervals (totally 8 intervals in a day). The proposed method uses 4 of 8 intervals in daytime (from 6 am to 6 pm) to forecast the PV output. PV output forecast is assumed as an average during 15 days around the target day whose weather condition is same.

In fact, the weather forecast by JMA contains error. For example, even if the forecast is F, the actual weather could be C or R. Since the JMA employs three weather conditions in forecast, the number of possible transition scenarios is \(3^4 (81)\). However, it is difficult to consider all 81 scenarios in the above optimization problem because the size of problem is too large to solve in the practical computation time. Therefore, scenarios are reduced into suitable number considering scenario distance \[10\]. Process of scenario reducing algorithm and redistribution are written as follows.

\[
(1\text{st step}) \\
 c_{kj} = \max \{P_{\text{PV}}^k(\omega_j) - P_{\text{PV}}^k(\omega_i)\}, \quad k, j = 1, \cdots, N \tag{19}
\]

\[
c_{ij}^{(l)} = \min_{i \in J} c_{kj}, l = 1, \cdots, N \tag{20}
\]

\[
z_{ij}^{(l)} = p^i \cdot c_{ij}^{(l)}, l = 1, \cdots, N \tag{21}
\]

\[
l_i \in \arg \min_{i \in J} z_{ij}^{(l)}, J^{(l)} := \{l\} \tag{22}
\]

\[
(s\text{-th step})
\]

\[
c_{ij}^{(l)} := \min_{i \in J} c_{kj}, l \notin J^{(l*-1)}, k \in J^{(l*-1)} \cup \{l\} \tag{23}
\]

\[
z_{ij}^{(l)} := \sum_{i \in J} z_{ij}^{(l-i)}, l \notin J^{(l*-1)} \tag{24}
\]

\[
l_i \in \arg \min_{i \in J} z_{ij}^{(l)}, J^{(l-i)} := J^{(l-i)} \cup \{l\} \tag{25}
\]

\[
(\text{Redistribution}) \\
\hat{q}^i = p^i + \sum_{j \notin J} z_{ij}^{(l)}, \quad \text{for each } j \notin J \tag{26}
\]

\(J_i := \{i \in J_i | j(i)\} \) and \(j(i) = \arg \min_{\omega \in \omega_j} (\omega_i, \omega_j) \) for each \(i \in J\) where \(c_{kj}\) is the distance between scenario \(k\) and \(j\), i.e., the maximum difference between PV outputs in \(k\) and \(j\) in this paper [kW] and \(z_{ij}\) is the probability distance of each scenario. Superscript represents the iteration count. \(N\) and \(n\) are the number of scenarios before and after the scenario reduction. Probability of the reduced scenario is redistributed to the remaining scenarios.

IV. CASE STUDY

A. Simulation Conditions

The effectiveness of the proposed scheduling algorithm is tested by computational simulations in which the actual demand data and the solar radiation data measured at the DCMG site for 20 days in from May to August in 2013 are used. The weather forecasts by JMA in the same days are also used in the simulations. Here, the occurrence probabilities of the weather condition scenario are shown in Table I. The average loads in weekday and holiday, shown in Fig. 4, are used as the demand forecast data. The EV runs 40 km from 6:00 AM to 3:00 PM in weekday, as scheduled.

The operation schedules obtained by the proposed algorithm with single scenario (S1), five scenarios (S5), and ten scenarios (S10) are shown in Figs. 5, 6 and 7, respectively. The actual PV outputs were larger than the forecasts through the day. The purchased powers and PV output scenarios in Figs. 5, 6, and 7 correspond to the weather condition scenario “FCCF”. The battery and EV are charged until 6:00AM since the CO2 emission rate of grid power is lower. Conversely, the battery and EV are discharged in daytime. Estimated total CO2 emissions in the day were 60.8 [kg-CO2] in S1, 61.4 [kg-CO2] in S5, and 60.9 [kg-CO2] in S10. Actually, the S1 is best in three schedules because the weather conditions assumed in the scheduling and used in the evaluation are same. The major differences among three results are \(P_{\text{pv}}\). In S1 (Fig.5), the battery is scheduled to be

![Fig. 3 Images of line loss and its piecewise approximation](image-url)
charged only when the PV output is larger than demand. In S5 (Fig. 6), the scenario whose weather condition is F from 9:00 am to 0:00 pm is included in the five considered scenarios, and as a result, the battery is scheduled to be charged in that duration by the $P_{PV}$. Therefore, for the original weather forecast, the $P_{PV}$ is smaller than the expectation, and as a result, the $P_{grid}$ and CO$_2$ emission become larger than those of S1. In S10 (Fig. 7), the scenarios whose weather conditions are F or C from 9:00 am to 0:00 pm are included in the ten considered scenarios. Therefore, the result for the original forecast becomes middle of S1 and S5.

In order to evaluate the advantages of operation scheduling considering plural scenarios, simplified real-time operation with 30-minute time step was simulated for S1, S5 and S10. In this real-time simulation, the differences between the forecast data and actual data are absorbed by the CONV firstly, and if the CONV power becomes zero, the surplus power is absorbed by modifying the operation of the battery and EV. Modification of the battery and EV would lead to deviation of the SOC from 50% at the end of day. In this case, the resultant final SOCs are used as initial SOCs in the day-ahead scheduling for the next day. Furthermore, if the surplus power is too large and the battery and EV cannot absorb, the PV is shut down.

Simulation results for one day are shown in Figs. 8, 9 and 10, as examples of the real-time operation. In S1 and S5, the

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig4.png}
\caption{Load forecast data in weekday and holiday}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig5.png}
\caption{Operation schedule by S1}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig6.png}
\caption{Operation schedule by S5}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig7.png}
\caption{Operation schedule by S10}
\end{figure}
battery and EV could not absorb the surplus power at 2:00 PM and as a result, the PV was shut off. On the other hand, operation schedule by S10 could absorb that surplus power. The resultant CO₂ emissions in this day were, 74.0 [kg-CO₂] in S1, 71.2 [kg-CO₂] in S5, and 70.0 [kg-CO₂] in S10, respectively. Since the schedule by S1 considered no forecast error, the surplus power occurred from 9:00 am to 3:00 pm due to forecast error. Therefore, the battery could not perform with schedule and the battery was fully charged at that time. An increase of CO₂ emission was caused by shutting down of PV. On the other hand, in S5, the surplus power from 9:00 am to 12:00 pm was considered, however, surplus power from 12:00 pm to 15:00 pm was not considered. Therefore, the battery could not absorb surplus power because the battery was fully charged. PV was shut off by S5, CO₂ emission was increased. In S10, EV did not discharge from 12:00 pm to 15:00 pm, because middle of scenario F and C was considered. Therefore, net surplus power was smaller than S1.

The relationship between the considered scenario number (from 1 to 10) and the total CO₂ emission is shown in Fig.11. The normalized CO₂ emissions in days with relatively large weather forecast errors and with accurate forecast are shown in Fig. 12 (the CO₂ emissions in S1 is regarded as 1). As shown in Fig. 12, if the weather forecast is accurate, the schedule with less scenarios can reduce CO₂ emissions. However, if weather forecast has errors, particularly the actual PV output is larger than the forecast, the schedule with more scenarios is better. As a result, the schedule with 9 scenarios showed the best performance in Fig. 11 and the resultant total CO₂ emission was estimated as 2200.3 [kg-CO₂] while S1 resulted in 2206.5 [kg-CO₂]. From this result, it can be said that the taking the plural forecast scenarios into consideration in scheduling process is effective to improve the performance of DCMG operation.

V. CONCLUSION

This paper proposed a day-ahead optimal scheduling method considering the PV output forecast errors as scenarios. The numerical case studies showed that the proposed scheduling can reduce the CO₂ emissions effectively.

Remaining works are verification of advantages of the proposed method based on longer observation data. Implementation of the proposed method in actual DCMG and the field-tests are also future work.

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