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Reliability-Aware Energy Scheduling for Microgrids

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Abstract: Energy scheduling plays a critical role in the safe and economical operation of the Microgrid. Several methods exist that can be leveraged to improve the cost efficiency of Microgrid operation in grid-connected mode. However, existing works overemphasize the economic benefit of Microgrid operation in grid-connected mode such that in case of sudden transition to islanded mode, the operation reliability, an important performance index in practical operation can't be guaranteed. In this paper, a two-stage scheduling scheme is proposed that takes the reliability issue into consideration by leveraging the upstream grid failure probability. Through real-world data sets based simulation evaluation, we evaluate our proposed two-stage scheduling scheme and validate its effectiveness.

Keywords: Microgrid, Advanced energy storage, Lyapunov optimization, Reliability.

1. INTRODUCTION

To coordinate the contradiction between the macrogrids strict standard for grid-connection and the massive deploy requirements of intermittent and uncontrollable renewable energy source, the concept of Microgrid is proposed in Lasseter and Paigi (2004). Microgrid is actually part of distribution network located downstream the distribution substation through a point of common coupling. Different from the macrogrid, a typical Microgrid is operated in one of the two modes: islanded mode or interconnected mode. With such design paradigm, the Microgrid is expected to increase the cost-efficiency and reliability of distribution networks, see Lasseter and Paigi (2004), Lu et al. (2013).

Effective energy scheduling schemes stay at the central of safe and economical operation of the Microgrid. Actually, there exists a large body of research work (Narayanaswamy et al. (2012), Lu et al. (2013)), involving the optimal scheduling of Microgrid or Macrogrid to achieve economical operation while guaranteeing the various physical constraints.

However, overemphasizing the importance of economic benefit of Microgrid operation in grid-connected mode may compromise the operation reliability once the upstream grid fails suddenly. Specifically, existing scheduling methods may discharge too much during the periods the electricity prices are relative "higher". Once the upstream grid fails, there may be no enough energy in the batteries such that we have to resort to backup generators and load-shedding to maintain the balance between supply and demand. This inevitably degrades the reliability of Microgrid operation. In view of this, we advocate that reserving enough energy for the possible Macrogrid failure/disturbance in grid-connected operation is especially important, which can prevent the frequent starting of fast-responding generators and/or massive load-shedding.

Actually, the implementation of such idea is hampered by several difficulties: 1) the arrival processes of load demand and renewable energy are all stochastic, can't be accurately known until their realization; 2) how much energy to be reserved depends on the upstream grid failure probability. The higher the probability is, the more energy should be reserved to combate such uncertainty. That is to say, the balance between cost-efficiency and reliability should be considered prudently.

In this paper, in order to address the above challenges, we propose an energy scheduling framework that takes into account the cost-efficiency and reliability jointly. For cost-efficiency, it consists of two points: firstly, to maximize the economic gain of renewable energy. secondly, to leverage the price diversity in electricity market. For reliability, it is expected to minimize the load loss in islanded mode. Specifically, the energy scheduling process consists of two stages: day-ahead planning and real-time scheduling. At the beginning of each day, the decision that how much electricity to purchase from day-ahead market is made to maximize the value of renewable generation, based on the statistical information of the following day's load demand, renewable energy generation, day-ahead electricity prices and expected real-time ones. It's necessary to note that for some simplifying assumptions, the original optimization problem can be decoupled into single time slot. Then at the beginning of each fine-grained time slot, renewable supply and load demand have been realized, the information of real-time prices and possibility that Microgrid loses

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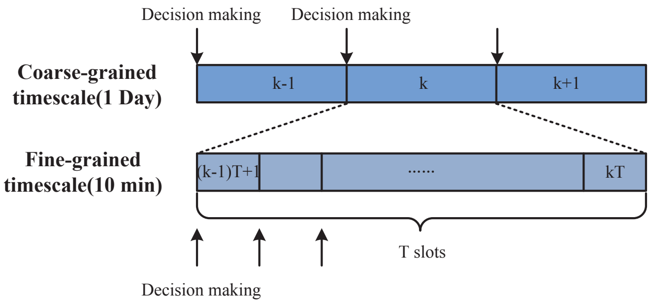

Fig. 1. Illustration of the two timescale structure.

support from upstream grid have been obtained. The real-time charging, discharging and purchasing decision have to be established. Rather than just taking advantage of the relative cheap electricity during certain fine-grained time slot at this stage as usual works done, we define a "risk cost" as the consequence of sudden supply shortage caused by upstream grid failure and advocate that the energy stored in the battery can be regarded as a reserve for the islanded operation to reduce such financial loss, thereby improving the power supply reliability. Based on Lyapunov optimization technique, an online scheduling scheme is proposed.

2. MODEL AND PROBLEM FORMULATION

2.1 System Model

In this paper, we consider the Microgrid energy scheduling problem under the framework of discrete-time model. From a long-term perspective, we divide the time into coarse-grained time slots, say days, and each coarse-grained time slot is further divided into T fine-grained time slots. The fine-grained time slot set of day k is denoted by $\mathcal{T}_k$. Each fine-grained time slot $t \in \mathcal{T}_k$ may represent 10-minutes or 5-minutes. Thus, the day k can be represented by $t \in [(k-1)T+1, kT]$, $k \in \mathbb{N}^+$, as illustrated by Fig. 1.

1) Energy Storage Model In this paper, we only consider a set of battery energy storage system like advanced lead acid batteries, and make the following assumptions: (i) energy loss only happens during the charging process, (ii) the operating cost of a Microgrid is dominated by the cost incurred by purchasing electricity from electricity market rather than by operating and maintenance cost of batteries. We denote $S(t)$ as the state of the battery energy storage system at the beginning of the t th period or at the end of $t-1$ th period. Thus the state of the battery energy storage system evolves as:

$$S(t+1) = S(t) + \eta C(t) - D(t), \tag{1}$$

where $\eta < 1$ is the efficiency factor of charging process. Besides that, the charging and discharging process are also constrained by rate limits, expressed as:

$$0 \le C(t) \le C^{\max}, 0 \le D(t) \le D^{\max}, \tag{2}$$

where $C^{\max}$ and $D^{\max}$ are the maximum energy the energy storage system can charge and discharge during each time slot respectively. Noting that the charging and discharging process can't be performed simultaneously during the same time slot for reliability consideration, it can be modeled as follows:

$$\begin{cases} C(t) > 0 \Rightarrow D(t) = 0 \\ D(t) > 0 \Rightarrow C(t) = 0. \end{cases} \tag{3}$$

We denote the capacity of the energy storage system as $S^{\max}$. At last, to prevent the situation that the battery is overdischarged to the extent that it brings about irreversible destruction to the battery, we define a threshold $S^{\min}$ based on the specification of the actual system, for example the Depth of Discharge (DoD) which determines the maximum fraction of power that can be withdrawn. It determines $S^{\min}$ according to the following equation:

$$S^{\min} = (1 - DoD) \times S^{\max}. \tag{4}$$

Thus we have:

$$S^{\min} \le S(t) \le S^{\max}. \tag{5}$$

2) Renewable Energy Model Here, we assume the renewable energy generated by renewable energy source (RES) like wind and/or solar energy, depending upon the actual composition of the Microgrid. During each time slot t, it is a random variable denoted as $E_r(t)$. Additionally, we represent the probability density function (p.d.f.) of such random variable as $f_{E_r}(e_r, t)$. Actually there exists a maximum value for $E_r(t)$, denoted as $E_r^{\max}$. So this constraint can be expressed as:

$$0 \le E_r(t) \le E_r^{\max}. \tag{6}$$

3) Load Demand Model In this paper, we will make the following assumptions for the load demands $L(t)$. (i) the load demand must be served right in time slot t; (ii) we may have the exact knowledge of the probability distribution of load demands $L(t)$, the p.d.f. of which can be denoted as $f_L(l,t)$; (iii) $L(t)$ is i.i.d over time slots, end-user's electricity consumption decision is not affected by the amount of electricity generated by RES, real-time and day-ahead electricity prices; (iv) there exits a finite constant $L^{\max}$ such that $L(t) \le L^{\max}$, $\forall t$.

4) Reliability Index For the reliability modelling, we denote the possibility that the upstream grid experiences a failure for each fine-grained time period as $p_l(t)$, *i.e.*, the possibility that Microgrid loses the support of external power source. The exact value of this possibility can be calculated by the Microgrid control center (MGCC) based on measurement of various physical quantities or obtained from historical data.

In this paper, a strong assumption that whether upstream grid fails is independent across time slots is made for simplicity, although it is not the case in practice. According to the actual operating conditions, the transition from grid-connected mode to islanded mode which is triggered by upstream grid fault events happens rarely. Thus, we can assume that $0 \le p_l(t) \le p_l^{\max} \ll 1$ and the time duration in each islanded mode would be no longer than one time slot. In islanded mode, the backup generators will start. Due to its fast-responding characteristics (1–5 minutes), compared with the time duration of each time slot, we can assume that these generators can always reach its rated power and the total amount of electricity generated is E_{dg}. Hence, the system reliability metrics, time-average expected energy not served (EENS) can be expressed as:

$$\lim_{t\to\infty} \inf \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\left\{p_l(\tau)[L(\tau) - E_r(\tau) - D(\tau) - E_{dg}]^+\right\}. \tag{7}$$

We define the "risk cost" as the penalty paid by Microgrid management entity for all the unserved load or the cost incurred by operating diesel generators (DG) as backup power supply when upstream grid failure occurs, mathematically expressed as:

$$C_{ps}[L(t) - E_r(t) - D(t) - E_{dg}]^+ + C_{pg}E_{dg}. \tag{8}$$

In the above formula, we assume the MGCC should pay C_{ps} for per unit load loss (load shedding) and C_{pg} for per unit electricity generated by DG.

5) Day-ahead Planning and Real-time Scheduling Here, we consider both the day-ahead planning and real-time scheduling according to the two-stage property of electricity market.

In this paper, we will denote the per-unit-cost of electricity from day-ahead electricity market as $P^{dh}(t)$ and real-time electricity market as $P^{rt}(t) \in [P^{rt,\min}, P^{rt,\max}]$, $t \in \mathcal{T}_k$.

For the day-ahead planning, MGCC decides how much electricity to buy from the day-ahead electricity market, denoted as $E_g^{dh}(t)$.

For the real-time scheduling, we should decide how much electricity to buy from real-time electricity market at the beginning of each fine-grained time slot, denoted by $E_g^{rt}(t)$, $t \in \mathcal{T}_k$, the action of charging and discharging after the renewable energy, demand load has been realized. Thus, in real-time period, to balance the demand and supply for the sake of Microgrid stability, we have:

$$E_g^{dh}(t)+E_g^{rt}(t) + D(t) - C(t) + E_r(t) = L(t). \tag{9}$$

As a matter of fact, constrained by the limited power exchange rate at the point of common coupling (PCC), the electricity provided by electricity market is bounded by $E_g^{\max}$, expressed as

$$E_g^{rt}(t) + E_g^{dh}(t) \le E_g^{\max}. \tag{10}$$

Finally, we assume the following conditions on system parameters:

$$E_g^{\max} - L^{\max} \ge C^{\max}. \tag{11}$$

It can be interpreted as the fact that the energy supply can always be abundant to accommodate both load demand and battery. According to assumption (11), we can get the inequality $E_g^{\max} + E_r(t) - L(t) \ge 0, \forall t$, which means the load demand can be supplied by renewable energy and Macrogrid without resorting to battery.

2.2 Problem Formulation

Given the model described above, we define the expected operating cost which is composed of the cost of electricity procurement and risk cost for a single fine-grained time slot t as follows:

$$\begin{aligned}\mathbb{E}[Cost(t)] = \mathbb{E}\{[1 - p_l(t)][E_g^{rt}(t)P^{rt}(t) + E_g^{dh}(t)P^{dh}(t)] \\ + p_l(t)\{C_{ps}[L(t) - E_r(t) - D(t) - E_{dg}]^+ \\ + C_{pg}E_{dg}\}\}.\end{aligned} \tag{12}$$

Then, we define the time average expected operating cost of a Microgrid as

$$C_{av} = \lim_{t\to\infty} \inf \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}[Cost(\tau)]. \tag{13}$$

Thus, the objective of our problem to find a policy π that determine the amount of electricity purchased from day-ahead market, *i.e.*, $E_g^{dh}(t)$, $t \in \mathcal{T}_k$; the action of charging and discharging for battery energy storage system, *i.e.*, $C(t)$ and $D(t)$; and the amount of electricity purchased from real-time market $E_g^{rt}(t)$, $t \in \mathcal{T}_k$, if necessary every fine-grained time slot, to minimize the long-term operating cost of Microgrid, subject to the constraints described above.

Our problem can be formulated as the following stochastic control problem, called **Problem One**:

$$\begin{aligned}\underset{E_g^{dh}(t),E_g^{rt}(t),C(t),D(t)}{\text{minimize:}} \quad & C_{av} = \lim_{t\to\infty} \inf \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}[Cost(\tau)] \\ \text{subject to:} \quad & (2), (3), (5), (9), (10).\end{aligned}$$

Let us denote the optimal policy as π^{opt} that chooses actions $\mathbb{A}^*(t) = \{E_g^{rt,*}(t), C^*(t), D^*(t), E_g^{dh,*}(t)\}$, $t \in \mathcal{T}_k$, $k \in \mathbb{N}^+$ to minimize the time average operating cost while guaranteeing all the constraints listed above. The optimal value under such policy can be denoted as C_{av}^*.

Actually, it's not an easy work to reach such an aggressive goal. The main reason for such difficulty can be collected as follows:

(1) The information we can get depends on the time instants at which we make decision.
(2) Time-coupling property brought about by the limited capacity constraint (5) in real-time scheduling period.
(3) The tight coupling between two stage decision variables, which means that the day-ahead energy procurement decisions impact the real-time scheduling policy and vice versa.

As a matter of fact, both the electricity tariff structure and time-dependent information prompt us to adopt a two-stage decision-making framework, *i.e.*, day-ahead planning and real-time scheduling.

3. DAY-AHEAD PLANNING

In this section, we first present the construction of day-ahead planning algorithm to utilize the renewable energy as much as possible. Besides the distribution knowledge of renewable energy and load demand, at the day-ahead planning stage we can also obtain the day-ahead electricity prices $P^{dh}(t)$ for day k and expected real-time ones $\mathbb{E}\{P^{rt}(t)\}$ through historical data. Based on these information, we should determine the quantities $E_g^{dh}(t)$, $t \in \mathcal{T}_k$.

The decision making at this stage relies on the following fact and assumption: 1) the real-time decision would not affect the day-ahead decision reversely. 2) both variable $E_r(t)$, $L(t)$ are i.i.d. across the fine-grained time slots, which means there is no correlation between two successive time slots. According to 1), we do not have the necessity to consider the action of batteries at this stage, meaning that the term $C(t)$, $D(t)$ can be ignored in Eq. (9).

Thus, the original problem can be simplified as follows:

$$\begin{aligned}\min_{E_g^{dh},E_g^{rt}}: &\liminf_{t\to\infty}\frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}\left[E_g^{rt}(\tau)P^{rt}(\tau)+E_g^{dh}(\tau)P^{dh}(\tau)\right],\\ \text{s.t.}\quad & 0\le E_g^{dh}(t)\le E_g^{\max},\\ & E_g^{dh}(t)+E_g^{rt}(t)+E_r(t)=L(t).\end{aligned}$$

Note that there exists no temporal correlation in the aforementioned optimization problem, thus such optimization problem can be further simplified as follows, denoted as **Problem Two**.

$$\begin{aligned}\underset{E_g^{dh}(t)}{\text{minimize:}}\ & \mathbb{E}\{E_g^{dh}(t)P^{dh}(t)+\\ & [L(t)-E_r(t)-E_g^{dh}(t)]^+P^{rt}(t)\}\\ \text{subject to:}\ & 0\le E_g^{dh}(t)\le E_g^{\max},\forall t.\end{aligned}$$

Here, we define an auxiliary random variable $A(t)=L(t)-E_r(t)$, with its p.d.f. denoted as $f_A(a,t)$, which measures the difference between load demand and renewable energy. In addition, we denote $\mathbb{E}\{P^{rt}(t)\}$ as $\bar{P}^{rt}(t)$ for convenience. The following lemma gives the optimal decision for the MGCC regarding to the decision variable $E_g^{dh}(t)$.

Lemma 1: *The optimal objective value for the above optimization problem is presented as:*

$$E_g^{dh,*}(t)=\begin{cases}0 & P^{dh}(t)>\bar{P}^{rt}(t)\\ \min(F_A^{-1}(1-\dfrac{P^{dh}(t)}{\bar{P}^{rt}(t)},t),E_g^{\max}) & \text{otherwise.}\end{cases}\tag{14}$$

Proof. The proof is omitted due to space limitation.

The detail of the day-ahead planning process is presented in Algorithm 1.

Algorithm 1: Day-ahead electricity purchasing algorithm

Input:
Day-ahead electricity price $P^{dh}(t)$; Expected real-time electricity prices $\bar{P}^{rt}(t)$, $t\in\mathcal{T}_k$.

Output:
The electricity purchased day-ahead $E_g^{dh}(t)$.

1: **for** $t:=(k-1)T+1$ to kT **do**
2: calculate how much electricity to purchase from day-ahead market, *i.e.*, $E_g^{dh}(t)$ according to Eq. (14).
3: **end for**

4. REAL-TIME SCHEDULING

At real-time scheduling period, renewable supply and load demand have been realized, the information of real-time electricity prices and possibility that Microgrid loses support from upstream grid have also been obtained. The main optimization objective for this stage is to improve system reliability and economic benefits.

Actually, the optimization problem at this stage has the same form with that defined in **Problem One**, despite that $E_g^{dh}(t)$ has been determined for each time period of the following day.

Traditionally, this issue can be settled by the well known dynamic programming or Markov decision process. However, both of them require statistics of all system input process, besides that it also suffers from the notorious "curse of dimensionality" problem. However, the recently developed Lyapunov optimization method, (Neely et al. (2010), Yao et al. (2012), Guo et al. (2012)) shows that it perfectly fits the scheduling problem for time-varying system, without the need for any future knowledge of input process, in spite of the fact that it is originally designed for dynamic control of queueing system in wireless system (Neely et al. (2005)).

Our real-time scheduling algorithm design is based on the Lyapunov drift method. By taking into account the operating cost term, we can obtain a stable control policy which can get a tradeoff between battery capacity and operating cost. Before going on to construct the Lyapunov function, we first define

$$F(D(t),t)=p_l(t)C_{ps}[L(t)-E_r(t)-D(t)-E_{dg}]^+.\tag{15}$$

Denote its maximum and minimum derivative with respect to $D(t)$ as $\beta^{\max},\beta^{\min}$. Then we introduce a virtual queue as

$$X(t)=S(t)-V(P^{rt,\max}+\beta^{\max})-D^{\max}-S^{\min},\tag{16}$$

which tracks the state of battery energy storage system. In Eq. (16), the parameter V is defined as positive. Moreover, by selecting the maximum value of V properly, denoted as $V^{\max}$, we can always ensure the constraint (5), *i.e.*, the battery capacity constraint. Note that $S(t)$ is the actual state of battery energy storage system, whose dynamics evolves according to Eq. (1). Thus, it can be easy to derive the dynamics of $X(t)$ as follows:

$$X(t+1)=X(t)+\eta C(t)-D(t).\tag{17}$$

With the virtual queue introduced, we now define our Lyapunov function, which is the scalar measure of "system congestion" as follows:

$$W(t)=\frac{1}{2}X^2(t).\tag{18}$$

The Lyapunov drift $\Delta(t)$ is defined as the conditional expected change of Lyapunov function between two neighboring time slots, mathematically represented as follows:

$$\Delta(t)=\mathbb{E}[W(t+1)-W(t)\,|X(t)].\tag{19}$$

Thus, the "drift-plus-penalty" term can be obtained by adding a penalty term to the above equation with a parameter V defined earlier to adjust the emphasis given to either battery capacity (system congestion) or operating cost. Here the penalty term is defined as the expected operating cost during a fine-grained time slot conditioned on $X(t)$, *i.e.*, $\mathbb{E}\{Cost(t)\,|X(t)\}$. So we can write the "drift-plus-penalty" term as:

$$\Delta(t)+V*\mathbb{E}\{Cost(t)\,|X(t)\}.\tag{20}$$

Next, we will show that the "drift-plus-penalty" term has an upper bound in **Lemma 2**, which is critical for our control algorithm design.

Lemma 2: *Define $V>0$, under all feasible control decisions, which satisfy the constraints of **Problem One**, the "drift-plus-penalty" term is bounded as follows:*

$$\begin{aligned}&\Delta(t)+V*\mathbb{E}\{Cost(t)\,|X(t)\}\\ &\le B_1+\mathbb{E}\{X(t)[\eta C(t)-D(t)]\,|X(t)\}\\ &+V*\mathbb{E}\{Cost(t)\,|X(t)\}.\end{aligned}\tag{21}$$

where $B_1=\frac{1}{2}\max[(\eta C^{\max})^2,(D^{\max})^2]$.

Proof. The proof is omitted due to space limitation.

Based on the result delivered by lemma 2 and the framework of Lyapunov optimization method, we will always choose control actions that minimize the R.H.S. of inequality (21), *i.e.*, the upper bound of the "drift-plus-penalty" term. To be specific, It's the term

$$\mathbb{E}\{X(t)[\eta C(t) - D(t)]\,|X(t)\} + V * \mathbb{E}\{Cost(t)\,|X(t)\}.$$

Thus, at the beginning of each fine-grained time slot, the following **Problem Three** should be solved:

$$\begin{aligned}\text{min:}\ & \mathbb{E}\{X(t)[\eta C(t) - D(t)] + V * \{[1 - p_l(t)]E_g^{rt}(t)P^{rt}(t) \\ & + p_l(t)C_{ps}[L(t) - E_r(t) - D(t) - E_{dg}]^+\}\,|X(t)\} \\ \text{s.t.}\ & (2), (3), (9), (10).\end{aligned}$$

Actually, the solution of the above-mentioned optimization problem can be presented in a analytical form. The main principle can be elaborated as follows: first we should decompose **Problem Three** into two optimization subproblems since only one of $C(t)$ and $D(t)$ can be nonzero. Then the two sub-problems are solved separately. Finally, the solution with lower optimal objective value is selected as the control policy.

Define

$$\begin{aligned}G(C(t), D(t)) = {} & X(t)[\eta C(t) - D(t)] \\ & + V * \{[1 - p_l(t)]P^{rt}(t)[L(t) \\ & - E_r(t) + C(t) - D(t) - E_g^{dh,*}(t)] \\ & + p_l(t)C_{ps}[L(t) - E_r(t) - D(t) - E_{dg}]^+\}.\end{aligned}$$

For the sub-problem that sets $C(t) = 0$, we can obtain $D(t)$'s constraint as

$$0 \le D(t) \le D_t^{\max} := \min\{L(t) - E_r(t) - E_g^{dh,*}(t), D^{\max}\}.$$

In this sub-problem, the optimal value for $D(t)$ depends on $D(t)$'s coefficient in the objective function. Specifically, when

$$X(t) < -V[1 - p_l(t)]P^{rt}(t) - Vp_l(t)C_{ps}.$$

satisfies, defined as Condition I, we should choose the minimum value for $D(t)$. Conversely, when

$$X(t) > -V[1 - p_l(t)]P^{rt}(t) - Vp_l(t)C_{ps}.$$

satisfies, defined as Condition II, we should choose the maximum value for $D(t)$.

Similarly, for sub-problem that sets $D(t) = 0$, $C(t)$'s constraint can be presented as

$$C_t^{\min} := \max\{0, E_r(t) - L(t) + E_g^{dh,*}(t)\} \le C(t) \le C^{\max}.$$

In this sub-problem, the optimal value for $C(t)$ depends on $C(t)$'s coefficient in the objective function. Specifically, when

$$X(t) < \frac{-V[1 - p_l(t)]P^{rt}(t)}{\eta}.$$

satisfies, defined as Condition III, we should choose the maximum value for $C(t)$. Conversely, when

$$X(t) > \frac{-V[1 - p_l(t)]P^{rt}(t)}{\eta}.$$

satisfies, defined as Condition IV, we should choose the minimum value for $C(t)$.

According to the combination of above conditions, we can separate the feasible range of $X(t)$ into several parts. For each part, the optimal objective values of the two subproblems can be easily compared, thus providing the optimal control policy. The detail of the real-time scheduling rule is elaborated in Algorithm 2.

5. PERFORMANCE ANALYSIS

After presenting the above two algorithms, in this section we will present the performance bound.

Theorem 1: *Define the maximum value of V, i.e., $V^{\max}$ as $\frac{S^{\max} - S^{\min} - D^{\max} - \eta C^{\max}}{\beta^{\max} - \beta^{\min} + P^{rt,\max} - P^{rt,\min}}$, and suppose the initial battery energy level $S(0)$ satisfies $S^{\min} \le S(0) \le S^{\max}$. Then the algorithms 1 and 2 can provide the following property regarding to the time-average cost.*

(1) The battery energy level $S(t)$, $\forall t \in \mathbb{Z}^+$, satisfies the condition: $S^{\min} \le S(t) \le S^{\max}$.
(2) All control decisions of the above algorithms are feasible.
(3) The time-average cost incurred by our algorithms is within bound B_2/V of the optimal objective value C_{av}^*.

Proof. The proof is omitted due to space limitation.

6. SIMULATION EVALUATION

6.1 Experiments Setup

For the simulation scene considered here, real-world traces and system configuration can be stated as follows: for the renewable energy supply, we obtain the related data of a wind farm with the rated capacity 30MW, from the Western Wind Resource Dataset, then rescale it to the order of a typical Microgrid. The power demand for each time period is assumed to be uniformly distributed in [5.00MWh, 5.33MWh] during time period [8AM, 10PM], uniformly distributed in [4.66MWh, 5.00MWh] during time period [10PM, 8AM]. In real time, the electricity prices is selected from the interval of [67$/MWh, 124$/MWh] in a uniform way. In day-ahead time, the electricity prices are set to be constant, namely 80$/MWh. For the variable $p_l(t)$, it's assumed to be a constant 1/1000 for most of the time

Algorithm 2: Real-time electricity scheduling algorithm

Input:
Real-time electricity price $P^{rt}(t)$; The probability that Macrogrid fails $p_l(t)$; Load demand $L(t)$; Renewable energy generation $E_r(t)$;
Output:
Charging decision $C(t)$; Discharging decision $D(t)$; Real-time electricity purchasing $E_g^{rt}(t)$;

if Condition I & Condition III hold **then**
  $\{C(t), D(t)\} = \{C^{\max}, 0\}$
else if Condition II & Condition III hold **then**
  $\{C(t), D(t)\} = \arg\min\{G(0, D_t^{\max}), G(C^{\max}, 0)\}$
else if Condition I & Condition IV hold **then**
  $\{C(t), D(t)\} = \{0, 0\}$
else
  $\{C(t), D(t)\} = \{0, D_t^{\max}\}$
end if
Purchase real-time balancing electricity $E_g^{rt}(t)$ according to Eq. (9);
Update the queues using Eq. (1) and (17).

Table 1. The comparison among time average operating cost of different schemes.

Scheme	Time average operating cost ($)
Scheme *I*	481.832
Scheme *II*	408.142
Scheme *III*	408.146

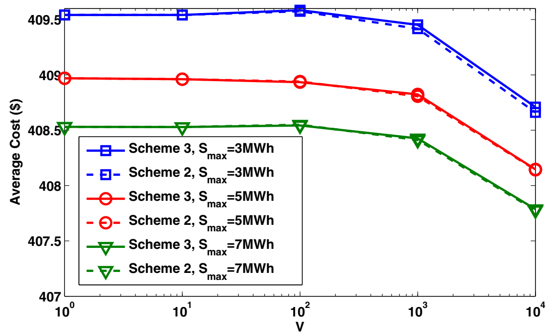

Fig. 2. Average purchasing cost with different setting of $V = \{1, 10, 100, 1000, 10000\}$

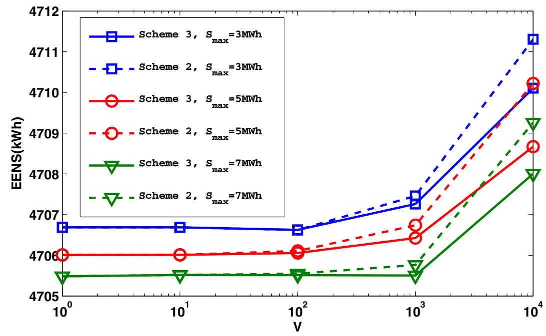

Fig. 3. EENS with different setting of V

slot, with the others 9/10. For system configuration, the capacity of the battery system is set to be 5MWh, which is a typical size for a campus-wide Microgrid. At the same time, we set $C^{\max}$ and $D^{\max}$ as 666kWh/slot. For the parameter DoD and η, we set it as 0.8 and 0.9 respectively, thus $S^{\min} = 1$MWh. The parameter $E_g^{\max}$ is set to be 8MWh/slot. At last, the parameters C_{ps} and C_{pg} are set as 0.3\$/kWh.

6.2 Scheduling Schemes for Comparison

We compare three schemes in our simulation. (i) Scheme I: the scheme that doesn't schedule the charging and discharging actions at the real-time period; (ii) Scheme II: the scheme that doesn't consider the reliability issue; (iii) Scheme III: the two-stage scheme proposed in our paper.

6.3 Results and Analysis

Note that the time period we consider is a whole season. Generally speaking, this time duration consists of 90 days. For the situation that every fine-grained time slot denotes 10 minutes, the total number of slots is 12960.

First, we compare time average operating cost achieved by Scheme I with that achieved by Scheme II and III. For Scheme II and III, we set the parameter V to be 10000. As depicted by Tab. 1, a significant cost reduction, nearly 73\$ can be achieved by scheduling charging and discharging actions.

Second, how the performance of scheme II and III depends upon different setting of control parameter V is investigated. For different $V = \{1, 10, 100, 1000, 10000\}$, how time average operating cost changes is plotted in Fig. 2. As it can be seen, the time average procurement cost decreases with time. The larger V is, the more cost reduction we can obtain. This finding just confirms the fact that whether more emphasis is put on cost depends upon control parameter V. Moreover, under the condition that $S^{\max}$ and V are fixed, the time average procurement cost of Scheme II is slightly lower than that of scheme III, for the reason that enhancing the reliability of Microgrid sacrifices the economic performance.

Third, for the reliability issue, we examine how much performance improvement can be achieved by Scheme III compared with Scheme II. From Fig. 3, we can observe that as V increases, EENS of Scheme III is much smaller than that of Scheme II, which is one of the performance metrics that characterizes the reliability of Microgrid operation. With the results provided by Fig. 2 and Fig. 3 together, we can conclude that Scheme III obtain a much greater performance improvement in reliability at the cost of a much less performance degradation in economy.

7. CONCLUSION

In this paper, we propose an energy scheduling framework for Microgrids that jointly considers the reliability and economy issue. The framework incorporates two parts: day-ahead planning and real-time scheduling. For day-ahead planning, we aim to exploit renewable energy potential; for real-time scheduling, we aim to promote the reliability of Microgrid operation while taking advantage of the price diversity in electricity market. Through simulation evaluation, we demonstrate the effectiveness of our approach. In the future work, we shall investigate how the flexible loads can be utilized to further improve the performance.

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