Leaky Bucket-Inspired Power Output Smoothing with Load-Adaptive Algorithm

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Abstract—The renewables will constitute an important part of the future smart grid. As a result, the growing portion of renewable generation in the power grid will bring challenges to the operations of the power grid because of the fluctuation and intermittency properties of renewables. In order to make the operations of power grid stable and reliable, the power outputs from renewable energy sources must be smoothed. In this paper, we propose a scheme inspired from the idea of the leaky bucket mechanism for smoothing the power output from a renewable energy system. In our proposed method, the settings of energy storage size and power output level have significant effects on the system performance and thus needs to be determined. An optimization framework is thus proposed for storage and power output planning of the renewable energy system. To operate our proposed scheme practically, a load-adaptive power smoothing algorithm is devised aiming to match the power output level with the actual load in the grid. Our simulation studies show that the proposed algorithm can reduce the operation cost comparing to other algorithms and maintain high renewable energy utilization.

I. INTRODUCTION

Accelerated by the greenhouse gas emissions caused by the utilization of fossil fuels, global warming becomes one of the significant problems in the 21st century. The needs of reducing greenhouse gas emissions draw the attentions of governments and societies to environmentally-friendly and sustainable energy sources. In recent years, the renewables (such as solar and wind) have gained increasing popularity and the involved infrastructure investment has increased substantially. For example, the installed capacity of wind power in the United States (U.S.) contributed 4.44% of total electrical energy in 2014, and it has been expected to reach 20% by 2030 [1]. There is an emerging trend that the utilization of renewables will significantly increase in the next-generation smart grid.

However, the development of renewable generation poses many challenges [2]. The growing renewable generation may jeopardize the smooth operation of utility grid due to the fluctuation and intermittency of renewables. Moreover, the renewable generated power is hard to predict. The uncertainty induced by the renewable power supply also brings difficulty to the operations of power grid.

With the challenges mentioned above, research on the integration of renewable generation gains popularity in recent years. Several methods have been proposed to help stabilize the operations of power grid with renewable generation, such as demand response [3], [4], smart charging of electric vehicles [5], [6], and optimal scheduling for power network with renewable generation [1]. Most of the existing work assumes that the renewable generated power can be accurately predicted. Nevertheless, based on the current technologies, such prediction still suffer from certain short-term errors, getting worse in the long term [7]. The integration of renewables in the grid becomes a tough problem since both the power supply and demand possess stochastic properties. A smooth power supply profile is very important and highly preferable because it can reduce the uncertainty of power supply and thus increase the reliability of the power grid. As a result, it is fundamental for smoothing the power output from a renewable energy system before it is injected to the utility grid.

The key to implement power output smoothing for a renewable energy system lies in how to regulate the renewable generation with stochastic properties. In this work, we propose a power output smoothing scheme inspired from the leaky bucket mechanism for constant load. Suppose that a renewable source is attached with storage constituting a renewable energy system. Some power distribution architectures, such as [8], require a constant power supply. With our scheme, the renewable energy system can be controlled as a constant power source to serve the grid at a pre-defined power output level and it is suitable for critical loads, which requires smooth power supply for operation. In the design, we need to configure the energy storage size and the power output level, which are critical to the overall system performance. Some of the previous work that focuses on storage sizing does not consider the power output level of the renewable energy system [9], [10]. In fact, the energy storage size and the power output level should be jointly determined since they influence the system performance simultaneously. In this work, an optimization framework is proposed to solve this storage and power output planning problem.

The power output smoothing scheme provides a constant power output, making the renewable generation a reliable power source for the grid. However, the load demands may vary with time. To serve the time-varying loads, most of the previous work applies the optimization techniques to control
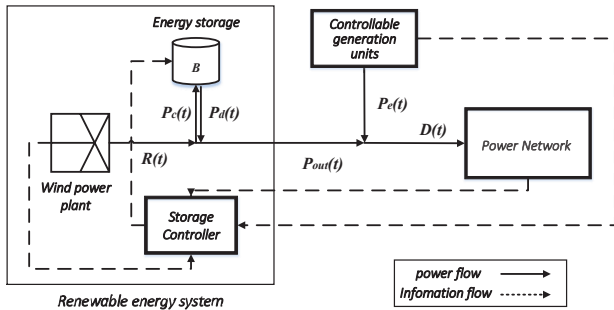
Fig. 1. Architecture for the power grid.

or schedule the renewable generated power, which are time-consuming and need prediction information [1], [11]. Some previous work using heuristic algorithm to solve this problem mostly focuses on a single perspective, such as, operation cost reduction [12]. In this work, we propose a heuristic load-adaptive power smoothing algorithm to adaptively change the power output level to meet the time-varying loads by jointly considering the actual load demands, the current renewable generation, the state of charge (SOC) of energy storage, and the electricity price. By communicating with other entities in the grid, the algorithm can reduce operation cost and enhance the renewable energy utilization.

To summarize, the contributions of this paper are given as follows:

- We propose a power output smoothing scheme to make the renewable energy system a reliable power source for the grid;
- An optimization framework is devised for energy storage and power output planning for the renewable energy system. Convex relaxation is adopted to transform the original optimization problem into a solvable mixed-integer linear program (MILP).
- A load-adaptive power smoothing algorithm is designed to reduce operation cost and enhance renewable energy utilization.

The rest of this paper is organized as follows. The system model is introduced in Section II. Section III introduces the power output smoothing scheme, in which the energy storage size and power output reference are determined through optimization. A load-adaptive power smoothing algorithm is proposed to adapt to the demand variation in Section IV. The simulation results of the proposed algorithm are examined in Section V and the paper is concluded in Section VI.

II. System Model

Consider a renewable energy system connecting to a power network, as shown in Fig. 1, indicating the power and information flows. Consider that the time horizon is divided into slots, each of which lasts for Δt minutes. The total operation time has duration of T time slots, which is indexed by $t \in \{1, 2, ..., T\}$. All grid operations can only be changed at the boundaries of the time slots. We model the total demand in

the power network, as the network load, which requires power supply from the renewable energy system, with equivalent load of $D(t)$ kW. It should be noted that $D(t)$ is not a single load but the equivalent aggregated load of the power network. The renewable energy system includes a wind power plant, an energy storage, and a storage controller. The renewable generated power at Time t is represented by $R(t)$ kW. The energy storage has size of B kWh where $B > 0$ and its construction cost is c_e dollars/kWh. T_L denotes the total lifetime of the energy storage. It gets charged and discharged at $P_c(t) \leq \overline{P}_c(t)$ and $P_d(t) \leq \overline{P}_d(t)$, respectively, where $\overline{P}_c(t)$ and $\overline{P}_d(t)$ are the maximum charging and discharging powers in kW. The charging and discharging efficiencies are defined as $0 < \eta < 1$ and $0 < \beta < 1$, respectively. The state of charge (SOC) of the energy storage is represented by $S(t)$ kWh. The storage controller controls the charging or discharging of the energy storage to change the power output. The actual power output from renewable energy system, $P_{out}(t)$ kW, is given by:

$$P_{out}(t) = R(t) - P_c(t) + P_d(t). \tag{1}$$

Suppose that the renewable energy system is utilized to serve the network load $D(t)$. To meet the network load demand, the other generation units in the smart grid are required to compensate the discrepancy by injecting power of $P_e(t)$ kW satisfying $P_e(t) \geq 0$, such that

$$P_{out}(t) + P_e(t) = D(t). \tag{2}$$

If $P_{out}(t)$ is larger than $D(t)$, $R(t)$ can be curtailed by the wind power plant to maintain the contracted power output. The unit cost of buying electricity from the controllable generation unit is denoted as $p(t)$ dollars/kW.

III. Power Output Smoothing for Constant Load

In this Section, we assume that the network load is constant. The renewable energy system makes a contract with the power grid and acts as a constant power source to serve the network load. The network load $D(t)$ kW maintains at the level supported by the contracted power output C kW, such that the renewable energy system can provide a good power output reference for the network load. We will relax this constant network load assumption in Section IV. We design a power output smoothing scheme for the renewable energy system. The principle of the power output smoothing is firstly introduced and then an optimization problem for determining the optimal storage size and power output reference is discussed.

A. Design Principle

The key to implement power output smoothing lies in how to regulate the power sources with stochastic properties. With energy storage, the renewable energy system has more capabilities to control the power output. A scheme to control the energy storage is thus required in order to smooth the power output for practical utilization. To find our solution, we find that the stochastic power sources share some similarities with the stochastic traffic sources. In fact, a mechanism to smooth
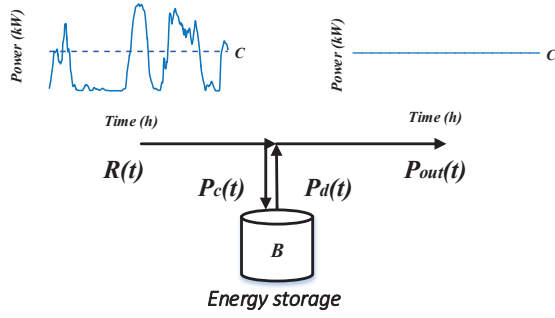
Fig. 2. Power output smoothing scheme.

Algorithm 1 Power output smoothing scheme

Input: Real-time data for renewable generated power $R(t)$, storage SOC $S(t)$, storage size B, $\overline{P}_c(t)$, $\overline{P}_d(t)$.

Output: $P_c(t)$, $P_d(t)$.

1: **for** each time slot Δt **do**
2:     Compute the charging demand $G_c(t) = \max\{R(t) - C, 0\}$.
3:     Compute the discharging demand $G_d(t) = \max\{C - R(t), 0\}$.
4:     Compute the maximum charging rate before battery is full at the end of this time slot $M_c(t) = \frac{B - S(t)}{\eta \Delta t}$.
5:     Compute the maximum discharging rate before battery is empty at the end of time slot $M_d(t) = \frac{S(t)\beta}{\Delta t}$.
6:     Compute $P_c(t) = \min\{G_c(t), M_c(t), \overline{P}_c(t)\}$.
7:     Compute $P_d(t) = \min\{G_d(t), M_d(t), \overline{P}_d(t)\}$.
8:     Update $S(t+1) = S(t) + \eta P_c(t)\Delta t - \frac{P_d(t)}{\beta}\Delta t$.
9: **Return** $P_c(t)$, $P_d(t)$.
10: **end for**

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the stochastic traffic sources, called leaky bucket mechanism, has been proposed in [13] and showed its effectiveness in traffic shaping for stochastic traffic sources [14], [15]. A scheme that is inspired from the leaky bucket mechanism can be applied for smoothing the power output from the renewable energy system. In our scheme, the energy management of the energy storage can be considered as the way how the leaky bucket handles the fluid. We define C as the power output reference for the renewable energy system in kW. The renewable energy system thus serves the network load with constant power $C = D(t)$ kW. The energy storage is controlled to equalize $P_{out}(t)$ and C in case of power imbalance, as shown in Fig. 2.

An algorithm to implement the power output smoothing scheme is devised in Algorithm 1. In step 2–3, the charging and discharging demand are computed in order to equalize $P_{out}(t)$ and C, respectively. In step 4–5, the maximum charging and discharging rate considering the SOC constraints are computed. In step 6–7, P_c and P_d are computed by jointly considering the charging and discharging demands, the SOC constraints, and the charging and discharging bounds. Our algorithm aims to maintain the power output of renewable energy system constant, so as to meet the needs of the network load with a flat smooth power supply profile.

It should be noted that the proposed power output smoothing scheme is not a simple extension of the leaky bucket mechanism. In fact, power cannot be directly injected to the energy storage as the way that the fluid flows into the leaky bucket. This increases the power losses substantially because of the charging and discharging losses of the energy storage. In our scheme, as shown in Fig. 2, the energy storage only compensates for the power imbalance between $P_{out}(t)$ and C. Moreover, we also need to consider the SOC constraints, the charging and discharging bounds, and charging and discharging efficiencies in our power output smoothing scheme.

For the proposed scheme, the energy storage size B kWh and the power output reference C kW have great influences on the system performance. Thus, there is a need to properly configure their values. To do this, we formulate the storage and power output planning problem to determine their optimal values.

B. Storage and Power Output Planning Problem

Our objective is to provide the power supply with higher power output reference, leading to higher renewable energy utilization and higher contract revenue. Meanwhile, we try to avoid power shortage and constrain the energy storage size. The objective function should capture the storage construction cost, operation cost, and the revenue made from the renewable energy system. The electricity cost stemmed from the controllable generation unit C_g dollars is given by:

$$C_g = \sum_{t=0}^{T} P_e(t)p(t)\Delta t = \sum_{t=0}^{T} [C - P_{out}(t)]^+ p(t)\Delta t, \quad (3)$$

where $[x]^+$ means $\max\{x, 0\}$.

The construction cost for energy storage C_e dollars is represented by:

$$C_e = c_e B \frac{T}{T_L}. \quad (4)$$

It describes the averaged construction cost of the energy storage in the operation period of T time slots [16]. For simplicity, the capacity fade of energy storage is ignored in our model since the capacity fade is not significant during the storage lifetime [17].

The contract revenue is given as:

$$R_c = r_c C \frac{T}{T_a}, \quad (5)$$

where r_c dollars/kW is the annual contract revenue for each unit of power supply and T_a is the duration of the contract period in time slots.

Hence, the objective function f can be expressed as:

$$f = C_g + C_e - R_c. \quad (6)$$

The charging and discharging powers of energy storage follow the design principles introduced in Section III-A. Note that the energy storage is controlled to equalize $P_{out}(t)$ and C in case of power imbalance, considering the charging and discharging bounds $\overline{P}_c(t)$ and $\overline{P}_d(t)$, and the SOC constraints.

The charging power $P_c(t)$ kW is thus formulated as:

$$P_c(t) = \min\{\max\{R(t) - C, 0\}, \frac{B - S(t)}{\eta \Delta t}, \overline{P}_c(t)\}, \quad (7)$$

where $\max\{R(t) - C, 0\}$ is the amount of excessive power in kW, $\frac{B - S(t)}{\eta \Delta t}$ is the maximum charging rate before battery is full at the end of time slot, and $\overline{P}_c(t)$ gives the charging bound.

Similarly, the discharging power $P_d(t)$ kW is given by:

$$P_d(t) = \min\{\max\{C - R(t), 0\}, \frac{S(t)\beta}{\Delta t}, \overline{P}_d(t)\}, \quad (8)$$

where $\max\{C - R(t), 0\}$ is the amount of power shortage, $\frac{S(t)\beta}{\Delta t}$ is the maximum discharging rate before battery is empty at the end of time slot, and $\overline{P}_d(t)$ gives the discharging bound.

Since the charging and discharging of the energy storage cannot happen simultaneously, we have:

$$P_d(t) \cdot P_c(t) = 0. \quad (9)$$

The evolution of SOC through Time t is denoted as:

$$S(t+1) = S(t) + \eta P_c(t)\Delta t - \frac{P_d(t)}{\beta}\Delta t, \quad (10)$$

where $S(0)$ is the initial SOC. Furthermore, the storage SOC is bounded by the energy storage size, which is as follows:

$$0 \le S(t) \le B. \quad (11)$$

The power output reference C kW should not exceed the maximum contracted power output $\overline{C}$ kW. This means that:

$$0 \le C \le \overline{C}. \quad (12)$$

Therefore, the overall optimization problem for storage and power output planning is given as:

$$\begin{aligned} \underset{B,C}{\text{minimize}} \quad & f \\ \text{subject to} \quad & (7)\text{--}(12). \end{aligned} \quad (13)$$

Solving (13) gives the optimal B and C for storage and power output planning. Due to (7), (8), and (9), the problem is non-convex and cannot be solved easily.

C. Problem Relaxation

Here, we show that Problem (13) can be relaxed to form a convex problem. To do this, we transform Constraint (7) into:

$$\begin{cases} 0 \le P_c(t) \le a_0 \overline{P}_c(t) & (14) \\ 0 \le P_c(t) \le \frac{B - S(t)}{\eta \Delta t} & (15) \\ 0 \le P_c(t) \le R(t). & (16) \end{cases}$$

Constraint (8) can also be transformed into:

$$\begin{cases} 0 \le P_d(t) \le a_1 \overline{P}_d(t) & (17) \\ 0 \le P_d(t) \le \frac{S(t)\beta}{\Delta t} & (18) \\ 0 \le P_d(t) \le C. & (19) \end{cases}$$

Note that a_0 and a_1 need to satisfy:

$$a_0 + a_1 = 1, \ a_0, a_1 \in \mathcal{N} \quad (20)$$

In fact, (14)–(20) are convex and are sufficient conditions for (7), (8), and (9). Then, we have a relaxed problem:

$$\begin{aligned} \underset{B,C,P_c(t),P_d(t)}{\text{minimize}} \quad & f \\ \text{subject to} \quad & (10)\text{--}(12), (14)\text{--}(20). \end{aligned} \quad (21)$$

Theorem 1. *Suppose that the cost induced from the controllable generation unit $p(t)$ is constant. The optimal solutions for B and C in (21) are these of (13).*

Proof. It is easy to see that the feasible region of Problem (13) is a subset of the feasible region of Problem (21). Comparing the storage charging and discharging constraints (7), (8), and (9) in (13) with (14)–(20) in (21), we divide the storage charging and discharging constraints (14)–(20) in Problem (21) into four cases: (i) $0 \le P_c(t) < \max\{R(t) - C, 0\}$ and $P_d(t) = 0$; (ii) $\max\{R(t) - C, 0\} < P_c(t) \le R(t)$ and $P_d(t) = 0$; (iii) $P_c(t) = 0$ and $0 \le P_d(t) < \max\{C - R(t), 0\}$; and (iv) $P_c(t) = 0$ and $\max\{C - R(t), 0\} < P_d(t) \le C$.

Compared with (7), (8), and (9), the above four cases correspond to the states of the energy storage (i) under-charging; (ii) over-charging; (iii) under-discharging; and (iv) over-discharging, respectively. We can conclude from (3) and (6) that f cannot be reduced by adopting (i) and (iv) since (i) and (iv) only result in a smaller $S(t)$ without reducing C_g. Given that $p(t)$ is a constant, we can conclude from (3) and (6) that f cannot be reduced by adopting (ii) and (iii) since C_g cannot be reduced by curtailing current power output and reserving energy for future use. Therefore, by deriving C_g and $S(t)$ based on $P_c(t)$ and $P_d(t)$, it can be proved that, for all the four situations, given B and C, Problem (13) always achieves a smaller or the same value of f than Problem (21). Since the feasible region of Problem (13) is a subset of the feasible region of Problem (21), coupled with the above results, we can conclude that, solving Problem (13) for optimal B and C is equal to solving Problem (21) for optimal B and C. Thus, the optimal solutions for B and C in Problem (21) is also optimal for Problem (13). ∎

With this theorem, we can obtain the solution of the original problem (13) by solving the relaxed problem (21), which is an MILP.

IV. LOAD-ADAPTIVE POWER SMOOTHING ALGORITHM

The proposed power output smoothing scheme is ideal for its constant power output reference C kW. In real grid operations, the network load $D(t)$ kW that the renewable energy system serves may vary around the power output reference C kW with time. In this section, a load-adaptive power smoothing algorithm is developed to alter the power output reference to meet the load variations by taking the network load, current renewable generation, and electricity price into account. Because $D(t)$ changes with time, the power output reference also needs changing to adapt to the load demand.

The time-varying power output reference is thus denoted as $C(t)$ kW, which is the dynamic power output reference C kW with time. By employing the advanced grid communication facilities, the network load demand $D(t)$ kW and electricity price $p(t)$ dollars/kW can be updated and made available at the renewable energy system. We further show that, by jointly considering the above information, the operation cost can be reduced and the renewable utilization can be improved.

The pseudocode of the algorithm is shown in Algorithm 2. It iterates at the beginning of each time slot and each iteration consists of two parts: determining $C(t)$ in Steps 2–3 and equalizing $P_{out}(t)$ and $C(t)$ in Steps 4–5. In Step 2, three indicators includes SOC indicator M_{SOC}, renewable generation indicator M_{RG}, and price indicator M_p are defined and calculated to measure the grid information. We define the threshold for the storage SOC as S_{th} kWh. The SOC indicator M_{SOC} is defined to measure the extent that the SOC is below the threshold:

$$M_{SOC} = \frac{[S_{th} - S(t)]^+}{S_{th}}. \tag{22}$$

The renewable generation indicator M_{RG} is defined to measure the current level of renewable generated power:

$$M_{RG} = \frac{R_{max} - R(t)}{R_{max}}, \tag{23}$$

where R_{max} denotes the maximum renewable generated power. The price indicator M_p is defined to measure the current electricity price:

$$M_p = \frac{p_{max} - p(t)}{p_{max} - p_{min}}, \tag{24}$$

where p_{max} and p_{min} denote the highest and lowest electricity prices, respectively. M_{SOC}, M_{RG}, and M_p are then computed based on $S(t)$, $R(t)$, and $p(t)$. In Step 3, $C(t)$ is determined by jointly considering the above indicators:

$$C(t) = D(t)(1 - M_p(\alpha M_{SOC} + \mu M_{RG} M_{SOC})). \tag{25}$$

Intuitively, if the current electricity price is low, which means that M_p approaches to one, $C(t)$ is curtailed so that the system can save enough energy for the situation when the electricity price goes high. In this way, the system can save the operation cost. The curtailment level is determined by jointly considering the renewable generation indicator and the SOC indicator, where α and μ are curtailment coefficients. When the SOC is above S_{th} and the current renewable generated power is high, the curtailment vanishes so that the algorithm can maintain high renewable generation utilization. Steps 4–5 implement the power output smoothing scheme as (7) and (8) to determine the $P_c(t)$ and $P_d(t)$, where C is replaced by $C(t)$:

$$P_c(t) = \min\{\max\{R(t) - C(t), 0\}, \frac{B - S(t)}{\eta \Delta t}, \overline{P}_c(t)\} \tag{26}$$

$$P_d(t) = \min\{\max\{C(t) - R(t), 0\}, \frac{S(t)\beta}{\Delta t}, \overline{P}_d(t)\}. \tag{27}$$

The storage SOC is updated (Step 6). $P_c(t)$ and $P_d(t)$ are returned as the control signals to control the energy storage (Step 7).

Algorithm 2 Load-adaptive power smoothing algorithm
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Input: Real-time data for renewable generated power $R(t)$, the network load demand $D(t)$, storage SOC $S(t)$, electricity price $p(t)$, storage size B, $\overline{P}_c(t)$, $\overline{P}_d(t)$.
Output: $P_c(t)$, $P_d(t)$.
 1: **for** each time scale Δt **do**
 2:     Compute M_{SOC}, M_{RG}, and M_p with $M_{SOC} = \frac{[S_{th} - S(t)]^+}{S_{th}}$, $M_{RG} = \frac{R_{max} - R(t)}{R_{max}}$, $M_p = \frac{p_{max} - p(t)}{p_{max} - p_{min}}$.
 3:     Compute $C(t) = D(t)(1 - M_p(\alpha M_{SOC} + \mu M_{RG} M_{SOC}))$.
 4:     Compute $P_c(t) = \min\{\max\{R(t) - C(t), 0\}, \frac{B - S(t)}{\eta \Delta t}, \overline{P}_c(t)\}$.
 5:     Compute $P_d(t) = \min\{\max\{C(t) - R(t), 0\}, \frac{S(t)\beta}{\Delta t}, \overline{P}_d(t)\}$.
 6:     Update $S(t+1) = S(t) + \eta P_c(t)\Delta t - \frac{P_d(t)}{\beta}\Delta t$.
 7: **Return** $P_c(t)$, $P_d(t)$.
 8: **end for**
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V. PERFORMANCE EVALUATION

A. Simulation Setup

We evaluate our proposed power output smoothing scheme and the load-adaptive power smoothing algorithm with a case study of a small-scale wind power generator located in the north of Los Angeles, California. We consider a set of real data recorded for the whole 2012 with the metering interval of five minutes [18]. The network load of $D(t)$ kW is assumed to follow the normal distribution with mean of 8 kW and variance equal to 1 kW^2. The electricity price for the controllable generation unit is time-varying and the historical pricing data is obtained from [19]. The durations of the whole operation period T and a time slot Δt are set to one year (365 days) and one minute, respectively. Due to the randomly generated $D(t)$, the simulations are run for 100 times with different random seeds.

B. Scenarios for Comparison

We compare five scenarios for power output smoothing: (S1) without storage (base scenario), (S2) with storage using a utilization-based algorithm, (S3) with storage using a price-based algorithm, (S4) with storage using the power output smoothing scheme described in Section III, and (S5) with storage using the proposed load-adaptive power smoothing algorithm described in Section IV.

S1 is considered as the base case for reference in which no energy management method is implemented. In S2, the storage gets charged or discharged for any imbalance between the renewable power supply and the network load demand. When the storage is fully charged or empty, it stops operating until it regains its capability of charging and discharging. Thus, we only control the charging and discharging power as $P_c(t) = \min\{\max\{R(t) - D(t), 0\}, \frac{B - S(t)}{\eta \Delta t}, \overline{P}_c(t)\}$ and $P_d(t) = \min\{\max\{D(t) - R(t), 0\}, \frac{S(t)\beta}{\Delta t}, \overline{P}_d(t)\}$, respectively. It should be noted that S2 gains the optimal renewable energy utilization so it is used as a benchmark for the

comparison of renewable energy utilization. In S3, the price-based algorithm curtails the power output reference when the electricity price becomes high. The power output reference $C(t)$ kW is determined by the current electricity price $p(t)$ dollars and the network load demand $D(t)$ kW as $C(t) = D(t)(1 - \phi M_p)$, where M_p is the price indicator defined in (24) and ϕ (set to 0.1) is the coefficient that determines the effect of the price signal. $P_c(t)$ and $P_d(t)$ can be computed with (26) and (27) given $C(t)$. S3 takes electricity price into account and aims to reduce the operation cost compared to S2. In S4, given C, $P_c(t)$ and $P_d(t)$ are computed with (7) and (8). C is set as eight, which equals the mean of $D(t)$. In S5, the threshold of energy storage is set as $S_{th} = 0.2B$. Coefficients α and η are both set to 0.5.

C. Performance Metrics

We consider two performance metrics: C_{avg} and U_{RG}. C_{avg} is the daily average cost, which is defined as:

$$C_{avg} = \frac{T_d}{T} \sum_{t=0}^{T} \max\{(D(t) - P_{out}(t)), 0\} p(t) \Delta t, \quad (28)$$

where T_d is the time period of 24 hours. This is the daily average operation cost for the whole time horizon. U_{RG} represents the renewable energy utilization and measures the actual renewable penetration in serving the network load. It is given as:

$$U_{RG} = \frac{\sum_{t=0}^{T} \min\{D(t), P_{out}(t)\} \Delta t}{\sum_{t=0}^{T} D(t) \Delta t}. \quad (29)$$

An algorithm resulting in lower C_{avg} and higher U_{RG} indicates better performance.

D. Simulation Results

We perform four tests to evaluate the performance of our methods. In first test, we examine our proposed power output smoothing scheme, i.e., S4, for the ideal constant load. In the second and third, we compare the four scenarios S1, S2, S3, and S5 in the presence of time-varying load in terms of operation cost and renewable utilization, respectively. In the fourth, we test the capability of the load-adaptive power smoothing algorithm (S5).

1) Test 1 : We focus on constant load and compare S1 and S4 in terms of renewable energy utilization. This allows us to investigate the capability of the power output smoothing scheme in serving the ideal constant load. Fig. 3 shows the corresponding utilization with different storage size B. It reveals that, when the energy storage size increases, the utilization of the power output smoothing scheme improves but the marginal utilization gain decreases.

2) Test 2: We compare the four scenarios, S1–S3, and S5, in the presence of time-varying load in terms of daily average cost. The results are given in Fig. 4 with 95% confidence interval. We can see that the cost is the highest in S1 than in the others with storage and thus storage can help reduce the operation cost. Among those with storage,
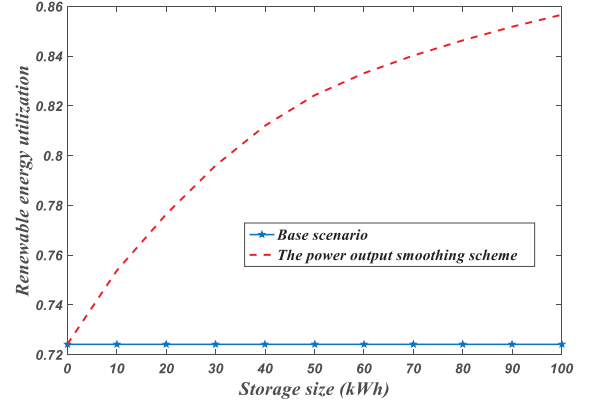

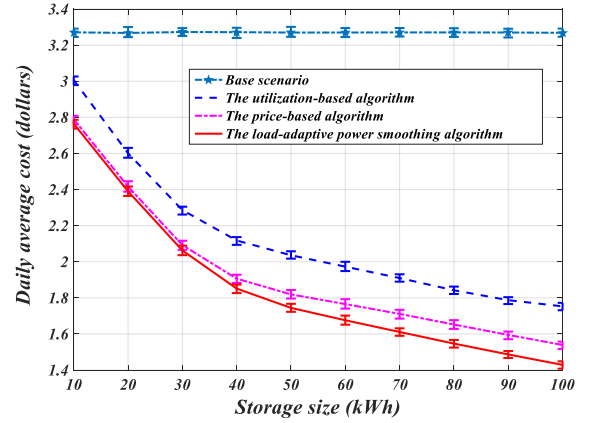Fig. 3. Renewable energy utilization gain of using power output smoothing scheme.

Fig. 4. Comparison on daily average cost among different algorithms.

the load-adaptive power smoothing algorithm outperforms the utilization-based and the price-based algorithms. When the storage size increases, the gain between the load-adaptive algorithm and the others becomes larger. It is because the algorithm gives the system with larger capability to response to the price signal.

3) Test 3: Next, we perform a similar test as Test 2 but we do the comparison in terms of renewable energy utilization. Fig. 5 depicts the performance under the four scenarios, with 95% confidence interval. The utilization-based algorithm gains the optimal renewable energy utilization since it always aims at meeting the load demand without considering the price. Among those with storage, the price-based algorithm earns the lowest utilization since it only responds to the price signal. When the storage size is small, e.g., $B = 10$ kWh, the price-based algorithm has even a lower utilization than that of the base scenario as it curtails its power output to save energy reserve for future cost reduction. Although the utilization-based algorithm performs a little better than the load-adaptive power smoothing algorithm, the utilization gap between them becomes smaller when the storage size increases.
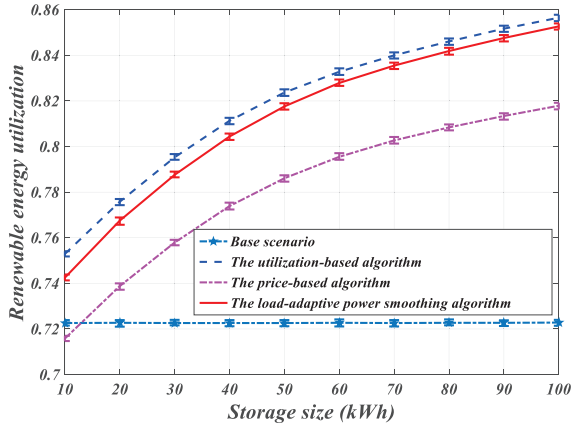
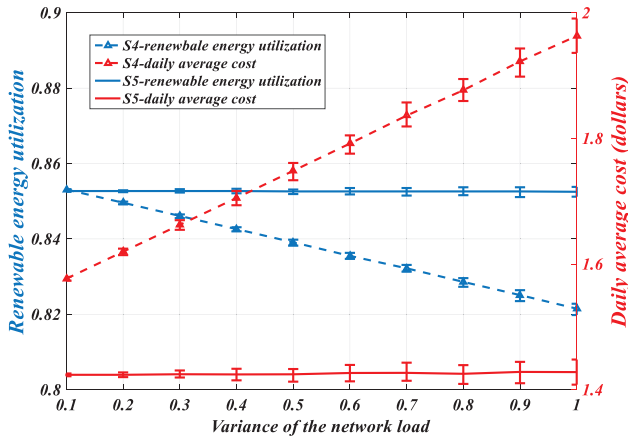Fig. 5. Comparison on renewable energy utilization among different algorithms.

Fig. 6. Gain of the load-adaptive power smoothing algorithm with time-varying load.

4) Test 4: We focus on the load adaptability of our proposed methods. We compare the power output smoothing scheme in S4 and the load-adaptive power smoothing algorithm in S5 under different variances of time-varying network load. Note that the former is designed for constant load but it can still function in time-varying load conditions. The storage size is set as 100 kWh. The results are given in Fig. 6 with 95% confidence interval. From Fig. 6, we see that the load-adaptive power smoothing algorithm has a lower daily average cost and a higher renewable energy utilization because it can adaptively alter the power output reference to track the actual network load demand. As the load variance increases, the performance of the power output smoothing scheme deteriorates drastically while the load adaptive power smoothing algorithm can maintain the daily average cost and renewable energy utilization.

VI. CONCLUSION

This paper investigates how to smooth the power output of the renewable energy system for practical utilization. In this paper, we introduce a renewable power output smoothing scheme to serve the constant load inspired by the leaky bucket mechanism. In this scheme, an optimization method is developed to determine the optimal energy storage size and the power output reference. We show the optimization problem can be convexified under certain assumptions, so that the original non-convex optimization problem can be solved using MILP. To serve the time-varying load, a load-adaptive power smoothing algorithm is proposed to alter the power output reference based on the current renewable generation, the actual load demand and the electricity price. Our simulation shows that the algorithm can reduce operation cost and maintain high renewable utilization level.

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