Optimal Energy Storage Management for Microgrids with ON/OFF Co-Generator: A Two-Time-Scale Approach

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Abstract—**In this paper, we study the energy storage management of microgrids with combined heat and power (CHP) co-generator and renewable energy. There are two kind of demands in the microgrid, power demand and heat demand. The power demand can be satisfied by the electricity from grid, CHP co-generator, renewable energy and battery; The heat demand is meet by the natural gas, CHP co-generator and the thermal tank. We aim to minimize the microgrid's operating cost by designing an intelligent energy storage management strategy based on the random system inputs, e.g., demands and electricity price and the CHP co-generator's on/off decision. We formulate the problem as a stochastic non-convex optimization programming, which is challenging to solve optimally. We apply the Lyapunov drift-plus-penalty method [1] to design an easy-to-implement energy management strategy with provable near-optimal performance and requires no statistical information of the power and heat demands. Moreover, extensive empirical evaluations using real-world traces are provided to study the effectiveness of the proposed algorithm in practice.**

I. Introduction

The increasingly intelligent usage of distributed energy evokes the development of smart microgrid, which can orchestrate the renewable energy, energy storage and the centralized power grid to meet different demands by designing intelligent energy management strategies [2]. An important feature of future microgrid system is the efficiently and effectively usage of distributed energy (e.g., wind and solar resources) to minimize operating cost and reduce greenhouse gas emissions for the growing environmental concerns [17], [3].

The introduction of energy storage devices (e.g. battery and thermal tank) and CHP co-generator promise a high improvement on the efficiency of distributed energy usage [12], [14], [15], [16]. There are three important roles for the energy storage device in a microgrid. First, it is used to smooth power output fluctuations to enhance the system's reliability [4], [5]. Second, it can act as a backup for power outage in a fast-responding action to alleviate the negative effects [21], [22]. Third, the utilization of energy storage can reduce the operating cost by intelligent charging/ discharging in a more environmentally friendly way [11], [12]. The distributed storage plays an important roles in power grid design and evolution, and in particular will create additional design choices for microgrid's operating cost reduction [19], [20].

By generating both power and heat energy simultaneously, a CHP co-generator can achieve a much higher energy efficiency than other separate energy generating systems [18]. Furthermore, with the augmentation of CHP generation technology and its distributed characteristic, microgrids can often be much more economical than using centralized grid supply and separate heat supply [8], [9].

In this paper, we aims to design an energy storage management strategy with intelligent energy scheduling to minimize the microgrids operating cost based on the random system inputs, e.g., demands, electricity price and the CHP co-generator's on/off decision.

The contributions of this paper are summarized as follows:

1) We formulate the microgrid's energy storage management problem into a stochastic non-convex integer programming to minimize the operating cost, which captures the randomness system dynamics and the physical constraints.
2) We tackle the stochastic integer programming problem by applying a two-timescale Lyapunov optimization technique. We then develop a battery and thermal tank energy management algorithm which can approximately achieve the optimal average cost and with easily implementation and low complexity features.
3) By evaluations using real-world data traces, we observe that the proposed algorithm corroborate our theoretical findings.

II. System Model and Problem Statement

The system model is shown in Fig.1. We assume that the system operates in discrete time with time slot $t \in \{0, 1, 2, \cdots\}$. We then define T as the size of a frame which is consisted of a group of time slots and $T_{\rm m}$ denotes the set of slots in a frame size m, i.e. $T_{\rm m} \triangleq \{\rm mT, \cdots, (m+1)\mathit{T}-1\}$.

A. System Model

1) Local co-generation(CHP): In each time slot, the co-generator can generate electricity in the amount of $\eta_{\rm ce}P_{\rm c}(t)$ and generate thermal energy in the amount of $\eta_{\rm ch}P_{\rm c}(t)$,

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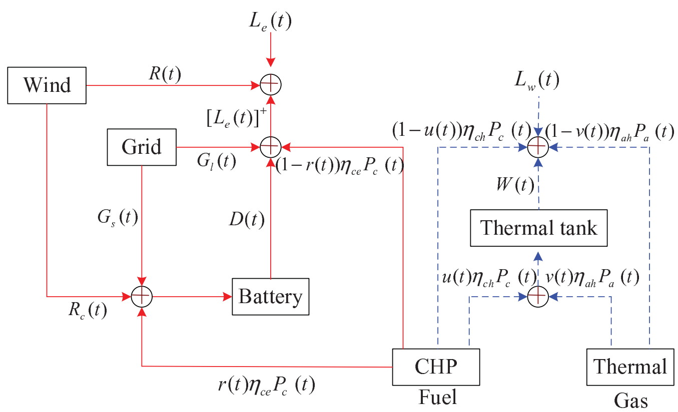

Fig. 1: Illustration of the System Model

respectively. The generated electricity can be used to meet the net power demand directly in the amount of $(1-r(t))\eta_{ce}P_c(t)$ or charge into the battery in the amount of $r(t)\eta_{ce}P_c(t)$. The generated heat energy $\eta_{ch}P_c(t)$ can be used to meet the heat demand directly in the amount of $(1-u(t))\eta_{ch}P_c(t)$ or charge into the thermal tank in the amount of $u(t)\eta_{ch}P_c(t)$, respectively. The formula $\mathrm{y(m_t)}$ represents the on/off decision of the local generator: $\mathrm{y(m_t)}=1$ represents switching on and $\mathrm{y(m_t)}=0$ denotes switching off in frame $\mathrm{m_t}$, which $\mathrm{m_t}=[t/T]+1$ is defined as the number of slots in a frame.

2) Centralized power grid: The system obtains power from centralized grid in the amount of $G_l(t)+G_s(t)$. We assume that the electricity in the amount of $G_l(t)$ is used for satisfying demands directly and the power in the amount of $G_s(t)$ can be supplied for charging the battery. We have $0\le G_l(t)+G_s(t)\le G_{max}$ and $0\le G_l(t)\le G_{l,max}$, $0\le G_s(t)\le G_{s,max}$, where $G_{l,max}$ is the upper bound of electricity from the grid to meet the demand directly and $G_{s,max}$ is the upper bound of power from grid for charging the battery. We assume that the maximum electricity demand can always be satisfied even only by power grid, so we have $L_{e,max}\le G_{max}$, where $L_{e,max}$ is the upper bound of $L_e(t)$. Here, $L_e(t)$ is denoted as power demand at each time slot.

3) External gas supply: The natural gas $\eta_{ah}P_a(t)$ is used to meet the heat demand directly in the amount of $(1-v(t))\eta_{ah}P_a(t)$, and charge the heat energy to the thermal tank, in the amount of $v(t)\eta_{ah}P_a(t)$. In our proposed algorithm, the heat demand can be satisfied by the co-generation and natural gas in an intelligent way.

4) Renewable energy: The available renewable energy at time t is denoted as $R(t)$, which is assumed to be an i.i.d. stochastic process. We assume that the renewable energy will be used first to meet the power demand. The excess renewable energy which is defined as $R_c(t)$ is used to charge the battery. We assume the renewable power level is bounded, i.e., $0\le R(t)\le R_{\max}$, and $0\le R_c(t)\le[-L_e(t)]^+$, where $[-L_e(t)]^+=\max\{R(t)-L_e(t),0\}$.

5) Power and heat demands: $[L_e(t)]^+$ represents the net power demand, which is the residual power demand that is not satisfied by renewable energy at time t, i.e., $[L_e(t)]^+=\max\{L_e(t)-R(t),0\}$. From Fig.1, we have:

$$[L_e(t)]^+=G_l(t)+D(t)+(1-r(t))\eta_{ce}P_c(t)\mathrm{y(m_t)} \quad (1)$$

The heat demand $L_w(t)$ is assumed to be an i.i.d. stochastic process. The heat from co-generation $(1-u(t))\eta_{ch}P_c(t)$, the heat acquired from external natural gas $(1-v(t))\eta_{ah}P_a(t)$, and the heat discharged from the thermal tank $W(t)$ (we will provide more details about $W(t)$ in the thermal tank model) can balance the heat demand. The heat demand is assumed to be satisfied at any time slot, then we have:

$$L_w(t)\le(1-v(t))\eta_{ah}P_a(t)+(1-u(t))\eta_{ch}P_c(t)\mathrm{y(m_t)}+\mathrm{W(t)} \quad (2)$$

We then define the maximum heat demand in each time slot as $L_{w,max}$. We assume the following constraint holds: $L_{w,\,max}\le\eta_{ah}P_{a,\,max}$, where $P_{a,\,max}$ is the maximum amount of the natural gas used for generating heat energy in each time slot. Here η_{ah} are defined as the conversion efficiencies from gas to the thermal energy. Parameter $r(t)$ denotes the percentage of co-generated power that is used to charge the battery. Therefore $(1-r(t))$ denotes the percentage of co-generated power that meet the net power demand directly. $u(t)$ is defined as the dispatch ratio from CHP to thermal tank, $v(t)$ denotes the dispatch ratio from thermal source to thermal tank.

B. Battery Model and Thermal Tank Model

1) Battery model: The state of the charge (SOC) level of the battery $B(t)$ evolves according to the following equation:

$$B(t+1)=B(t)-\eta_d D(t)+\eta_c[R_c(t)+G_s(t)+r(t)\eta_{ce}\mathrm{P_c(t)y(m_t)}] \quad (3)$$

Where η_d is the discharging co-efficient of battery and η_c is the charging co-efficient. We can find that the battery must satisfy constraints of capacity and charge/discharge in any slot t.

$$0\le B(t)\le B_{max},\ 0\le D(t)\le D_{max} \quad (4)$$

$$0\le G_s(t)+r(t)\eta_{ce}P_c(t)\mathrm{y(m_t)}+\mathrm{R_c(t)}\le\mathrm{T}\cdot\mathrm{C_{char}} \quad (5)$$

where B_{max} is the capacity of the battery, D_{max} is the maximum amount of electricity discharged by the battery in each time slot. $T\cdot C_{char}$ is the maximum amount of electricity charged to the battery in each frame.

2) Thermal tank model: The thermal tank model is:

$$T(t+1)=T(t)-\eta_\beta W(t)+\eta_\alpha[u(t)\eta_{ch}P_c(t)\mathrm{y(m_t)}+\mathrm{v(t)}\eta_{ah}\mathrm{P_a(t)}] \quad (6)$$

where $T(t)$ is the heat level of thermal tank in slot t. We have:

$$0\le T(t)\le T_{max},\ 0\le W(t)\le W_{max} \quad (7)$$

$$0\le v(t)\eta_{ah}P_a(t)+u(t)\eta_{ch}P_c(t)\mathrm{y(m_t)}\le\mathrm{Th_{char}}\cdot\mathrm{T} \quad (8)$$

Similarly, T_{max} is the capacity of the thermal tank and $W_{\max}$ represents the thermal tank discharging rate constraint. $Th_{char}\cdot T$ is the maximum amount of heat charged to thermal tank in each frame.

C. Problem Statement

Based on the previously described system components, we define the system state at time slot t as:

$$Q_{\mathrm{t}} \triangleq [L_{\mathrm{e}}(t), L_{\mathrm{w}}(t), R(t), C(t), B(t), T(t)] \quad (9)$$

We assume Q_{t} to be i.i.d. over time, but those elements within Q_{t} can be arbitrarily correlated. At each time slot t, the microgrid system design its control decisions only based on current system state Q_{t} information, any future system statistics is not needed.

Through jointly scheduling the renewable energy, centralized power acquiring, power and heat energy storage, and co-generation, the microgrid system can reach the target of minimizing the long-term time-averaged operating cost. In particular, the control vector at time slot t is defined by:

$$U_{\mathrm{t}} \triangleq [G_{\mathrm{l}}(t), G_{\mathrm{s}}(t), P_{\mathrm{c}}(t), P_{\mathrm{a}}(t), R_{\mathrm{c}}(t), r(t), u(t), v(t)] \quad (10)$$

The system total cost at time slot t consists of the cost of electricity acquired from the power grid, the fuel consumption of the co-generation, and the natural gas used for heat supply and switching and sunk cost:

$$f(t) = C(t)[G_{\mathrm{l}}(t)+G_{\mathrm{s}}(t)]+C_{\mathrm{f}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t})+\mathrm{C_g}\mathrm{P_a}(\mathrm{t})+\mathrm{C_m}\mathrm{y}(\mathrm{m_t}) \quad (11)$$

It should be noticed that any statistics of the stochastic process $C(t)$ is not depended on in our algorithm. The real-time power grid electricity price is denoted by $C(t)$, which is bounded by $C_{\min}$ and $C_{\max}$. $C_{\min}$ and $C_{\max}$ is the lowest and highest real-time electricity price. So we have $C_{\min} \leq C(t) \leq C_{\max}$. In this paper, we assume that the fuel price C_{f} and the natural gas price C_{g} are constant in every time slot. Our online algorithm is also feasible when the fuel price and natural gas price are in real environment since our algorithm is on the basis of current system states, which includes the natural gas price and fuel price. The problem can be formulated as the following stochastic optimization problem:

$$\text{P1: } \min \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{f(t)\} \quad (12)$$

subject to

$$[L_{\mathrm{e}}(t)]^{+} = G_{\mathrm{l}}(t) + D(t) + (1-r(t))\eta_{\mathrm{ce}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t}) \quad (13)$$

$$L_{\mathrm{w}}(t) \leq (1-v(t))\eta_{\mathrm{ah}}P_{\mathrm{a}}(t) + (1-u(t))\eta_{\mathrm{ch}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t}) + \mathrm{W(t)} \quad (14)$$

$$B(t+1) = B(t) - \eta_{\mathrm{d}}D(t) + \eta_{\mathrm{c}}[R_{\mathrm{c}}(t) + G_{\mathrm{s}}(t) + r(t)\eta_{\mathrm{ce}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t})] \quad (15)$$

$$T(t+1) = T(t) - \eta_{\beta}W(t) + \eta_{\alpha}[u(t)\eta_{\mathrm{ch}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t}) + \mathrm{v(t)}\eta_{\mathrm{ah}}\mathrm{P_a(t)}] \quad (16)$$

$$0 \leq B(t) \leq B_{\max}, \quad 0 \leq T(t) \leq T_{\max} \quad (17)$$

$$0 \leq G_{\mathrm{s}}(t) + r(t)\eta_{\mathrm{ce}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t}) + \mathrm{R_c(t)} \leq \mathrm{C_{char}} \quad (18)$$

$$0 \leq v(t)\eta_{\mathrm{ah}}P_{\mathrm{a}}(t) + u(t)\eta_{\mathrm{ch}}P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t}) \leq \mathrm{Th_{char}} \quad (19)$$

$$0 \leq u(t) \leq 1, \quad 0 \leq v(t) \leq 1 \quad (20)$$

$$0 \leq D(t) \leq D_{\max}, \quad 0 \leq W(t) \leq W_{\max} \quad (21)$$

$$G_{\mathrm{l}}(t), G_{\mathrm{s}}(t), P_{\mathrm{c}}(t), P_{\mathrm{a}}(t), R_{\mathrm{c}}(t), r(t), u(t), v(t) \geq 0 \quad (22)$$

At the beginning of each frame, the local generator makes a decision on choosing the on/off statement by solving a mixed-integer stochastic optimization programming. We then jointly decide other components($G_{\mathrm{l}}(t)$, $G_{\mathrm{s}}(t)$, $P_{\mathrm{c}}(t)$, $P_{\mathrm{a}}(t)$, $R_{\mathrm{c}}(t)$, $r(t)$, $u(t)$, $v(t)$) in each time slot. Solving P1 is challenging and we aim to propose an algorithm that is easy to implement and does not require any system statistics.

III. The Co-generation System Scheduling Algorithm

A. Problem Relaxation

Lyapunov optimization techniques can guarantee the average consumption which equals the average generated energy in the long term, however P1 cannot be solved directly by the stochastic optimization framework because of constraints in (17). We take expectations on the both sides of (15) and (16), then we have

$$\text{P2: } \min_{U_{\mathrm{t}}} \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{f(t)\} \quad (23)$$

$$\text{s.t. } \overline{D(t)} = \eta_{\mathrm{c}}[\overline{R_{\mathrm{c}}(t)} + \overline{G_{\mathrm{s}}(t)} + \eta_{\mathrm{ce}}\overline{r(t)P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t})}] \quad (24)$$

$$\overline{W(t)} = \eta_{\alpha}[\eta_{\mathrm{ch}}\overline{u(t)P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t})} + \eta_{\mathrm{ah}}\overline{v(t)P_{\mathrm{a}}(t)}] \quad (25)$$

$$(13), (14), (18), (19), (20), (21), (22)$$

After those operations, we finally obtain P2, which fits the stochastic optimization framework. P2 extends the limitation of Battery and Thermal tank storage. It no longer restricts the value of $B(t)$ and $T(t)$ in every time slots, instead, restricts them in the whole process. Under the condition that the solutions can meet the constraints (17) for $\forall t \in T$, the framework are available to P1.

B. Online Algorithm

To simplify the following discussion, we define two queues $E(t)$ and $X(t)$ as follows:

$$E(t) = B(t) - \theta, X(t) = T(t) - \varepsilon \quad (26)$$

where θ and ε are two queue offsets, which are constants and will be specified in the following section. First we define the Lyapunov function in the following way: $Q(t) = \frac{1}{2}[E(t)]^2 + \frac{1}{2}[X(t)]^2$. Then define the T-slot conditional Lyapunov drift as an conditional expectation of the system inputs: $\Delta(t) = \mathbb{E}\{Q(t+T) - Q(t)|(E(t), X(t))\}$.

$$\begin{aligned}
\Delta(t) &+ V\mathbb{E}\{f(t)\} \\
\leq BT &+ V\mathbb{E}\{C(t)[L_{\mathrm{e}}(t)]^{+}|E(t)\} + V\mathbb{E}\{C_{\mathrm{m}}\mathrm{y}(\mathrm{m_t})\} \\
&+ \mathbb{E}\{E(t)\eta_{\mathrm{c}}R_{\mathrm{c}}(t)|E(t)\} \\
&- \mathbb{E}\{D(t)[E(t)\eta_{\mathrm{d}} + VC(t)]|E(t)\} \\
&- \mathbb{E}\{\eta_{\beta}W(t)X(t)|X(t)\} \\
&+ \mathbb{E}\{G_{\mathrm{s}}(t)[\eta_{\mathrm{c}}E(t) + VC(t)]|E(t)\} \\
&+ \mathbb{E}\{P_{\mathrm{c}}(t)\mathrm{y}(\mathrm{m_t})[\mathrm{r(t)}\eta_{\mathrm{ce}}\eta_{\mathrm{c}}\mathrm{E(t)} + \eta_{\alpha}\eta_{\mathrm{ch}}\mathrm{u(t)X(t)} \\
&\quad - (1-r(t))\eta_{\mathrm{ce}}VC(t) - \eta_{\mathrm{ce}}VC(t) + VC_{\mathrm{f}}]\} \\
&+ \mathbb{E}\{P_{\mathrm{a}}(t)[\eta_{\alpha}\eta_{\mathrm{ah}}v(t)X(t) + VC_{\mathrm{g}}]|X(t)\}
\end{aligned} \quad (27)$$

Here, the parameter V represents the tradeoff between the capacity of battery and average cost. Minimizing (27) over all the feasible control policies in each time slot is our main idea of the proposed algorithm. In other words, we observe the system states $B(t)$, $T(t)$, $L_{\rm e}(t)$, $C(t)$, $L_{\rm w}(t)$, and in each slot of a frame, the system determine the variables $G_{\rm l}(t)$, $G_{\rm s}(t)$, $r(t)$, $P_{\rm c}(t)$, $P_{\rm a}(t)$, $R_{\rm c}(t)$, $D(t)$.

Based on the above analysis, we can get our online algorithm by solving the following optimization problem:

$$\text{P3:} \min \quad G_{\rm s}(t)H_{\rm s}(t) + P_{\rm c}(t)H_{\rm c}(t) + P_{\rm a}(t)H_{\rm a}(t) - D(t)H_{\rm d}(t) - W(t)H_{\rm w}(t) + R_{\rm c}(t)E(t) \tag{28}$$

subject to

$$G_{\rm l}(t) + D(t) + (1 - r(t))\eta_{\rm ce}P_{\rm c}(t){\rm y}({\rm m_t}) = [{\rm L_e(t)}]^+ \tag{29}$$

$$0 \le G_{\rm s}(t) + r(t)\eta_{\rm ce}P_{\rm c}(t){\rm y}({\rm m_t}) + {\rm R_c(t)} \le {\rm C_{char}} \tag{30}$$

$$0 \le D(t) \le D_{\max}, \qquad 0 \le W(t) \le W_{\max} \tag{31}$$

$$(1 - v(t))\eta_{\rm ah}P_{\rm a}(t) + W(t) + (1 - u(t))\eta_{\rm ch}P_{\rm c}(t){\rm y}({\rm m_t}) \ge {\rm L_w(t)} \tag{32}$$

$$0 \le u(t)\eta_{\rm ch}P_{\rm c}(t){\rm y}({\rm m_t}) + {\rm v(t)}\eta_{\rm ah}{\rm P_a(t)} \le {\rm Th_{char}} \tag{33}$$

$$0 \le r(t) \le 1, \qquad P_{\rm c}(t), G_{\rm l}(t), G_{\rm s}(t), P_{\rm a}(t) \ge 0 \tag{34}$$

Here

$$H_{\rm R_c}(t) = \eta_{\rm c}E(t), \qquad H_{\rm s}(t) = \eta_{\rm c}E(t) + VC(t) \tag{35}$$

$$H_{\rm c}(t) = r(t)H_{\rm r}(t) + u(t)H_{\rm u}(t) + H_{\rm b}(t) \tag{36}$$

$$H_{\rm r}(t) = \eta_{\rm c}\eta_{\rm ce}E(t){\rm y}({\rm m_t}) + \eta_{\rm ce}{\rm VC(t)y(m_t)} \tag{37}$$

$$H_{\rm u}(t) = \eta_{\rm ch}\eta_{\alpha}X(t){\rm y}({\rm m_t}), \qquad {\rm H_v(t)} = \eta_{\alpha}\eta_{\rm ah}{\rm X(t)} \tag{38}$$

$$H_{\rm b}(t) = VC_{\rm f} - \eta_{\rm ce}VC(t){\rm y}({\rm m_t}), \quad {\rm H_w(t)} = \eta_{\beta}{\rm X(t)} \tag{39}$$

$$H_{\rm a}(t) = H_{\rm v}(t)v(t) + VC_{\rm g}, \;\; H_{\rm d}(t) = \eta_{\rm d}E(t) + VC(t) \tag{40}$$

Observing equation (28), we can find that it includes the product of $P_{\rm c}(t)$ and $H_{\rm c}(t)$ where $H_{\rm c}(t)$ is a function of $r(t)$ and $u(t)$. Meanwhile, it includes the product of $P_{\rm a}(t)$ and $H_{\rm a}(t)$ where $H_{\rm a}(t)$ is a function of $v(t)$. It follows that P3 is an non-convex optimization problem because its Hessian matrix is not always positive determinated. By a deep investigation of P3, we find that $D(t)$ and $W(t)$ can be decoupled from $H_{\rm d}(t)$ and $H_{\rm w}(t)$.

Taking $D(t)H_{\rm d}(t)$ and $W(t)H_{\rm w}(t)$ into account at first. If $H_{\rm d}(t) \ge 0$, it is clearly that $D(t) = \min\{D_{\max}, L_{\rm e}(t)\}$; otherwise $D(t) = 0$. If $H_{\rm w}(t) \ge 0$, $W(t) = W_{\max}$; otherwise, $W(t) = 0$. Therefore, we need to focus on the key part of (28) which is listed as follow:

$$\min \quad G_{\rm s}(t)H_{\rm s}(t) + P_{\rm c}(t)H_{\rm c}(t) + P_{\rm a}(t)H_{\rm a}(t) + R_{\rm c}(t)E(t) \tag{41}$$

s.t. (30), (31), (33)

We discuss the solutions to minimize P3 when the local generator is on or off, respectively.

IV. Empirical Evaluations

A. Parameters and Settings

Electricity and Natural Gas Prices: PG&E [10] provides the grid electricity prices and the natural gas price $\$0.42/therm$. The grid electricity prices can be observed in Fig.2. From the trace, the power demand can be satisfied at every time slot. And the peak power from the grid $G_{\max}$ is assumed to be $32MWh$. The electricity demand and the price are both related to the time slot. We obtain cheap grid energy during night to charge the power storage device and generate cheaper energy and use the power discharged from the power storage device to serve the demand during daytime according to the circumstance so that we can reduce the microgrid operating cost.

Wind Power Trace: We obtain the wind power traces from [7]. We work with power output data with a resolution of an offshore wind farm right outside San Francisco within 1 hour which installed 12MW capacity during the month. The net electricity demand which equals the value of subtraction results of electricity demand and wind power is shown in Fig.2.

Demand Trace: California Commercial End-Use Survey (CEUS) [6] provided us the data of the demand traces. We consider a college in San Francisco which consumes about 154 GWh electricity and 5.1×10^6 therms gas per year as our model. The data of hourly electricity and heat demands of the college for year 2002 are recorded. We only pick out the trace during a week so that the illustration can be simplified. We can observe the heat demand trace which shows regular daily patterns in peak and off-peak hours, and typical weekday and weekend variations clearly in Fig.3.

Power Storage Model: We assume that $\eta_d = 1.1$ and $\eta_c = 0.9$. Besides, maximum charging speed $C_{\rm char}$ and discharging speed $D_{\max}$ are both assumed to be $20MW$.

Local Heating System: All the heat demands can be satisfied in a flexible heating system by itself because of its adequately large capacity. We can calculate the unit heat generation cost to be $c_g = \$0.0173/KWh$ when the efficiency of the heating system is set to 0.8 according to [13].

Local Generator Model:A generator is adopted except that the full output of the generator $P_{\rm c,max}$ is scaled up to $20MW$ in this paper. The fuel cost per unit time consumed by CHP to generate an additional unit of energy $c_{\rm f}$ is set to be $\$0.01727/KWh$. The conversion efficiency from fuel to heat $\eta_{\rm ch}$ is set to be 1.8. The one-slot generator sunk cost is also set to be $c_{\rm m} = \$400/h$, which includes the amortized capital cost and maintenance cost according to a similar setting from [32]. Besides, an on/off period of 4 hours is assumed, i.e., the length of frames T is set to be 4 hours.

B. Algorithm Performance vs. V

We use a line chart called Fig.4 to compare the average one-slot cost with different values of V. From this chart, we can see that the average cost of three kinds of algorithm are decrease slightly as the value of V increases, but the tendency of **chpoff** is not as obviously as others.

Fig.4 displays the average cost of **chpon**, **chpoff** and **chponoff**. Comparing the green line and blue line, we can get a lower cost project when co-generator device are included in our system. What's more, if adding a switch to CHP, we

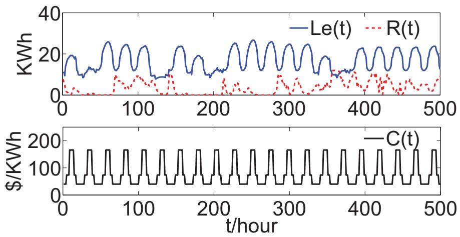

Fig. 2: Data traces of power demand.

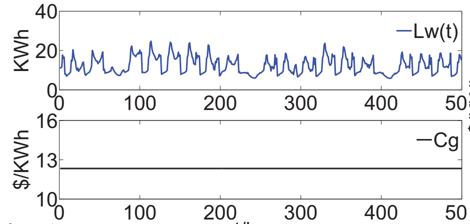

Fig. 3: Data traces of heat demand and gas market prices.

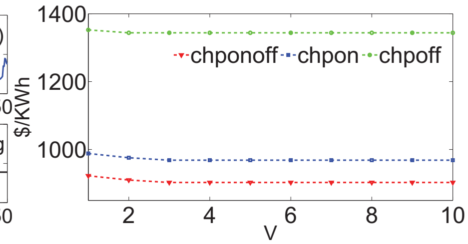

Fig. 4: Average cost vs. V.

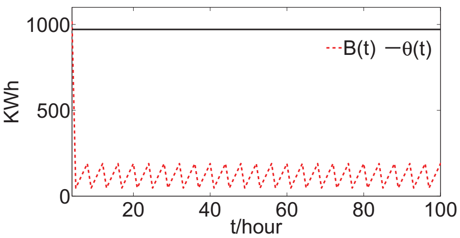

Fig. 5: Battery power level $B(t)$.

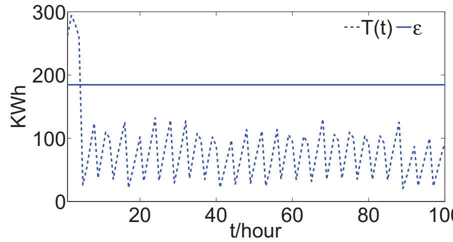

Fig. 6: Thermal tank energy level $T(t)$.

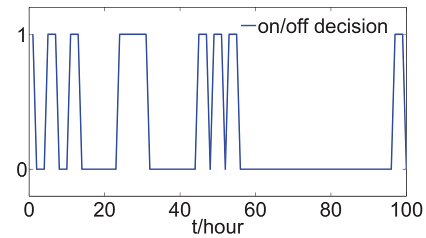

Fig. 7: The on/off decision of co-generator.

can get the smallest cost when the switch adaptively decide its on/off actions (c.f. Fig.7).

C. Behavior of Our Algorithm

Battery power level $B(t)$ under our algorithm **chponoff** when $V = 5$ is showed in Fig.5. Eqn (18) constrains the level of battery, and from the chart we can see that it is actually between zero and the bound. But in practice, the bound is higher than the actual energy level, therefore our algorithm is also reliable in real-condition. Similarly, Fig.6 shows the thermal tank energy level $T(t)$ under **chponoff** when $V = 5$. And the thermal tank's bound is provided is Eqn (19).

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