A Novel Cost-Aware Multi-Objective Energy Management Method for Microgrids

Ali Hooshmand*, Babak Asghari†, Ratnesh Sharma†

Abstract—**This paper proposes a multi-objective energy management method for microgrids which include local generation sources, grid connection, energy storage units and various loads. Minimization of the energy cost and maximization of batterys lifetime in a microgrid are considered as two main objectives which are optimized simultaneously. To achieve these objectives, microgrids central controller must find the best pattern for charging and discharging the battery. To this purpose, there is a need to have information about time-of-use (TOU) grid electricity rates, forecasted load profile and renewable generation levels. Model predictive control (MPC) policy is then utilized for solving the optimization problem and real-time implementation in a closed-loop framework. The performance and effectiveness of the proposed method is verified by simulating a microgrid model with real yearly data for the demand and renewable generation profiles and TOU rates. It is shown that the saving in energy cost can be increased considerably by applying the proposed MPC algorithm instead of a static energy management approach. Furthermore, the proposed algorithm is capable of regulating the battery usage based on the expected lifetime by considering the battery life span maximization objective.**

***Keywords*: Microgrid, renewable energy sources, battery, model predictive control.**

I. Introduction

The development and evolution of the smart grids will result in the plug-and-play combination of intelligent structures called microgrids that will be linked with each other through particular channels for power, information, and control signals exchange [1, 2].

A microgrid is the integration of loads, energy resources, and storage devices. From the operating point of view, a microgrid is counted as one independent entity which is able to work either in grid-tied or islanded mode [3, 4]. Microgrid's energy resources can include utility connection, microgas turbines and renewable generations such as fuel cells, wind turbines, and solar panels. It is expected and desirable that a considerable amount of demand for each microgrid is supplied by its local generations. On the other hand, the intermittent nature of most distributed generations (DGs) such as wind and photovoltaic (PV) introduces a significant uncertainty in the operation of a microgrid. This makes the conventional unit commitment more erroneous and unreliable. Therefore, a real-time management framework as a supervisory control is an absolute necessary procedure within a microgrid similar to the various regulatory actions in conventional power systems. The first objective for this management system is real-time dispatching of energy generations in a way that minimizes the operational cost while it guarantees the balance between supply and demand at the presence of unpredictable variations of DGs.

In order to relax the issue of sudden unforecasted unbalances between supply and demand, energy storage devices are normally utilized. Among various types of storage devices, battery is the most favorable option and also one of the most expensive components of microgrids. In grid-tied microgrids, any shortage in the supply-side (power outputs from DGs and the scheduled power from the grid) should be met whether by the battery or by purchasing extra power from the grid or a combination of both. At the first glance, it might be preferred to use battery first. But irregular discharge pattern of battery might shorten its lifetime and incur a replacement cost for battery. Authors in [5] described three parameters mainly affecting a battery lifetime: 1- Depth of discharge (DoD) 2- Discharge power and 3- temperature. It is shown how discharge power in different DoDs can determine the battery life period. Based on this idea, in microgrids operation, it is beneficial to utilize battery's power in a way that maximizes its lifetime. Therefore, maximizing the battery's life span can be considered as another important objective in addition to minimizing the micorgrid's operational cost.

For maximizing the battery lifetime in parallel to minimizing the cost of energy, microgrid's central controller must find the best pattern for charging and discharging the battery package. To this purpose, there will be need to have some future information about time-of-use grid electricity rates, forecasted load profile, and predicted renewable generations level. Using these information, management system solves an optimization problem which results in optimal usage of storage unit. On the other hand, due to the errors in prediction of renewable generations and load real-time management system might operate microgrid in non-optimal points.

Model predictive control (MPC) is a class of control policies which uses a model that projects the behavior of the system under control. Based on this model, controller can predict the future response of the system to various control actions; and based on this prediction, makes the optimal solution. Different MPC techniques and theoretical development can be found in [6, 7]. In recent years, MPC has interested power system engineers in using this strategy for solving problems such as power system dispatching which highly depends on forecasted value of demand and renewable energy productions. In addition, due to its close-loop nature, it corrects any prediction error and therefore, helps system stability and robustness [8]. MPC can be appropriately embedded into the real-time management framework since it works dynamically and based on receding horizon control policy. It should also be noted that MPC is one of the few algorithms

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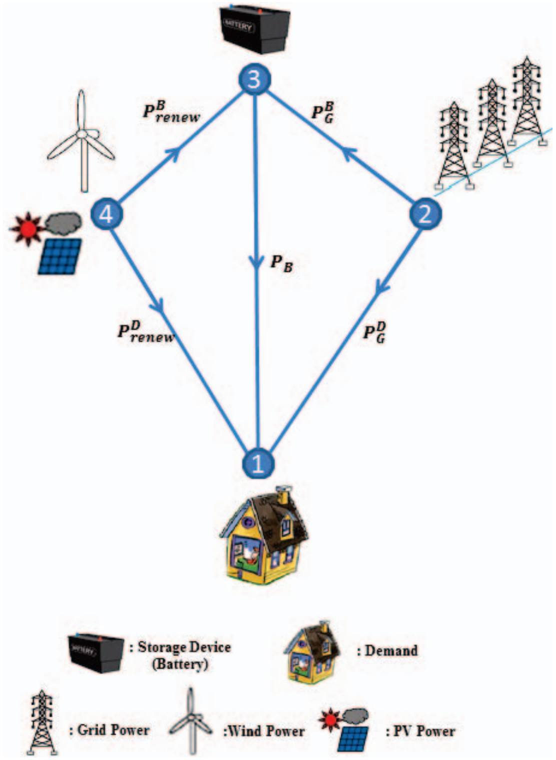

Fig. 1. Schematic of a typical microgrid

which can handle dynamic constraints such as battery state of charge (SoC) difference equation [9, 10]. In this paper, a novel multi-objective management system for real-time controlling of microgrids by using MPC strategy is proposed. Simulation results show the effectiveness of the proposed method in adjusting the battery lifetime and minimizing the cost of energy.

The rest of this paper is organized as follows: Section II describes the system modeling and problem formulation. Model predictive control policy and algorithm is then provided in Section III. The results of a numerical example based on real data are presented in section IV. Section V concludes the paper.

II. Problem Formulation

In this paper, a microgrid is considered as a directed graph which includes four nodes as follows:

- Node 1: Demand ($D(t)$)
- Node 2: Imported power from the grid ($P_G(t)$)
- Node 3: Battery unit
- Node 4: Total generated power by renewable sources such as PV and wind turbine ($P_{renew}(t)$)

As illustrated in Figure 1, $P_G(t)$ can be sent directly to demand node, $P_G^D(t)$, and/or stored in battery, $P_G^B(t)$. Hence, the following equality holds at each time, t:

$$P_G(t) = P_G^D(t) + P_G^B(t) \tag{1}$$

Since $P_{renew}(t)$ is uncontrollable with almost free marginal cost, it is beneficial to consume it directly by load, $P_{renew}^D(t)$, and/or store it in battery unit, $P_{renew}^B(t)$, as much as possible. $P^B(t)$ is battery discharge power which supplies the load. Considering the microgrid's graph and its elements, an optimization problem is defined in order to optimally dispatch different energy sources within the microgrid. Similar to other optimization problems, the proposed mathematical formulation has two main parts: Objective function which should be optimized, and static and dynamic constraints of microgrid which should be satisfied.

A. Objective Function

As mentioned above, there are two objectives for the proposed microgrid scheme that should be optimized: 1- Minimizing the cost of energy, 2- Maximizing the battery lifetime.

1) Energy Cost Minimization: In every power dispatching problem, primary objective is to schedule the generators output to reliably supply the power requested by end users. This scheduling should be implemented in a cost-efficient way. In Figure 1, cost of energy for the microgrid is equal to the cost of importing power from the grid. Hence, fisrt objective function J_1 is the grid power cost over the optimization window. We assume the marginal cost of grid power for any level of generation is constant. Therefore, J_1 is modeled by a linear equation as follows:

$$J_1 := \sum_{t=0}^{T} C_G(t) P_G(t) \tag{2}$$

where T is optimization horizon, $P_G(t)$ is imported power from grid at time t, and $C_G(t)$ is grid power marginal price at time t based on time-of-use rates.

2) Battery Lifetime Maximization: To formulate the objective of battery lifetime maximization and integrating it with energy cost minimization, the maximization problem is translated into a minimization one. To this purpose, we need to estimate battery lifetime using its cumulative discharges and its DoD [5]. For a battery cell which has been operated for a certain period of time, τ, and exprinced k discharge events, the estimated lifetime, BL, can be calculated as follows:

$$BL = \frac{L_R D_R C_R}{\sum\limits_{i=1}^{k} d_{eff}(i)} \tau \tag{3}$$

where C_R is rated amp-hour capacity at rated discharge current, D_R is DoD for which rated cycle life was determined, and L_R is cycle life at rated DoD and rated discharge current. $d_{eff}(i)$ is the effective discharge (ampere-hours) for a particular discharge event i and is calculated as follows:

$$d_{eff}(i) = (\frac{DoD(i)}{D_R})^{x_1} e^{x_2(\frac{DoD(i)}{D_R} - 1)} \frac{C_R}{C_A(i)} d_{act}(i) \tag{4}$$

where $DoD(i)$, $C_A(i)$, and $d_{act}(i)$ are DoD, actual capacity of a battery, and measured discharge ampere-hours for i^{th} discharge event respectively. Coefficients x_1 and x_2 are calculated by applying a curve fitting procedure to cycle life versus DoD data available from the battery data sheet. To perform curve fitting task, particle swarm optimization (PSO) technique is employed [11]. PSO is a curve fitting tool compatible with nonlinear battery characteristics.

Having the estimated lifetime, we can evaluate the number of battery replacements during the total life of the project. According to number of required replacements, equivalent uniform annual cost (EUAC) is calculated. Finally, once the EUAC is determined, the price of power extracted from the battery is calculated by dividing EUAC by the expected annual kWh usage of the battery

[12]. In summary, the cost of battery usage (second objective, J_2) can be modeled as follows:

$$J_2 := \sum_{t=0}^{T} C_B(D_B^{eff}) P_B(t) \tag{5}$$

where D_B^{eff} is battery cumulative effective discharge up to the start time of optimization window. Since receding horizon policy repeats the MPC optimization problem at each time step, D_B^{eff} is also updated at each time step. $C_B(D_B^{eff})$ is the price of battery power as a function of cumulative effective discharge.

By transferring battery lifetime maximization problem into a battery power cost minimization problem, we are able to embed two above-mentioned objectives into a single optimization problem in which the objective function, J, can be written as follows:

$$J := \sum_{t=0}^{T} C_G(t) P_G(t) + C_B(D_B^{eff}) P_B(t) \tag{6}$$

B. Constraints

The operational and physical constraints of problem are listed as follows:

1) Supply-Demand balance which is an equality constraint and the primary task of management system. This constraint is formulated as follows:

$$P_G^D(t) + P_B(t) + P_{renew}^D(t) = D(t) \tag{7}$$

which means the summation of generated power by grid, battery, and renewable source should be equal to demand at each time.

2) Battery state of charge (SoC) difference equation:

$$soc(t+1) = soc(t) - \alpha P_B(t) + \alpha P_G^B(t) + \alpha P_{renew}^B(t) \tag{8}$$

in which $soc(t)$ is battery SoC in ampere-hour (Ah) at time t, and α is a coefficient which changes kW unit into Ah.

3) Upper and lower bound for battery SoC which by considering the SoC difference equation (8) will be a dynamic inequality constraint:

$$soc^{min} \leq soc(t) \leq soc^{max} \tag{9}$$

4) All decision variables ($P_G^D(t)$, $P_G^B(t)$, $P_{renew}^D(t)$, $P_{renew}^B(t)$, and $P_B(t)$) are physical variables. Therefore, they are always greater than or equal to zero:

$$\begin{aligned} &P_G^D(t) \geq 0, P_G^B(t) \geq 0, P_B(t) \geq 0, \\ &P_{renew}^D(t) \geq 0, P_{renew}^D(t) \geq 0, \end{aligned} \tag{10}$$

5) Renewable inequality constraint which states that the summation of $P_{renew}^D(t)$ and $P_{renew}^B(t)$ should be less than or equal to available renewable generation at each time. Thus, we have:

$$P_{renew}^D(t) + P_{renew}^B(t) \leq P_{renew}(t) \tag{11}$$

in which $P_{renew}(t)$ is the available renewable power at time t based on forecasted profile of renewable generations.

6) Peak shaving inequality constraint which equips the management system with the ability of performing peak shaving task. By satisfying this constraint, management system guarantees that the total imported power from the grid at each time is less than a predetermined constant value, P_{PSH}. Therefore, we state this inequality constraint as follows:

$$P_G^D(t) + P_G^B(t) \leq P_{PSH} \tag{12}$$

It should be noted that this constraint is an optional objective for management system and is not a mandatory task for normal type of operation.

For defining and solving optimization problem, it is sufficient to pick $P_G^D(t)$, $P_G^B(t)$, $P_{renew}^D(t)$, $P_{renew}^B(t)$ as decision variables since other variables can be described based on this parameters. Hence, we can summarize the optimal dispatching problem for the finite horizon T as follows:

$$\begin{aligned} \min_{\substack{P_G^D, P_{renew}^D, \\ P_G^B, P_{renew}^B}} \quad & J := \sum_{t=0}^{T} C_G(t) P_G(t) + C_B(D_B^{eff}) P_B(t) \\ \text{subject to:} \quad & (7) - (12) \end{aligned} \tag{13}$$

III. Model Predictive Control

In this section, the principles of model predictive control (MPC), and how the proposed real-time management problem can be solved in MPC framework are briefly described. The interested reader is referred to [6, 10, 9] for an overview on different methods and recent research advancements in this area.

MPC is a control methodology utilizing a model of the system under control. Using the system model, MPC can predict the system behavior to different control actions. The typical system can be described in terms of a general difference equation as [13]:

$$x(t+1) = f(x(t), u(t)) \tag{14}$$

where $x(t) \in R^p$ is the state variable and $u(t) \in R^q$ is the system input at time t, $t \in \{0, \infty\}$. The function $f : R^p \times R^q \to R^p$ is a continues function. General form of constraints are also as follows:

$$x(t) \in \mathcal{X}, \quad u(t) \in \mathcal{U} \tag{15}$$

which means both state variables and system inputs are restricted by $\mathcal{X}$ and $\mathcal{U}$ sets respectively. The primary task for MPC is to navigate the state variable to a time-varying reference trajectory while the cost function is optimized as well. The cost function is optimized over the finite interval of optimization horizon, $k \in [0, T]$ where $T > 0$, and is expressed in general form as:

$$C(x, u) := \sum_{t=0}^{T} c(x(t), u(t)) \tag{16}$$

The function $c : R^p \times R^q \to R_+$ is a continues nonnegative function. By using the measured state variable as initial condition, MPC solve the optimization problem to find the optimal solution, $u^\star$, such that

$$C(x(0), u^\star) \leq C(x(0), u) \qquad \forall\ u \in \mathcal{U} \tag{17}$$

The optimal solution, $u^\star$, is a sequence of T elements as

$$u^\star := \{u^\star(0), u^\star(1), ..., u^\star(T-1)\}, \tag{18}$$

from which only the first element, $u^\star(0)$, is implemented as the control command. By applying the control command to the system, state variable vector at the next time step, $x(t+1)$, is obtained. This measured output is considered as initial condition for optimization problem in the next iteration based on receding horizon policy.

In order to build the model, we need to have some information about the system. In the management problem under study, for making the model of operation for microgrid, some current and future information such as forecasted load and renewable generations profiles, time-of-use grid electricity rates, current battery SoC, SoC model for battery charging and discharge, battery power pricing model, etc. are required. In this way, MPC will be able to perform the real-time management task based on following steps which have been illustrated in figure (2) as well:

Step 1: Current system information and system response to previous inputs are measured. In addition, forecasted profiles are updated for new optimization horizon.

Step 2: Based on update information, system model, optimization objective function, and constraints are updated.

Step 3: The proposed economic dispatching problem is solved which results in a sequence of control actions for each time instance of optimization horizon.

Step 4: The first control action is implemented which means the output of each energy source and battery is determined for current time. The rest of the control sequence will be ignored.

Step 5: System response (new level of battery SoC, battery power price, etc.) to control commands is measured and utilized as a feedback for next iteration to improve system performance.

Steps 4 & 5 together help the management system to perform a closed-loop control algorithm. Closed-loop characteristic makes the MPC to be robust and reliable for dealing with errors in system modeling and forecasting the renewable generations and load profiles.

Step 6: Horizon control recedes just one time step and MPC repeats the algorithm by going back to step 1.This step lets MPC to act as an on-line manager for microgrid which optimizes its behavior in every time step.

IV. Simulation Results & Discussion

For simulation purposes, a grid-tied microgrid is considered in this study which includes wind turbine and PV solar panels as DG resources, grid connection, a storage package, and a load. To highlight the effectiveness of proposed method, first, we illustrate the simulation results for one day operation of microgrid. To this purpose, 24-hour profiles of time-of-use grid electricity rate, load, and renewable generation have been extracted based on real data and are illustrated in Figure (3). As it can be seen, based on three different grid electricity tariffs during the day, three different types of region have been introduced which are named off-peak time, partial peak time, and peak time. An Intensium Flex High Energy Lithium-Ion battery package has been selected as the storage unit for simulation purpose. Table (I) describes the specifications of battery package. Model predictive optimization horizon is 12 hours and receding step is 20 minutes which means optimization problem over the next 12 hours is solved and repeated every 20 minutes. In addition, it is assumed that 12-hour prediction of renewable generation is not a perfect forecast and has some uncertainty. To consider the uncertainty of forecasting, a random prediction error profile is generated and combined with renewable generation daily profile. This profile states that the error propagates up to 50% during the 12 hours of forecasting. Figure (4) shows the error propagation along the optimization

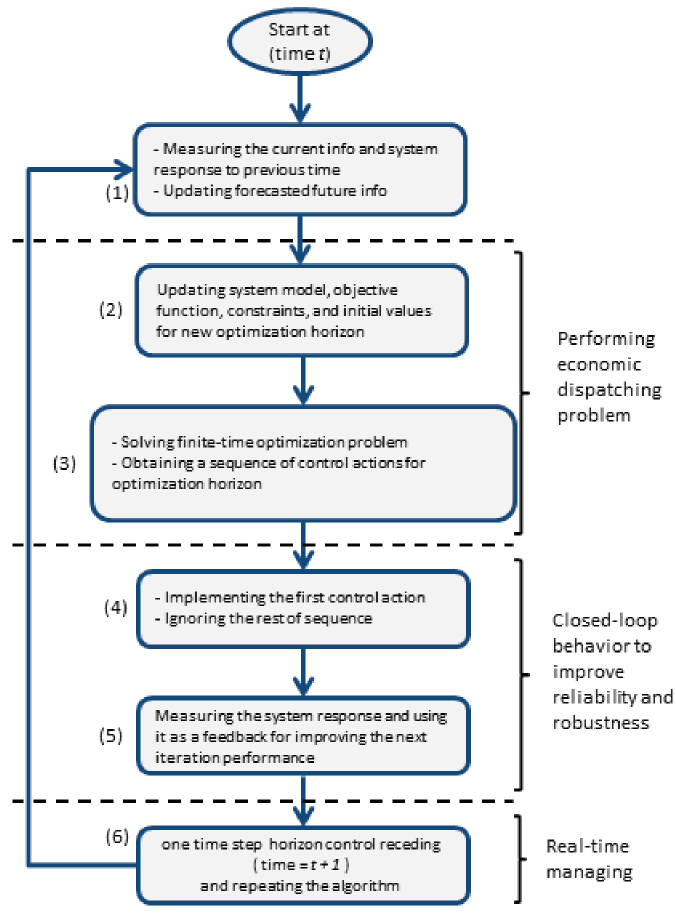

Fig. 2. MPC Flowchart

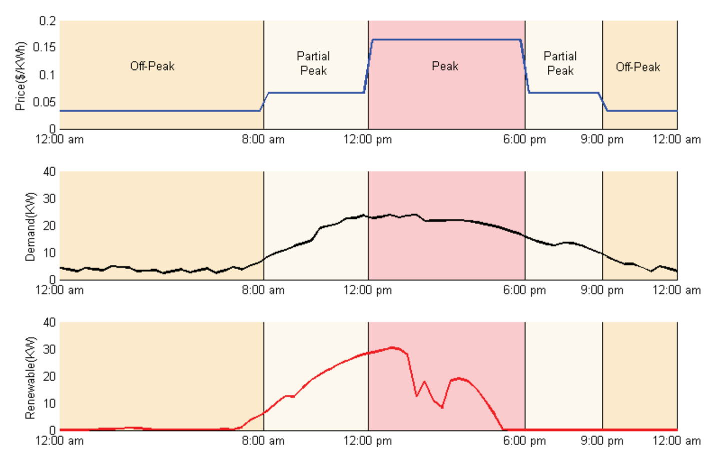

Fig. 3. Daily Profiles of grid electricity price, demand, and renewable generation

TABLE I
Characteristics of Intensium Flex High Energy Lithium-Ion Battery Package

Nominal voltage of each cell, V	48
Rated capacity, Ah	45
Rated lifetime at +20 °C, year	20
Rated life cycle	3000
Rated DoD	80%
NO. of cells in series, and parallel	18, and 1

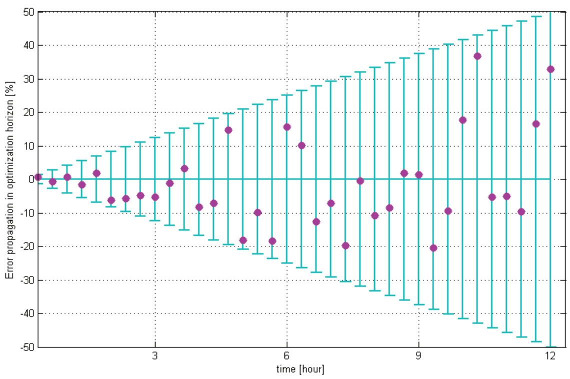

Fig. 4. Error propagation along the forecasting horizon

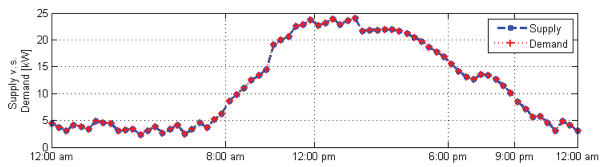

Fig. 5. Balance between supply and demand

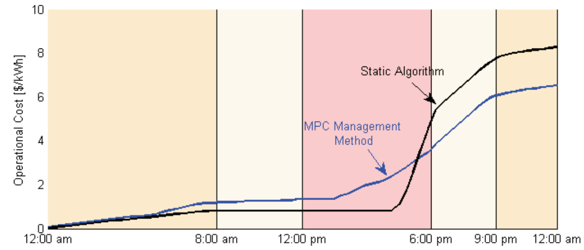

Fig. 6. Operational cost based on MPC management and static management strategies

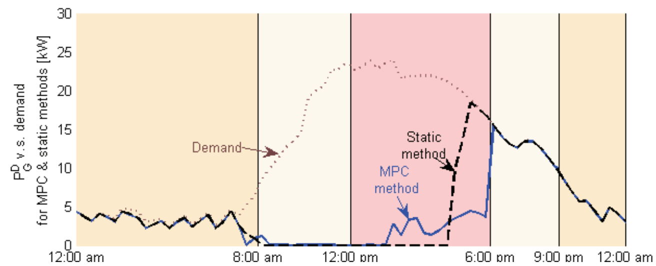

Fig. 7. Extracted power from the grid for sending directly to load for both MPC and static methods versus load

window. Finally it should be mentioned that since we focus on cost minimization and battery lifetime maximization objectives, peak shaving constraint is excluded from the MPC problem. But, adding peak shaving task to management system responsibilities is straightforward and does not change the formulation. Detailed dynamic models of microgrid components are developed in MATLAB environment along with the proposed management framework. In addition, MATLAB optimization toolbox is utilized to solve the MPC problem. Figure (5) illustrates the first task of management system which is the balance between total generation and demand. It means that the total output of energy sources, e.g. grid connection, renewable generations, and battery equals to demand at each time instance. In order to evaluate the performance of proposed energy management system, we compare the results of this method with the outcomes of static algorithm proposed in [11]. Authors in [11] have tried to optimize the operational cost and battery lifetime as well; but they optimize microgrid performance at each time instance independently and without considering the future conditions and information. Figure (6) illustrates the operational cost for one day operation of microgrid based on two management strategy, the proposed MPC management method and static algorithm in [11]. As it shows, initially the operational cost for MPC method is higher but this cumulative cost will stay below the operational cost curve of the static method after $6:00\ pm$. The total operational cost for static method is $\$8.27$ while the total operational cost for MPC method is $\$6.48$. It means utilizing the proposed management method will create the opportunity of 21.6% more saving in one-day operational cost. Now, we investigate the reasons which help the proposed management method to reduce the operational cost. To this end, we track the flow of power from microgrid energy sources. Figure (7) shows the extracted power from the grid for sending directly to load, P_G^D, for both MPC and static methods versus load. It shows that the static method extracts much more power from the grid in peak time in which the grid electricity price is in its maximum rate period. Figure (8.b) illustrates the power that charges the battery based on static algorithm. By looking at figure (8.a) we find that the battery is charged only when there is some exceeded renewable power. In this way, static method could charge the battery up to 70% of its full capacity, figure (8.c). Since the static method does not utilize any future information, the stored power will be discharged as soon as there will be any mismatch power for balancing the demand. On the other hand, figure (9.a) shows the battery charging power based on MPC management method. Since, this method can forecast the availability of renewable generation, it predicts that in peak time there is not enough renewable power to compensate the load. Hence, there will be need to import some power from the grid. To minimize importing expensive grid power in peak time, MPC stores some grid power but in off-peak period in which grid power is cheaper. This power has been shown by dashed line in figure (9.a). MPC stores this power up to a level that allows fully utilization of exceeded free-of-charge renewable power. Figure (9.b) depicts that MPC employs the full capacity of battery ($100\%SoC$) and discharges all permitted battery power ($80\%DoD$) in peak period in order to obtain the minimum operational cost.

For investigating the performance of the proposed management method in extending the battery lifetime, we need to operate the system for a longer time period. To this purpose, the microgrid is operated for 30 days using the monthly profiles of time-of-use grid electricity rate, load, and renewable generation. In addition, in order to demonstrate the advantage of considering battery lifetime maximization objective in MPC management algorithm, we run the MPC once with battery lifetime extension objective, and once without it. Figure (10) shows estimated battery lifetime over one month operation of microgrid for both cases. It shows that if battery lifetime extension objective is not included in our management strategy, battery lifetime will be around 18 years based on the obtained one-month usage pattern of battery. On the other hand, by including the battery lifetime maximization goal in MPC objective function, the proposed management system is

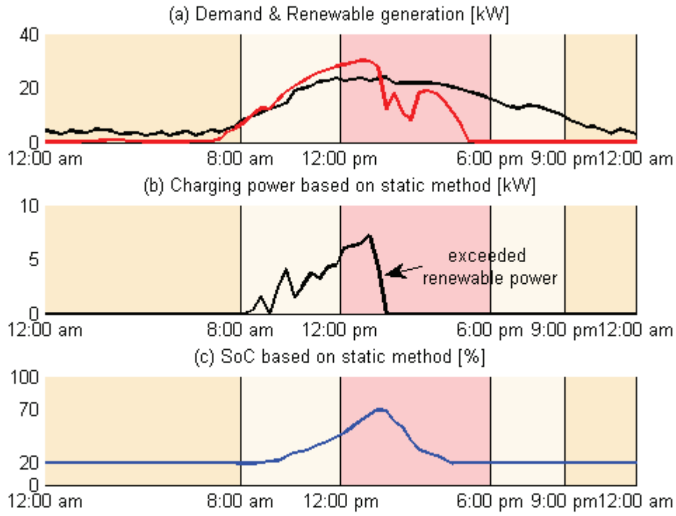

Fig. 8. (a) Demand & renewable generation, (b) Battery charging power, and (c) Battery SoC related to static method

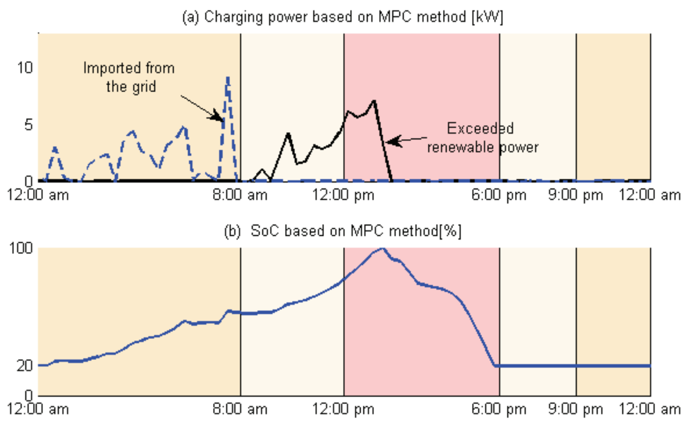

Fig. 9. (a) MPC-based battery charging power, (b) MPC-based battery SoC

able to utilize the battery package for its whole rated life span which is 20 years.

V. Conclusion & Future work

In this paper, we presented a multi-objective management system to control the operation of a microgrid. Two objectives were selected to obtain the optimal performance of the microgrid. First objective was minimization of energy operational cost; and the second one was maximization of battery lifetime. To implement the management algorithm, we proposed to use MPC as an efficient method to solve the underlying optimization problem. To investigate the performance of proposed management strategy, a microgrid including local renewable generations, grid connection, energy storage unit and a load was simulated in MATLAB environment. We compared the performance of MPC algorithm with static method proposed in [11]. It turned out that MPC method obtains 21.6% more saving in energy cost. To demonstrate the effectiveness of considering battery lifetime extension objective, we simulated one month operation of microgrid. It has been shown that by considering battery life span maximization objective, MPC is able to operate the battery for its whole rated life.

The authors are currently experimenting the performance of proposed multi-objective management method. The algorithm

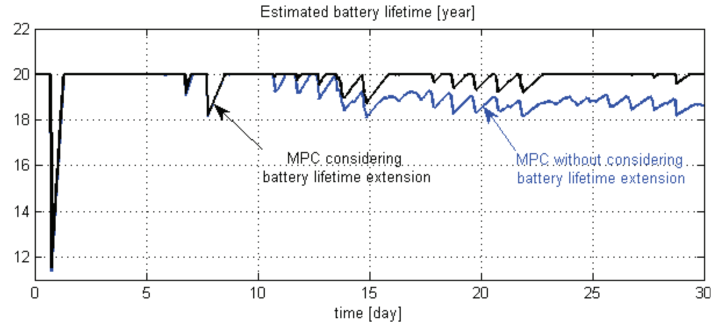

Fig. 10. Estimated battery lifetime over one month operation of microgrid

is implemented on the microgrid test-bed provided by Energy Management department at NEC Research Laboratories America, Inc., Cupertino, CA.

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