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Power flow management of microgrid networks using model predictive control

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ABSTRACT

In this paper, we present a power flow management method for a network of cooperating microgrids within the context of a smart grid by formulating the problem in a model predictive control framework. In order to reliably and economically provide the required power to the costumers, the proposed method enables the network of microgrids to share the power generated from their renewable energy sources and minimize the power needed from the micro gas turbines. To corroborate the viability of the proposed method, we will illustrate simulation results on a model consisting of three microgrids in a network.

1. Introduction

Smart grids, as the future generation of power systems, will include different types of generation option such as central, distributed, and intermittent sources. They allow consumers to interact with the utility to manage their consumption and minimize the cost of energy [1]. The development and evolution of smart grids will result in the plug-and-play integration of intelligent structures called microgrids that will be linked with each other through particular channels for power, information, and control signal exchange [2–4]. Fig. 1 shows the aforementioned topology. Each microgrid by itself can integrate loads and resources, e.g., wind, photovoltaic cells, biomass, and micro gas turbines, as shown in Fig. 2.

Taking advantage of the plug-and-play feature for implementation purposes, a microgrid can operate in either grid-connected mode or separated from the grid, the so-called islanded mode [6,7]. In addition to this ability for self-managing, the microgrids in a neighborhood can collaborate through information exchange and power channels. Taking advantage of self-managing and collaborating capabilities, microgrids can compensate for the deviations from predicted demand or forecasted renewable generations through buying or selling surplus electricity from other microgrids' gas turbines. This will allow them to participate less in spot markets for trading electricity, and they will only buy a predetermined needed power through forward contracts for the entire day including peak hours at a much lower rate.

In this paper, we assume that each microgrid has the ability to predict its own daily load curve and renewable energy generation profile. Due to the low cost of power generated from renewable sources, each microgrid first tries to supply the requested power by using the renewable sources and then, if needed, it uses its micro gas turbine, which is a controllable generation source within the microgrid. Moreover, if at some point the amount of produced renewable power within the microgrid *i* is higher than the demand, it can find a neighbor, say microgrid *j*, whose renewable generation is less than its demand; in this case, microgrid *i* will sell the surplus power to microgrid *j*. Based on this cooperation, the total cost of gas for the micro gas turbines will have to be minimized through solving an appropriately defined optimization problem. This is the scheduling problem we will address in the present paper.

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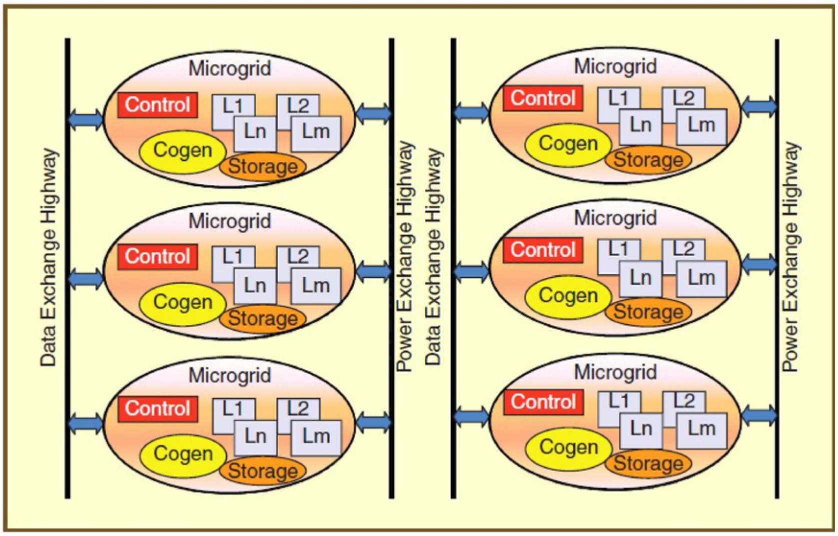

Fig. 1. Smart grid topology [1].

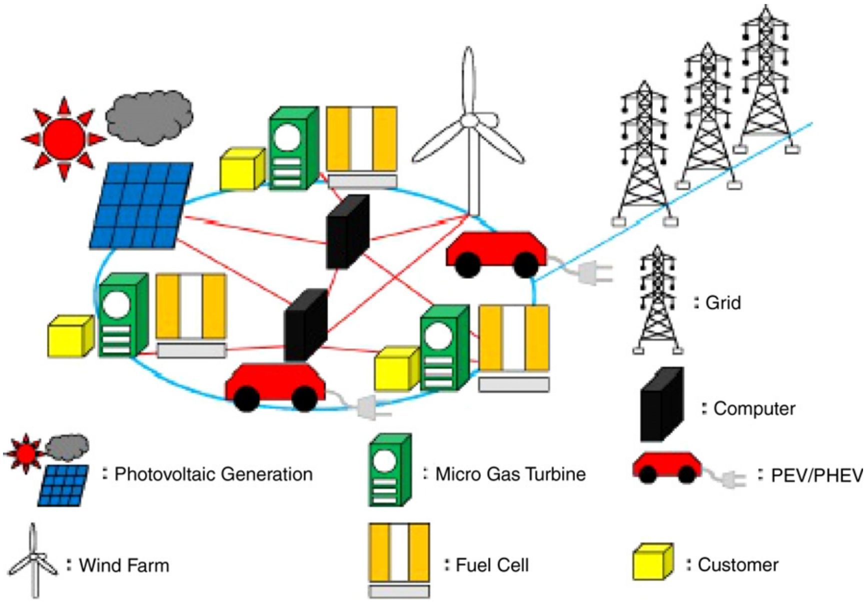

Fig. 2. A typical microgrid [5].

There have been several approaches for solving the described scheduling problem in the literature. In [8], dynamic programming has been employed to solve the corresponding optimization problem. However, the computational time and the dimension of scheduling problem based on dynamic programming will raise with the increase in dimension of the power system. In the 1980s, this problem was transformed into the minimization of the entire generation cost during a particular time interval; this problem was named dynamic economic dispatch (DED) [9,10]. Different methods were then proposed to address the DED problem, including the gradient projection method and Lagrange relaxation [11,12]. Unfortunately, DED violates the ramp rate constraint of generator units [13]. More importantly, the DED strategy is an open-loop control policy, and hence there will be no control over any digression from the forecasted values such as demand or any disturbance in the generators' output.

Model predictive control (MPC) is a powerful control policy, which uses a model to project the behavior of a dynamic system. Based on the model, the MPC law can predict the future response of the system to various control actions. At each iteration, MPC solves an optimization problem over a prediction time horizon based on current measured information of the system states, and determines the future optimal control actions. Only the first step of the control actions is implemented, and the rest will be ignored. The system response to this control input will be measured as the next available information for

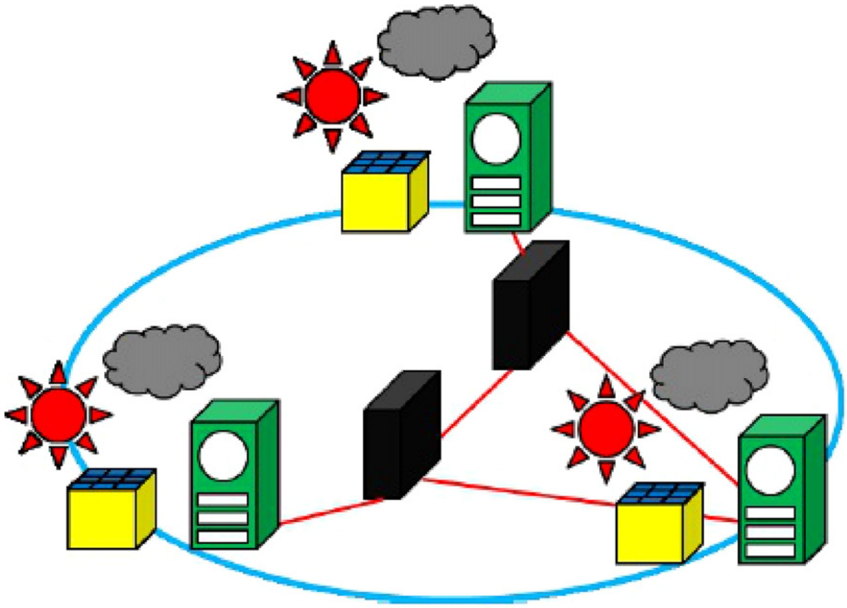

Fig. 3. An example illustrating the cooperation between microgrids in a network [5].

solving the optimization problem in the next iteration. Various theoretical developments for MPC techniques with different computational needs have been made in the past few decades [14–16]. In recent years, MPC has also attracted the attention of the power system community due to its ability to operate based on future behavior of the system and predictions. Therefore, for problems such as power system scheduling, which depends greatly on forecasted values of demand and renewable energy production, the MPC method would be very effective. In addition, due to its closed-loop nature, it corrects any error in prediction of the load and renewable generation within the next iteration and hence helps enhance the system stability and robustness [17,18]. Finally, it should be noted that MPC can handle power system constraints such as generator capacity, transmission line limitations, and ramp rate constraints [13,19,20]. Other advantages of MPC in power system management have been discussed in [21].

The present paper is organized as follows. Section 2 describes the model of microgrids we use for control design purposes. Multiple microgrids are considered, and their models are finally augmented. The model predictive control method and the underlying optimization problem are then descried briefly in Section 3. Simulation results on the model of a simple network with three microgrids are presented in Section 4. Section 5 concludes the paper.

2. System modeling

In this paper, we consider a network of microgrids including three nodes, as illustrated in Fig. 3. *It should be noted that the method presented here can be extended to a larger number of microgrids as well.* It is assumed that each node contains a micro gas turbine, as well as *a renewable source such as* a PV generator or a wind turbine. The power from the gas turbine is controllable, while that from the renewable sources is uncontrollable [22]. In our formulation, we denote the total power generated by the ith microgrid, the power generated by the ith micro gas turbine, the power produced by the ith renewable source, and the demand of the ith node by $G_i(t)$, $u_i(t)$, $G_i^{\text{renew}}(t)$, and $G_i^{\text{ref}}(t)$, respectively. For node i, the generated power $G_i(t)$ at each time instant depends on its generated power at previous sampled time, its renewable generation power, its neighbors' surplus renewable power, and its micro gas turbine output. The objective is to keep $G_i(t)$ as close as possible to $G_i^{\text{ref}}(t)$ for all the nodes. The daily load profile $G_i^{\text{ref}}(t)$ can be obtained in real time using short-term electricity demand forecasting techniques [23,24]. In addition, since the renewable source outputs are not controllable and their future profiles over a certain finite horizon time interval can be obtained in real time using weather forecasts, the power from renewable sources can be treated like a negative load in the scheduling problem. Hence, the problem can be formulated as that of minimizing $\|G_i(t) - G_i^{\text{setpoint}}(t)\|$, where $G_i^{\text{setpoint}}(t) = \max[0, (G_i^{\text{ref}}(t) - G_i^{\text{renew}}(t))] + \sum_j a_{ij} \min[0, (G_j^{\text{ref}}(t) - G_j^{\text{renew}}(t))]$, in which a_{ij} are coefficients defining the portion of the power of the ith node that comes from the surplus power of the jth node. The coefficients can be determined through a forward contract. The state equation corresponding to each microgrid can be given as

$$G_i(t+1) = G_i(t) + u_i(t) + w_i(t), \quad \text{for } i = 1, 2, 3, \tag{1}$$

where $w_i(t)$ is the zero-mean white noise used to describe the uncertainties from either the power generated by the uncontrollable sources or the errors in the demand forecast curve. The output equation for each node is the power measurement, i.e.,

$$y_i(t) = G_i(t), \tag{2}$$

assuming that the measurement noise is neglected. Moreover, there exists a physical constraint resulting from the limitation on the micro gas turbine generation as

$$0 \le u_i(t) \le u_i^{\max}. \tag{3}$$

Putting the system equations together for all the microgrids results in

$$\begin{aligned} G(t+1) &= AG(t) + Bu(t) + Fw(t) \\ y(t) &= CG(t), \end{aligned} \tag{4}$$

in which, for the specific network shown in Fig. 3,

$$\begin{aligned} G(t) &= [G_1(t), G_2(t), G_3(t)]^T \\ u(t) &= [u_1(t), u_2(t), u_3(t)]^T \\ w(t) &= [w_1(t), w_2(t), w_3(t)]^T \\ y(t) &= [y_1(t), y_2(t), y_3(t)]^T, \end{aligned} \tag{5}$$

and the system matrices A, B, C, and F are 3×3 identity matrices.

3. Model predictive control

To cope with the input constraints, as well as the aforedescribed model characteristics, a suitable control methodology is model predictive control, which has become popular using state-space design methods in recent years [25–27].

3.1. Augmented model

We first transform the standard state-space representation described earlier into a form appropriate for MPC design purposes, in which an integrator is also embedded [28]:

$$G(t+1) - G(t) = A(G(t) - G(t-1)) + B(u(t) - u(t-1)) + F(w(t) - w(t-1)). \tag{6}$$

The addition of the integrator is to ensure reference trajectory tracking. By defining

$$\begin{aligned} \Delta G(t) &= G(t) - G(t-1) \\ \Delta u(t) &= u(t) - u(t-1) \\ \epsilon(t) &= w(t) - w(t-1), \end{aligned} \tag{7}$$

we obtain

$$\begin{aligned} \begin{bmatrix} \Delta G(t+1) \\ y(t+1) \end{bmatrix} &= \begin{bmatrix} A & 0 \\ CA & I \end{bmatrix} \begin{bmatrix} \Delta G(t) \\ y(t) \end{bmatrix} + \begin{bmatrix} B \\ CB \end{bmatrix} \Delta u(t) + \begin{bmatrix} F \\ CF \end{bmatrix} \epsilon(t) \\ y(t) &= \begin{bmatrix} 0 & I \end{bmatrix} \begin{bmatrix} \Delta G(t) \\ y(t) \end{bmatrix}. \end{aligned} \tag{8}$$

Choosing a new state variable vector as $x(t) = [\Delta G(t)^T, y(t)^T]^T$, we have

$$\begin{aligned} x(t+1) &= Mx(t) + N\Delta u(t) + E\epsilon(t) \\ y(t) &= Hx(t). \end{aligned} \tag{9}$$

3.2. Prediction of state and output variables

In this section, based on the augmented model obtained, we calculate the predicted plant output using future control inputs as the adjustable variables. Suppose that, at time instant t, the state vector $x(t)$ is available through measurement. The future control trajectory is denoted by [28]

$$\Delta u(t), \Delta u(t+1), \ldots, \Delta u(t+N_c-1), \tag{10}$$

where N_c is the control horizon which determines the number of future control actions. The future state variables and outputs are predicted for N_p steps (prediction horizon) through given information $x(t)$. The parameter N_p is also the length of the optimization window, and $N_c \le N_p$. The chain of future state variables is

$$x(t+1|t), x(t+2|t), \ldots, x(t+N_p|t), \tag{11}$$

where $x(t+N_p|t)$ represents the predicted state at time instant $t+N_p$ using the information at the current time $x(t)$, which is equal to

$$x(t+N_p|t) = M^{N_p}x(t) + \sum_{j=0}^{N_c-1} M^{N_p-1-j}N\Delta u(t+j). \tag{12}$$

Note that in the equations above that are used for prediction, since the disturbance is white noise and its expected value is zero, the term related to disturbance does not appear. The prediction of outputs can be found by the use of predicted state variables as

$$y(t+N_p|t) = HM^{N_p}x(t) + \sum_{j=0}^{N_c-1} HM^{N_p-1-j}N\Delta u(t+j). \tag{13}$$

By defining new vectors as

$$\begin{aligned} Y &= [y(t+1|t)^T, y(t+2|t)^T, \ldots, y(t+N_p|t)^T]^T \\ \Delta U &= [\Delta u(t)^T, \Delta u(t+1)^T, \ldots, \Delta u(t+N_c-1)^T]^T, \end{aligned} \tag{14}$$

we obtain

$$Y = \Gamma x(t) + \Phi \Delta U \tag{15}$$

where

$$\Gamma = \begin{bmatrix} HM \\ HM^2 \\ \vdots \\ HM^{N_p} \end{bmatrix} \tag{16}$$

and

$$\Phi = \begin{bmatrix} HN & 0 & \cdots & 0 \\ HMN & HN & \cdots & 0 \\ HM^2N & HMN & \cdots & 0 \\ \vdots & & & \\ HM^{N_p-1}N & HM^{N_p-2}N & \cdots & HM^{N_p-N_c}N \end{bmatrix}. \tag{17}$$

Finally, it should be noted that all of the predicted variables (states and outputs) are calculated in terms of the current system state $x(t)$ and the future control actions.

3.3. Optimization

In this section, we define an objective function resulting in the control inputs to maintain the predicted output as close as possible to a set-point signal $r(t)$. By solving the problem of minimizing this cost function, an optimal control trajectory ΔU will be obtained that minimizes the error between the set-point and the predicted output. Suppose that the set-point vector is

$$R_s = \begin{bmatrix} r(t)^T & r(t+1)^T & \cdots & r(t+N_p-1)^T \end{bmatrix}^T. \tag{18}$$

Having the set-point vector R_s, the objective function J can be defined as

$$J = (R_s - Y)^T(R_s - Y) + \Delta U^T \bar{R} \Delta U, \tag{19}$$

where $\bar{R}$ is a tuning matrix used to shape the desired closed-loop performance. By expanding the vector Y, J can be rewritten as

$$J = (R_s - \Gamma x(t))^T(R_s - \Gamma x(t)) - 2\Delta U^T \Phi^T (R_s - \Gamma x(t)) + \Delta U^T(\Phi^T\Phi + \bar{R})\Delta U.$$

Taking the first derivative of the cost function J and using the necessary condition for minimization, we obtain

$$\frac{\partial J}{\partial \Delta U} = -2\Phi^T(R_s - \Gamma x(t)) + 2(\Phi^T\Phi + \bar{R})\Delta U = 0, \tag{20}$$

from which the optimal control trajectory is determined as

$$\Delta U = (\Phi^T\Phi + \bar{R})^{-1}\Phi^T(R_s - \Gamma x(t)). \tag{21}$$

Although the optimal solution vector ΔU contains the control inputs $\Delta u(t), \Delta u(t+1), \Delta u(t+2), \ldots, \Delta u(t+N_c-1)$, based on receding horizon control principle, we only implement the first sample of this sequence, i.e., $\Delta u(t)$, and ignore the rest of the sequence. When the next sampled data arrives, the more recent measurement is used to form the state vector $x(t+1)$ for calculation of the new sequence of control input. This procedure is iterated to provide the receding horizon control law.

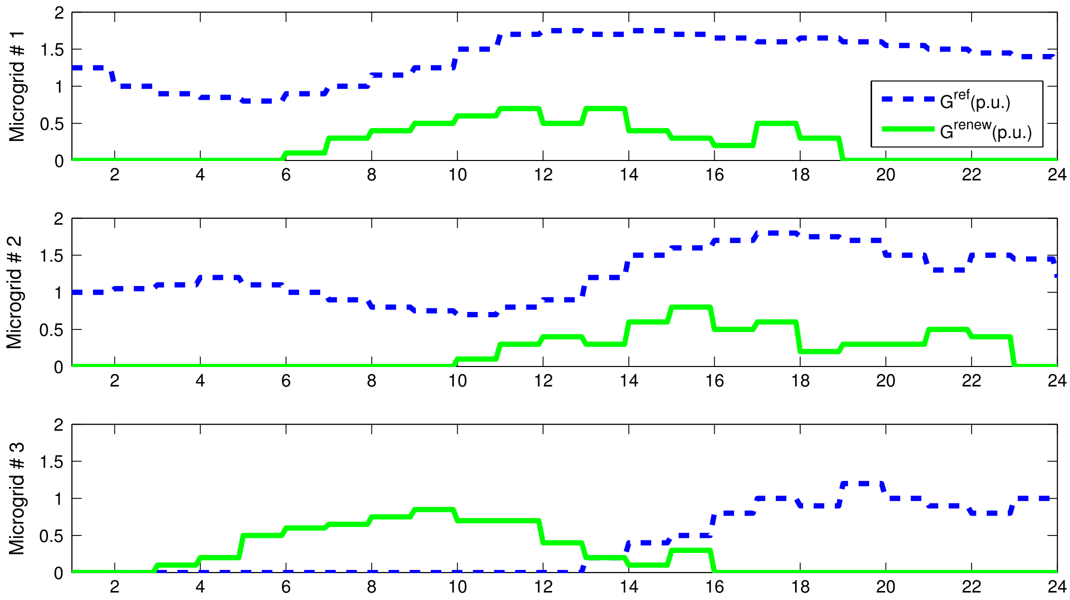

Fig. 4. Demand profile and daily power generated by the renewable energy sources.

4. Simulation results

In this section, we demonstrate the simulation results using an example to examine the performance of the proposed microgrid power management method described in the previous sections. First, we generate artificial data for microgrids in the network shown in Fig. 3 *with a step size of* 5 min. For optimization purposes, we have simulated the daily forecasted power generation profiles for the renewable source of each microgrid. These profiles are shown by solid lines in Fig. 4. Also, dashed lines in Fig. 4 illustrate the simulated demand profiles for each microgrid. It should be noted that all the values reported in this section are converted to per unit (p.u.). We have further assumed that the third microgrid has no power consumption during the first 13 h.

If the microgrids operate in islanded mode, which implies that there is no collaboration within the network, the difference between the demand profile and the renewable generation curve is used to generate the reference trajectory for each microgrid; this difference needs to be compensated for by using micro gas turbine power. The reference trajectories are shown in Fig. 5 by solid lines. Since the microgrids cannot collaborate with each other, there will be no chance to utilize the surplus renewable power at the third microgrid which has been illustrated by the black solid line. By taking advantage of the proposed method in this paper, which provides an opportunity for the microgrids to collaborate, this surplus power can be transferred to the neighbors to reduce the generated power of micro gas turbines. Here, it is assumed that the surplus power is split equally between the neighbors, which in our case means that $a_{ij} = 0.5$. The reduced power needed from the micro gas turbines is shown in Fig. 5 by dashed lines.

Finally, *it should be noted that the length of the optimization window N_p and control horizon N_c are assumed to be the same and equal to* 5. Fig. 6 illustrates the power generated by the micro gas turbines in each microgrid calculated using the MPC design strategy versus the reference trajectory. As can be inferred, the generated power, i.e., supply, compensates for the residual load reasonably well. The small perturbation of generated power is due to the errors in forecasting demand and renewable generation amounts. Hence, it can be concluded that the proposed model predictive optimization problem reduces the total cost of generation in the microgrid network by utilizing the inherent capability of employing the future behavior of the system and providing a collaboration opportunity between the microgrids in the network.

5. Conclusions

In this paper, we have investigated the problem of power flow management for a network of microgrids. To this end, we have defined an optimization problem, which besides achieving an optimal solution for minimum generation cost allows the microgrids in a network to collaborate with each other. This collaboration minimizes the power produced by the micro gas turbine, which is a unit with higher cost of generation. We then utilize the model predictive control approach to solve the optimization problem. An illustrative example has been finally used to demonstrate the effectiveness of the proposed microgrid management strategy.

The authors are currently examining the extension of this work to a distributed control scheme, where the microgrids exchange limited information with some of the neighbors with a direct connection. This eliminates the need for a central processor and improves the reliability and robustness of the control method. In addition, the authors are examining this

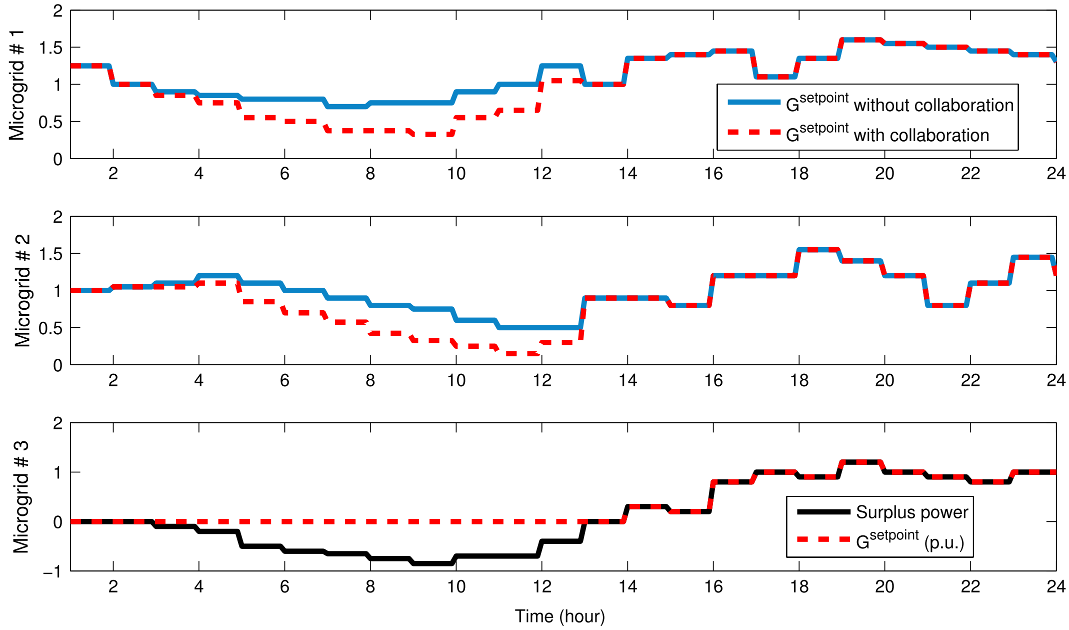

Fig. 5. The reference trajectory of each microgrid with and without collaboration opportunity.

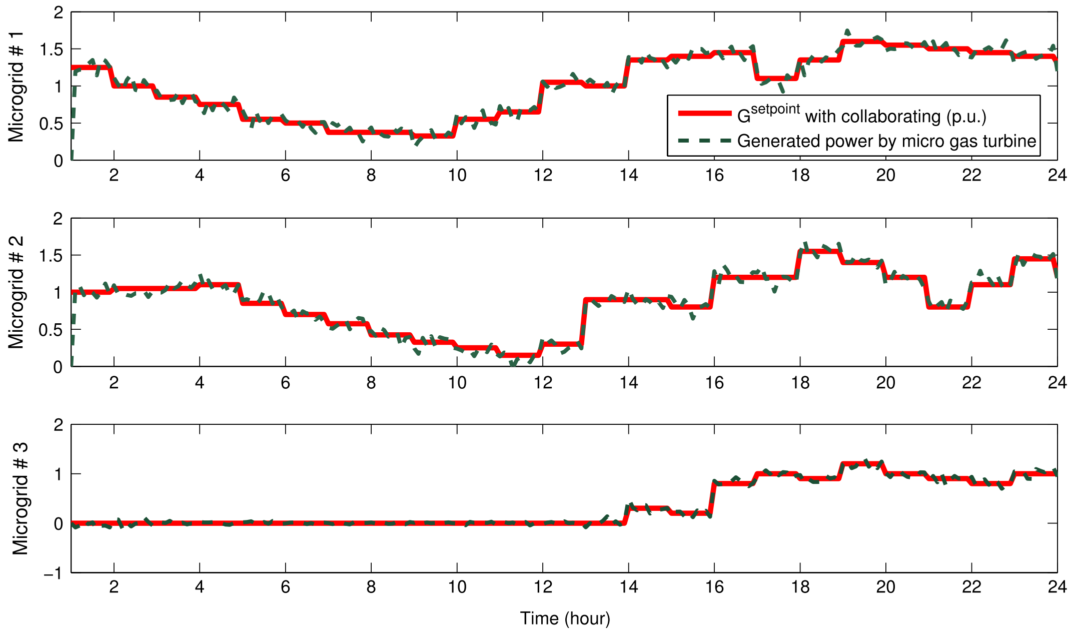

Fig. 6. The generated power from the micro gas turbine in the three microgrids versus the residual demand.

problem considering the market opportunity between microgrids for buying and selling their surplus power. This simply implies that the coefficients a_{ij} defining the portion of neighbor shares from this surplus power will be time varying and should be determined through various types of market contract.

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