Stochastic Distributed Control for Frequency Regulation in Energy Internet: An ADMM Approach

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***Abstract*—Facing the new changes of energy supply and demand pattern and the trend of international energy development, it is urgent to build a clean, low-carbon, safe and efficient energy Internet (EI) system. For a special EI scenario, in the sense that multiple AC microgrids (MGs) are interconnected without access to the main power grid, the EI system stability issue is of great importance. In this paper, a frequency regulation problem for such EI is investigated. It is notable that the system stochasticity caused by the large-scale access of renewable energy sources is taken into consideration. The frequency regulation issue is then transformed into a stochastic optimal control problem, and the ADMM-based decentralized control strategy is designed for each MG. In this manner, the proposed distributed control scheme can be more practical for the operation of large-scale EI systems. Numerical simulations are performed to validate the feasibility of the proposed method.**

***Index Terms*—Distributed control, energy Internet, frequency regulation, microgrids, renewable energy**

NOMENCLATURE

ADMM	Alternating direction method of multipliers.
BES	Battery energy storage.
EI	Energy Internet.
ER	Energy router.
FC	Fuel cell.
MG	Microgrid.
MT	Micro-turbine.
ODE	Ordinary differential equation.
PV	Photovoltaic panel.
RES	Renewable energy source.
SDE	Stochastic differential equation.
WTG	Wind turbine generator.
ΔP_{Load}	Load output power change.
ΔP_{PV}	PV output power change.
ΔP_{WTG}	WTG output power change.
ΔP_{BES}	BES output power change.
ΔP_{FC}	FC output power change.
ΔP_{MT}	MT output power change.
Δf	Frequency deviation.
ΔP_{ER}	ER output power change.
T_{Load}	Load time constant.
T_{PV}	PV time constant.
T_{WTG}	WTG time constant.
T_{BES}	BES time constant.
T_{FC}	FC time constant.
T_{MT}	MT time constant.
T_{ER}	ER time constant.
D	Damping coefficient.
M	Inertia constant.
k	Index of MG.

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I. INTRODUCTION

Under the background of the rapid and large-scale growth trend of RES and the severe problem of absorption of power generation by RES, how to continuously improve the power grid resource allocation ability and intelligence level to meet the requirement of intensive development of power base and large-scale access of RES, distributed loads, energy storage, interactive energy facilities, etc., has become an urgent problem [1]. It is the concept of EI that has been regarded as the solution to the aforementioned challenge [2], [3]. Within the scope of EI, it is recommended to optimize RES distribution according to the principle of both centralized development and decentralization [4].

Theoretical research on EI has been popular for the last five years, and significant advances on different topics have been made; see, e.g., [5]- [9]. If an EI scenario has no access to the utility grid and the main power generation depends on RESs, the problem of EI system stabilization is complicate, since power generation by RESs mainly depends on changeable weather condition [10], [11]. With the vigorous development of distributed energy resources, the monitoring data of large-scale RESs are increasingly abundant [12]. In [13], big data analysis for system stability evaluation strategy in EI has been extensively studied.

Regarding EI scenarios composed of multiple AC MGs, there are plenty of existing literatures concerning the frequency regulation problem; see, e.g., [14]- [16]. However, in most of these works, the proposed control schemes are centralized methods, which means that the control schemes are mainly obtained in a central node before they are distributed to the controllable devices. As the scale of the EI system grows continuously, there would be drastic increase of the calculation complexity related to these centralized control methods [17], [18]. For example, when the dimension of the investigated system in [14] and [15] increases significantly, the linear matrix inequality (LMI) approach appears to be invalid for solving the formulated H_∞ control problem. In this sense, the centralized approaches would be less practical to be applied in large-scale EI systems, which is the motivation of designing distributed control schemes in this paper.

In this paper, for each MG in EI, considering the stochasticity of power dynamics of PVs, WTGs, loads, SDEs are utilized to represent their power deviation. ODEs are used to model power change of BES, FC, MT, ER and AC bus frequency deviation. Then, the dynamical EI system is written as a constitutions SDE. In order to use the model predictive control (MPC) technique, the continuous system is rewritten into the corresponding discrete case. Next, the frequency regulation issue is formulated as a stochastic optimization problem, which is then solved by the ADMM approach [19]. In order to show the feasibility of the proposed approach, numerical examples are performed.

The main importance and contribution of this paper is highlighted as follows. This is the first time that a stochastic process based dynamical EI system is studied for decentralized stability control. We emphasize the investigated EI system has no access to the utility gird, and the main power generation of EI relies on RESs. By adopting the widely applied ADMM approach, we are able to dispatch part of the computation to individual MGs. Compared to the existing centralized methods, e.g., [14]- [16], the proposed distributed control scheme should be more practical for the operation of large-scale EI systems.

The rest of this paper is organized as follows. Firstly, in Section II, the short-term power dynamical model of EI is introduced. Then, the frequency regulation task is formulated in Section III, and the method for solving such control problem is provided in Section IV. The effectiveness and feasibility of the proposed control method are evaluated in Section V. Finally, Section VI summarizes this paper.

II. System Modeling

In this paper, a typical EI system consisting of N interconnected MGs is considered. It is assumed that for each pair of interconnected MGs, a corresponding ER is deployed to improve the power sharing efficiency as well as providing advanced communication services for the applications in EI. For literatures regarding ERs, readers can refer to [21]- [23], etc. As demonstrated in Fig. 1, the power sharing network constructed based on ERs could be represented by a undirected graphs denoted as $G(V, \xi)$. The MGs are designated by the vertex set $V = v_1, v_2, \dots, v_N$, and the connections among them are described with the edge set $\xi \subseteq V \times V$.

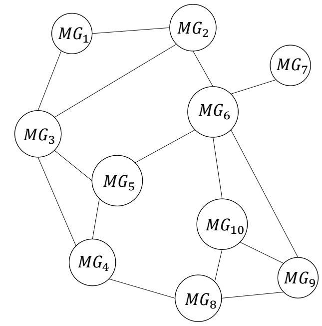

Fig. 1. Typical Energy Internet Scenario.

For the frequency regulation task concerned in this paper, the linearisation technique applied in [22]- [25] is utilized to obtain the short-term model of the considered EI system as follows. Without loss of generality, each MG in the system is considered to be consist of loads, PVs, WTGs, MTs, FCs and BESs. For the k-th MG, i.e., MG_k, in the EI system, the short-term dynamics of its components are depicted in (1) – (8).

$$d\Delta P^k_{Load} = -\frac{1}{T^k_{Load}}\Delta P^k_{Load}dt + C^k_{Load}\Delta P^k_{Load}dW^k_{Load}, \quad (1)$$

$$d\Delta P^k_{PV} = -\frac{1}{T^k_{PV}}\Delta P^k_{PV}dt + C^k_{PV}\Delta P^k_{PV}dW^k_{PV}, \quad (2)$$

$$d\Delta P^k_{WTG} = -\frac{1}{T^k_{WTG}}\Delta P^k_{WTG}dt + C^k_{WTG}\Delta P^k_{WTG}dW^k_{WTG}, \quad (3)$$

$$d\Delta P^k_{BES} = -\frac{1}{T^k_{BES}}(\Delta P^k_{BES} + r^k_{BES}\Delta f^k)dt, \quad (4)$$

$$d\Delta P^k_{FC} = \frac{1}{T^k_{FC}}(-\Delta P^k_{FC} + b^k_{FC}u^k_{FC})dt, \quad (5)$$

$$d\Delta P^k_{MT} = \frac{1}{T^k_{MT}}(-\Delta P^k_{MT} + b^k_{MT}u^k_{MT})dt, \quad (6)$$

$$d\Delta f^k = (-\frac{2D^k}{M^k}\Delta f^k + \frac{2}{M^k}\Delta P^k)dt. \quad (7)$$

$$\begin{aligned}\Delta P^k = & -\Delta P^k_{Load} + \Delta P^k_{WTG} + \Delta P^k_{PV} + \Delta P^k_{MT} \\ & \pm\Delta P^k_{BES} + \sum_{(j,k)\in\xi}\Delta P^{jk}_{ER}, \end{aligned} \quad (8)$$

where u_{FC}, u_{MT} stand for control input for FC and MT, and C_{Load}, C_{PV}, C_{WTG}, r_{BES}, b_{FC}, b_{MT} are system coefficients that can be obtained by parameter estimation methods.

Regarding the regulated power transmission via ERs, if $(j,k) \in \xi$, the power flows between MG_j and MG_k are denoted as P^{jk}_{ER} and P^{kj}_{ER}, respectively. In this paper, it is presumed that the bi-directional power transmission between any two interconnected MGs is not allowed at the same time. In this sense, both P^{jk}_{ER} and P^{kj}_{ER} depict the power flow between MG_i and MG_j, and their positive or negative sign only represent the flow direction, which means $P_{ER}^{jk} = -P_{ER}^{kj}$. The adjustment of the power flow of P_{ER}^{jk} is given in (9),

$$d\Delta P_{ER}^{jk} = \frac{1}{T_{ER}^{jk}}(-\Delta P_{ER}^{jk} + b_{ER}^{jk} u_{ER}^{jk})dt. \tag{9}$$

Based on the dynamic model introduced above, the proposed distributed model predictive control approach is developed in the following sections.

III. Problem Formulation

In this paper, we focus on designing a decentralized control scheme for a typical off-grid EI scenario. Assume the considered time period is $[0,T]$. Taking the step length Δt, a time series $\{0, \Delta t, \ldots, M\Delta t\}$ can be obtained after discretization, where $M = T/\Delta t$. Thus, the continuous-time system model in (1) – (9) is discretized as follows.

$$\begin{aligned}
\Delta P_{Load}^{k,i+1} &= (1 - \frac{1}{T_{Load}^{k}}\Delta t)\Delta P_{Load}^{k,i} + C_{Load}^{k}\Delta P_{Load}^{k,i}\Delta W_{Load}^{k,i},\\
\Delta P_{PV}^{k,i+1} &= (1 - \frac{1}{T_{PV}^{k}}\Delta t)\Delta P_{PV}^{k,i} + C_{PV}^{k}\Delta P_{PV}^{k,i+1}\Delta W_{PV}^{k,i},\\
\Delta P_{WTG}^{k,i+1} &= (1 - \frac{1}{T_{WTG}^{k}}\Delta t)\Delta P_{WTG}^{k,i} + C_{WTG}^{k}\Delta P_{WTG}^{k}\Delta W_{WTG}^{k,i},\\
\Delta P_{BES}^{k,i+1} &= (1 - \frac{1}{T_{BES}^{k}}\Delta t)\Delta P_{BES}^{k,i} + \frac{r_{BES}^{k}}{T_{BES}^{k}}\Delta f^{k,i}\Delta t,\\
\Delta P_{FC}^{k,i+1} &= (1 - \frac{1}{T_{FC}^{k}}\Delta t)\Delta P_{FC}^{k,i} + \frac{b_{FC}^{k}}{T_{FC}^{k}}u_{FC}^{k,i})\Delta t,\\
\Delta P_{MT}^{k,i+1} &= (1 - \frac{1}{T_{MT}^{k}}\Delta t)\Delta P_{MT}^{k,i} + \frac{b_{MT}^{k}}{T_{MT}^{k}}u_{MT}^{k,i})\Delta t,\\
\Delta f^{k,i+1} &= (1 - \frac{2D^{k}}{M^{k}}\Delta t)\Delta f^{k,i} + \frac{2}{M^{k}}\Delta P^{k,i}\Delta t,\\
d\Delta P_{ER}^{jk,i+1} &= (1 - \frac{1}{T_{ER}^{jk}}\Delta t)\Delta P_{ER}^{jk,i} + \frac{b_{ER}^{jk}}{T_{ER}^{jk}}u_{ER}^{jk}\Delta t.
\end{aligned}$$

Inspired by the model predictive control technique, the terms $\Delta P_{Load}^{k,i}$, $\Delta P_{PV}^{k,i}$ and $\Delta P_{WTG}^{k,i}$ in (8) are replaced by their expectations, respectively, such that the calculation burden for the proposed control scheme could be reduced significantly. Let us denote $\mathbf{E}$ by the mathematical expectation. Then, we have

$$\begin{aligned}
\Delta P^{k,i} = &-\mathbf{E}[\Delta P_{Load}^{k,i}] + \mathbf{E}[\Delta P_{WTG}^{k,i}] + \mathbf{E}[\Delta P_{PV}^{k,i}]\\
&+\Delta P_{MT}^{k,i} \pm \Delta P_{BES}^{k,i} + \sum_{(j,k)\in\xi}\Delta P_{ER}^{jk,i}.
\end{aligned} \tag{10}$$

For the k-th MG, at time step $t = i\Delta t$, the discrete model above could be rewritten as follows,

$$x^{k,i+1} = A^{k}x^{k,i} + B^{k}u^{k,i} + C^{k,i}, \tag{11}$$

where

$$\begin{aligned}
x^{k,i} &= [\Delta P_{Load}^{k,i}, \Delta P_{PV}^{k,i}, \Delta P_{WTG}^{k,i}, \Delta P_{FC}^{k,i}, \Delta P_{MT}^{k,i}, \Delta f^{k,i}, x_{ER}^{k,i}{}']',\\
x_{ER}^{k,i} &= [\ldots, \Delta P_{ER}^{jk,i}, \ldots]', (j,k)\in\xi.\\
u^{k,i} &= [u_{FC}^{k,i}, u_{MT}^{k,i}, \ldots, \Delta u_{ER}^{jk,i}, \ldots]', (j,k)\in\xi.
\end{aligned}$$

Further, we denote $X = [X^{0\prime}, X^{1\prime}, \ldots, X^{N\prime}]'$ and $U = [U^{1\prime}, U^{2\prime}, \ldots, U^{N\prime}]'$, where

$$\begin{aligned}
X^{k} &= [x^{k,0\prime}, x^{k,1\prime}, \ldots, x^{k,M\prime}]',\\
U^{k} &= [u^{k,0\prime}, u^{k,1\prime}, \ldots, u^{k,M-1\prime}]'.
\end{aligned}$$

Regarding the frequency regulation target, the optimal control problem for the investigated EI system is provided in (12).

$$\begin{aligned}
\min_{U,X}\quad & \sum_{i=1}^{M}\sum_{k=1}^{N} c_k(x^{k,i})\\
\text{s.t.}\quad & x^{k,i+1} = A^{k}x^{k,i} + B^{k}u^{k,i} + C^{k,i}, k\in V, i = 0,1,\ldots,M\\
& x^{k,0} = x_0^{k}, k = 0,1,\ldots,N\\
& P_{ER}^{jk} + P_{ER}^{kj} = 0, (j,k)\in\xi,
\end{aligned} \tag{12}$$

where $c_k(x^{k,i}) = \left|\Delta f^{k,i}\right|^2$, x_0^{k} is the initial value for the state of MG_k, $k = 0,1,\ldots,N$, $t_0 = 0$.

By minimizing the objective function in (12), we could obtain the optimal solution U. Adopting the model predictive control technique, the sub-optimal controller is obtained as $U^{*}(x_0, t_0) = [u^{1,0}, u^{2,0}, \ldots, u^{N,0}]'$.

IV. Methodology

As the scale of the EI system grows larger, the solution to (12) would require more computation resources. Here, the ADMM approach [19] has been applied.

Suppose that there are totally L ERs in the considered system. Firstly, we introduce an auxiliary variable $Z = [z^{1\prime}, z^{2\prime}, \ldots, z^{M\prime}]'$, where $z^{i} = [z^{1,i}, z^{2,i}, \ldots, z^{L,i}]'$ satisfying

$$\Delta P_{ER}^{jk,i} = z^{l_\xi(j,k),i}, \Delta P_{ER}^{kj,i} = -z^{l_\xi(j,k),i}, (j,k)\in\xi, i = 1,2,\ldots,M.$$

The term $l_\xi(j,k)$ denotes the element in $z^{i}, i = 1,2,\ldots,M$, corresponding to the power linkage between MG_j and MG_k. Thus, we have $l_\xi(j,k) = l_\xi(k,j)$ and $1 \le l_\xi(j,k) \le L$. Apparently, the equation constraints in (12) could be rewritten as

$$E_0 + E_1X + E_2U + E_3Z = \mathbf{0},$$

where E_0, E_1, E_2 and E_3 are coefficient matrices.

Noticed that the objective function in (12) could be rearranged as the sum of cost functions in individual MGs, we denote $\sum_{i=1}^{M} c_k(x^{k,i})$ as $C_k(X^k)$. In this sense, the optimization problem (12) is equivalent to the expanded problem in (13).

$$\begin{aligned}
\min_{X,U,Z}\quad & \sum_{k=1}^{N} C_k(X^k)\\
\text{s.t.}\quad & E_0 + E_1X + E_2U + E_3Z = \mathbf{0}
\end{aligned} \tag{13}$$

Then, the Lagrangian function could be defined as

$$\begin{aligned}
L_\rho(X,U,Z,\lambda) = &\sum_{k=1}^{N} C_k(X^k) + \lambda^{\intercal}(E_0 + E_1X + E_2U + E_3Z)\\
&+(\rho/2)\|E_0 + E_1X + E_2U + E_3Z\|_2^2,
\end{aligned} \tag{14}$$

where λ is the dual variable of X, U and Z, ρ is a scalar coefficient. The dual problem of (13) is obtained as

$$\max_{\lambda} g(\lambda),$$

where $g(\lambda) = \min_{X,U,Z} L_\rho(X,U,Z,\lambda)$.

Since $C_k(X^k)$ is convex for X^k, according to [19], by alternatively improving the original and dual variables as follows, the original variables X_s, U_s and Z_s should finally converge to the optimal solution for (13).

$$X_{s+1}, U_{s+1} = \text{argmin}_{X,U} L_\rho(X,U,Z_s,\lambda_s), \quad (15)$$

$$Z_{s+1} = \text{argmin}_{Z} L_\rho(X_{s+1},U_{s+1},Z,\lambda_s), \quad (16)$$

$$\lambda_{s+1} = \lambda_s + \rho(E_0 + E_1 X_{s+1} + E_2 U_{s+1} + E_3 Z_{s+1}). \quad (17)$$

Noticed that in (15), Z and λ are fixed as Z_s and λ_s , the minimization and update are equivalent to that of the distributed optimization problems as follows

$$X_{s+1}^k, U_{s+1}^k = \text{argmin}_{X^k,U^k} C_k(X^k) + \lambda_s^{k\top}(E_1^k X^k + E_2^k U^k) + (\rho/2)\|E_1^k X^k + E_2^k U^k + E_3^k Z_s^k\|_2^2, k = 1,2,\ldots,N, \quad (18)$$

$$Z_{s+1}^i = \text{argmin}_{Z^i} \lambda_s^{i\top} E_3^i Z^i + (\rho/2)\|E_1^k X_{s+1}^k + E_2^k U_{s+1}^k + E_3^k Z^k\|_2^2, \quad i = 1,2,\ldots,L, \quad (19)$$

$$\lambda_{s+1}^k = \lambda_s^k + \rho(E_0^k + E_1^k X_{s+1}^k + E_2^k U_{s+1}^k + E_3^k Z_{k+1}^k), \quad k = 1,2,\ldots,N. \quad (20)$$

In this sense, the update of X, U, Z and λ, could be executed locally inside individual MGs and ERs. Thus, the optimal control scheme for (12) could be obtained in a decentralized fashion.

To obtain the sub-optimal control scheme $U^*(x_0,t_0)$ at time t_0, the distributed optimal control problem (13) is constructed. A global optimization is executed in the control center, and multiple local optimization problems could be solved paralleled in different MGs. More specifically, the optimization of Z and λ must be achieved globally, but the detailed modeling of the MGs are no longer necessary to the control center. Instead, only the data of X_s^k and U_s^k, $k = 1,2,\ldots,N$, are required. Thus, the calculations for them could be accomplished within corresponding MGs in parallel. Two thresholds ε_1 and ε_2 are used to evaluate the convergence of the solution together with the following two criteria,

$$\|r_{s+1}\|_2^2 = \|\lambda_{s+1} - \lambda_s\|_2^2 \le \varepsilon_1,$$

$$\|s_{s+1}\|_2^2 = \rho\|Z_{s+1} - Z_s\|_2^2 \le \varepsilon_2.$$

The solution is considered to be converged when both of these criteria are satisfied. By adopting the ADMM approach, the global optimization problem (12) is divided into several optimization problems with smaller scales.

V. Numerical Example

To evaluate the feasibility and effectiveness of the proposed distributed control scheme, numerical examples are provided in this section.

Here, an EI system consisting of six MGs illustrated in Fig. 2 is investigated. Each MG in the considered system is presumed to be composed of loads, WTGs, MTs, FCs and BESs. The linkage of these MGs is depicted by the edges in Fig. 2. The parameters used in the simulation is generated

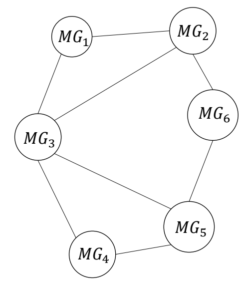

Fig. 2. A Energy Internet System With 6 Microgrids.

based on the typical values in Table I with small random variables following normal distributions. The simulated period

TABLE I
Typical Parameters for Simulation

Parameter	Value	Parameter	Value
T_{Load}	1.3	C_{Load}	0.9
T_{WTG}	2.1	C_{WTG}	0.9
T_{MT}	1.3	b_{MT}	3.1
T_{FC}	1.1	b_{FC}	2.6
T_{ER}	0.06	b_{ER}	2.1
T_{BES}	0.12	r_{BES}	1.1
D	0.012	M	0.2
ε_1	0.5	ε_2	1.0
ρ	10		

is $t \in [0, 1s]$, and the related optimization problems are solved under the environment of MATLAB 2018a.

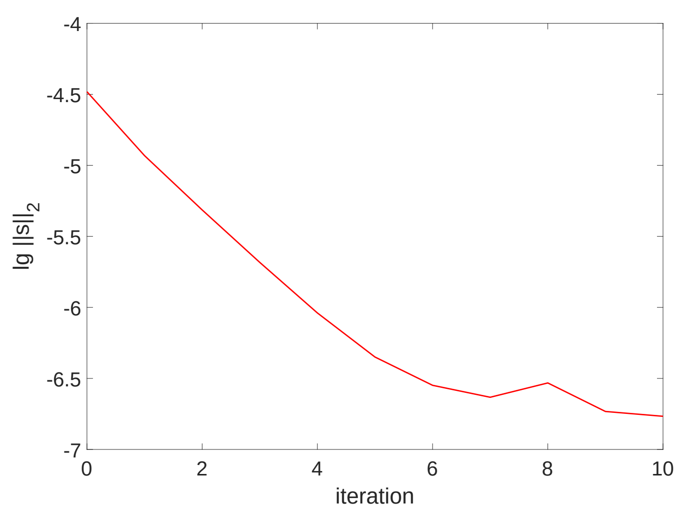

Fig. 3. Logarithmic convergence curve of s.

Firstly, to evaluate the convergence efficiency of the proposed control method, the logarithmic curve of s is illustrated in Fig. 3. It can be found that the solution of (13) converges rapidly. After the first iteration, s gets close to zero drastically, and then keeps rapid decreasing, which indicates the fast convergence of X, U and Z.

The fluctuation of the power of loads and WTGs in the considered EI are depicted in Fig. 4 and Fig. 5, respectively.

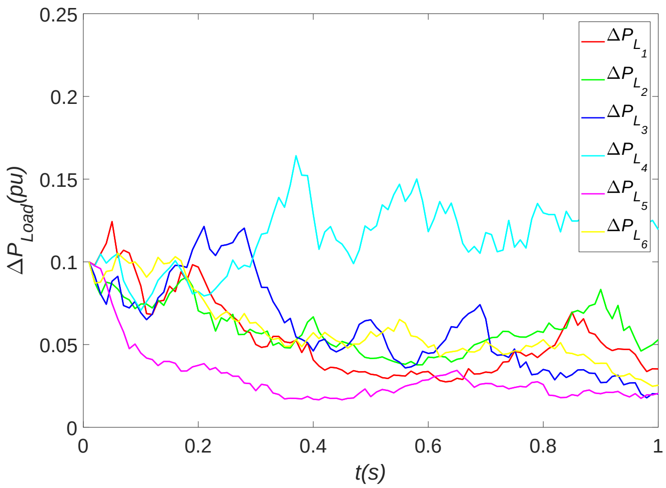

Fig. 4. Fluctuations of ΔP_{Load}.

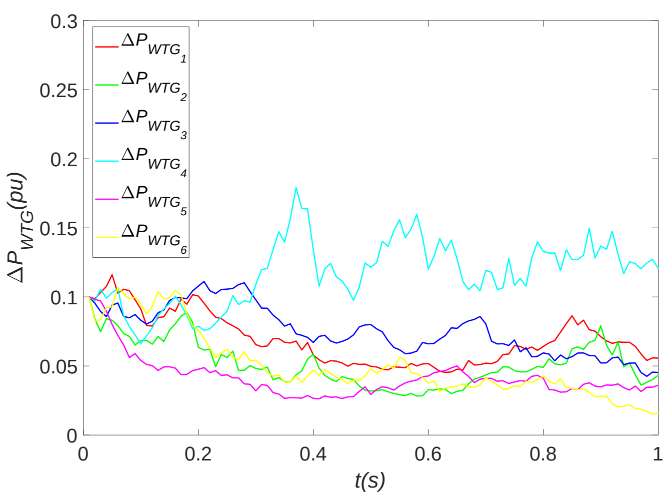

Fig. 5. Fluctuations of ΔP_{WTG}.

With the proposed distributed controller, the frequency deviation of the considered MGs are plotted in Fig. 6. It is clear that the frequency deviations are successfully restricted within a small range during the investigated time period.

The power adjustments of MTs and FCs under the proposed distributed controller during the simulated period are illustrated in Fig. 7. According to Fig. 7, the control inputs for the controllable devices are properly designated regarding the frequency deviations, which suggests the feasibility of the proposed control approach.

The regulated energy sharing via ERs are shown in Fig. 8, which indicates that the proposed control scheme is capable

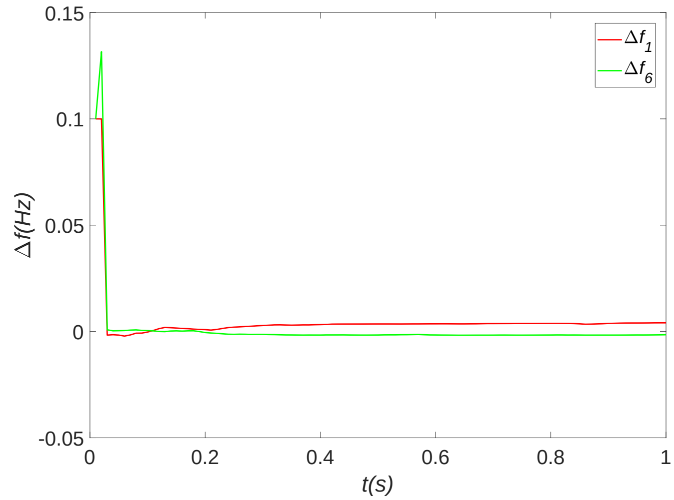

Fig. 6. The AC bus frequency oscillations Δf.

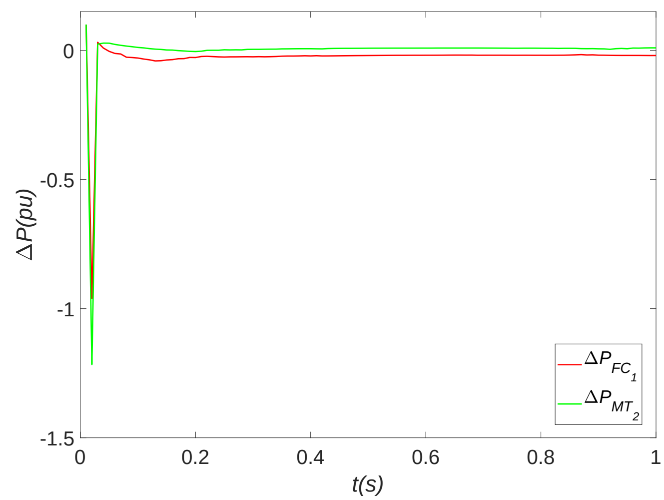

Fig. 7. The power adjustments of ΔP_{FC} and ΔP_{MT}.

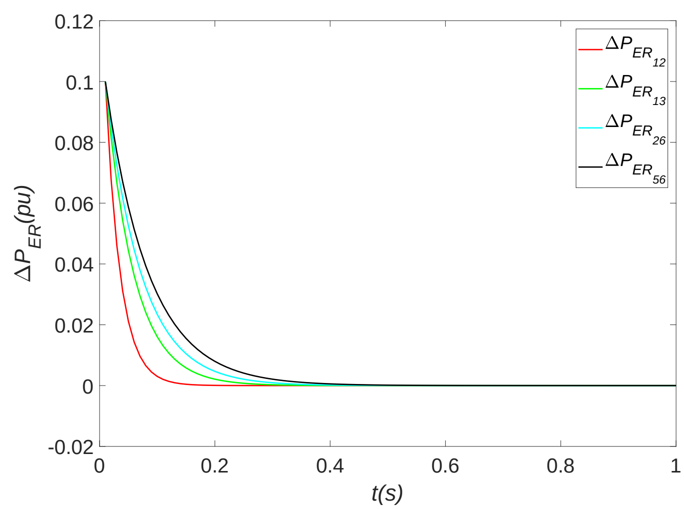

Fig. 8. The energy sharing regulations of ΔP_{ER}.

to alleviate the frequency oscillation effectively via the energy sharing though the ERs.

The numerical examples provided above properly shows the feasibility of the proposed distributed control scheme, and the efficacy of such method is evaluated.

VI. Conclusion

In this paper, a distributed control scheme has been designed for the off-grid EI scenario, such that each MG's AC bus frequency can be regulated. It is notable that such decentralized method is superior than the centralized one from the perspective that the distributed control method can solve EI system stability issues in a relatively large scale.

For the future work, more targets, including optimizing energy dispatch, price based demand response [26], and extending battery's service life [27], shall be considered simultaneously. Meanwhile, game theoretic approaches [28] might be adopted to solve such problem.

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