Decentralized Optimal Operations of Power Distribution System with Networked Microgrids

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***Abstract*—The coordinated operations of power distribution systems with networked microgrids can provide several benefits, such as improved reliability and resiliency of the power system, and the ability to incorporate renewable energy sources. However, limited communication bandwidth or privacy concerns can pose challenges to the operation of microgrids in power distribution systems. In this paper, we present a decentralized model and algorithm for the coordinated operation of power distribution systems with networked microgrids. The proposed approaches are based on distributed optimization and communication networks to exchange limited information among the different agents of the power system. Simulation results demonstrate the effectiveness of the proposed methods.**

***Index Terms*—Coordinated Operation, Power Distribution Systems, Networked Microgrids, Distributed Algorithms**

I. Introduction

The power industry is actively embracing networked microgrids as a promising solution to enhance the efficiency and resilience of power distribution grids. Microgrids, when interconnected with each other and the main power distribution system, enable resource sharing and dynamic balancing of supply and demand, leading to improved utilization of renewable energy, efficient energy storage, smart inverters [1] and enhanced grid reliability. Moreover, networked microgrids facilitate the seamless integration of decentralized energy sources like solar panels and electric vehicles into the power distribution system, as highlighted in previous research [2].

However, the coordinated operation of power distribution systems with networked microgrids poses challenges. Firstly, due to the increasing uncertainty of both the demand response and the availability of renewable energy sources, the operation of the power distribution system needs to be optimized in real-time. The increasing adoption of electric vehicles (EVs) has the potential to strain the existing distribution network, as the charging of EVs can lead to higher demand for electricity, particularly during peak hours. While renewable energy sources are dependent on weather conditions and are therefore not always available when needed due to the intermittent nature [3].

Secondly, limited communication bandwidth or privacy concerns can pose challenges to the multi-agent system. Distribution networks usually have a very limited amount of data that can be transmitted in a given period of time. In a microgrid, communication bandwidth may be limited due to the size and scale of the grid, or due to the availability of communication infrastructure. Limited communication bandwidth can make it difficult for microgrid control systems to exchange data and make decisions in real time, which can affect the stability and efficiency of the power grid. It can also make it difficult for microgrid users to access information about their energy usage or to participate in demand response programs. Privacy concerns can also impact the operation of a microgrid. Most microgrid hardware and software are proprietary, and the data collected by the microgrid is often owned by the microgrid operator. Microgrids usually refuse to disclose their data to other agents, such as the distribution system operators (DSOs). It is therefore important to develop a decentralized optimization framework to coordinate the operation of the power distribution system while not having access to the data of the other components of the power distribution system.

In this context, decentralized models and algorithms are preferred to optimize the operation of the power distribution system while taking into account the different objectives and constraints of the different components. An effective and robust communication framework is needed to exchange information among the different components of the power system, and to ensure the security and privacy of the data exchanged. Many existing works have focused on the coordinated operation of power distribution systems with networked microgrids. We refer to the survey paper [4] for a comprehensive review of the literature. [5] proposed a distributed sub-gradient based algorithm for the coordination of renewable generators in a microgrid. [6] proposed a fully distributed scalable multiple agent algorithm for optimal reactive control. [7] proposed a distributed algorithm for the voltage regulation in power distribution systems with high penetration of renewable energy sources and battery energy storage systems (BESS). [8] proposed a distributed algorithm based on the alternative direction method of multipliers (ADMM) for the optimal power flow problem in a radial distribution system. The prior works discussed several important aspects of distributed algorithms for power distribution systems, however, the coordination of BESSs, renewable energy sources and power distribution systems networks can be further enhanced by considering the microgrid integration, which is rarely investigated in the literature.

The ADMM is a distributed optimization algorithm widely used in the literature to solve distributed optimization problems [9]. In [10], a self-adaptive penalty parameter update scheme for ADMM was proposed. This paper presents decentralized models and algorithms for the coordinated operation of power distribution systems with networked microgrids. The proposed approaches are based on optimization techniques and use communication networks to exchange information among the different components of the power distribution system. ADMM is incorporated into the proposed framework to effectively solve the decentralized optimization problem. The effectiveness of the proposed methods is demonstrated through simulation results.

Our main contributions are summarized as follows:

- We proposed a distributed optimization framework for the coordinated operation of power distribution systems with microgrids. The proposed strategy is based on a consensus-based optimization algorithm and is designed to handle the complexity of such systems under the assumption of limited communication.
- We incorporated the ADMM algorithm into the proposed framework to effectively solve the optimization problem in a distributed manner.
- We studied the impact of increasing penetration of renewable energy resources on the effectiveness of the proposed approach through simulation results.

The remainder of this paper is organized as follows. Section II presents the system model and the problem formulation. Section III presents the decentralized algorithms for the coordinated operation of the power distribution system. Section IV shows the simulation results and Section V discusses the conclusions and future work.

II. Mathematical Model of Decentralized Power Distribution System Coordination

In this section, we first present a centralized coordination model for the power distribution system, then we present decentralized models for the coordinated operation model by considering the tree structure of the power distribution system.

A. Coordinated Model of Power Distribution System

In this section, we describe the centralized coordination model (CCM) for the power distribution system, where the DSO collects all the information from the microgrids and then makes the decision for the coordinated operation of the power distribution system.

Assume N is the set of nodes on the main branch of the DSO. With out loss of generality, let $n=1$ be the root node. let M_g be the set of nodes of MG g, where $g=1,2,\cdots,G$, and let $M=\bigcup_{g\in G} M_g$. Let $J\subset N$ be the nodes connected to a MG. $\mathcal{B}=N\coprod M$ is the set of all buses. We consider a power distribution system with $|G|$ microgrids connected to the main branch as subtrees. Each microgrid g is equipped with several renewable energy sources, an energy storage system, and a load demand. The objective is to optimize the operation of the power distribution system while taking into account the different objectives and constraints of the different components.

The CCM model in (1) is a centralized operation model considering the coordination of DSO and MGs to minimize the total generation cost while satisfying the active and reactive power balance constraints. In model (1), $\mathcal{T}$ denotes index set of operation time span. $T=|\mathcal{T}|$. $\mathcal{B}$ denotes index set of buses. $\mathcal{W}$ denotes index set of renewable energy sources. $\mathcal{G}$ denotes index set of thermal units. $\mathcal{D}$ denotes index set of loads. $\mathcal{S}$ denotes index set of storage units. Variables p and q denote the active and reactive power, respectively. Variables u denotes the voltage magnitude. Variables f denotes the line flow. Linear functions c_{it}^W and c_{it}^G denote the generation cost of renewable energy sources and thermal units, respectively. λ_t is the electricity price in the bulk power system.

In model (1), objective function is the minimization of the total generation cost of the power distribution system, including the BESSs charging/discharging cost, fixed and per unit of capacity cost of BESSs, and the generation cost of thermal units. (1b) and (1c) represent the active and reactive power balance constraints of the DSO. (1d) and (1e) represent the voltage constraints of the DSO. (1f) represents the line capacity constraint. (1g) - (1r) represent the box constraints of the variables. (1s) represents the BESS trajectory constraint.

$$\begin{aligned}
\min\ & \sum_{t\in\mathcal{T}}(\sum_{i\in\mathcal{W}} c_{it}^W(p_{it}^W)+\sum_{i\in\mathcal{G}} c_{it}^G(p_{it}^G)-\sum_{b\in\mathcal{B}} u_{b,t}^D(p_{b,t}^D) \\
& +\sum_{b\in B}\lambda_t(p_{b,t}^{root}+\sum_{i\in\mathcal{S}_b} p_{i,t}^{S,c}-\sum_{i\in\mathcal{S}_b} p_{i,t}^{S,d})) \qquad (1a)
\end{aligned}$$

$$\begin{aligned}
\text{s.t.}\quad & \sum_{(b,n)\in\mathcal{L}} f_{b,n,t}^P-\sum_{(m,b)\in\mathcal{L}} f_{m,b,t}^P=1_{b\in\mathcal{R}}p_{b,t}^{\text{root}}+ \\
& \sum_{i\in\mathcal{W}^b} p_{i,t}^W-\sum_{i\in\mathcal{S}_b} p_{i,t}^{S,c}+\sum_{i\in\mathcal{S}_b} p_{i,t}^{S,d}+\sum_{i\in\mathcal{G}_b} p_{i,t}^G-p_{b,t}^D, \\
& \forall b\in\mathcal{B},\forall t\in\mathcal{T}; \qquad (1b)
\end{aligned}$$

$$\begin{aligned}
& \sum_{(b,n)\in\mathcal{L}} f_{b,n,t}^Q-\sum_{(m,b)\in\mathcal{L}} f_{m,b,t}^Q=1_{b\in\mathcal{R}}q_{b,t}^{\text{root}}+ \\
& \sum_{i\in\mathcal{W}^b} q_{i,t}^W-\sum_{i\in\mathcal{S}_b} q_{i,t}^{S,c}+\sum_{i\in\mathcal{S}_b} q_{i,t}^{S,d}+\sum_{i\in\mathcal{G}_b} q_{i,t}^G-q_{b,t}^D, \\
& \forall b\in\mathcal{B},\forall t\in\mathcal{T}; \qquad (1c)
\end{aligned}$$

$$\begin{aligned}
& u_{m,t}-u_{n,t}=2\left(r_{m,n}\cdot f_{m,n,t}^P+x_{m,n}\cdot f_{m,n,t}^Q\right) \\
& -(r_{m,n}^2+x_{m,n}^2)\cdot l_{m,n,t},\forall(m,n)\in\mathcal{L},\forall t\in\mathcal{T}; \qquad (1d)
\end{aligned}$$

$$\begin{aligned}
& l_{m,n,t}u_{m,t}=(f_{m,n,t}^P)^2+(f_{m,n,t}^Q)^2, \\
& \forall(m,n)\in\mathcal{L},\forall t\in\mathcal{T}; \qquad (1e)
\end{aligned}$$

$$f_{m,n,t}^{P2}+f_{m,n,t}^{Q2}\le S_{m,n},\forall(m,n)\in\mathcal{L},\forall t\in\mathcal{T}; \qquad (1f)$$

$$\underline{V}_b^2\le u_{b,t}\le\overline{V}_b^2,\quad\forall b\in\mathcal{B},\forall t\in\mathcal{T}; \qquad (1g)$$

$$\underline{P_b^D}\le p_{b,t}^D\le\overline{P_b^D},\quad\forall b\in\mathcal{B},\forall t\in\mathcal{T}; \qquad (1h)$$

$$\underline{Q_b^D}\le q_{b,t}^D\le\overline{Q_b^D},\quad\forall b\in\mathcal{B},\forall t\in\mathcal{T}; \qquad (1i)$$

$$\underline{P_i^W}\le p_{i,t}^W\le\overline{P_i^W},\quad\forall i\in\mathcal{W},\forall t\in\mathcal{T}; \qquad (1j)$$

$$\underline{Q_i^W}\le q_{i,t}^W\le\overline{Q_i^W},\quad\forall i\in\mathcal{W},\forall t\in\mathcal{T}; \qquad (1k)$$

$$\underline{P_i^G} \le p_{i,t}^G \le \overline{P_i^G}, \quad \forall i \in \mathcal{G}, \forall t \in \mathcal{T}; \tag{1l}$$
$$\underline{Q_i^G} \le q_{i,t}^G \le \overline{Q_i^G}, \quad \forall i \in \mathcal{G}, \forall t \in \mathcal{T}; \tag{1m}$$
$$\underline{P}_i^{S,c} \le p_{i,t}^{S,c} \le \overline{P}_i^{S,c}, \forall i \in \mathcal{S}, \forall t \in \mathcal{T}; \tag{1n}$$
$$\underline{Q}_i^{S,c} \le q_{i,t}^{S,c} \le \overline{Q}_i^{S,c}, \forall i \in \mathcal{S}, \forall t \in \mathcal{T}; \tag{1o}$$
$$\underline{P}_i^{S,d} \le p_{i,t}^{S,d} \le \overline{P}_i^{S,d}, \forall i \in \mathcal{S}, \forall t \in \mathcal{T}; \tag{1p}$$
$$\underline{Q}_i^{S,d} \le q_{i,t}^{S,d} \le \overline{Q}_i^{S,d}, \forall i \in \mathcal{S}, \forall t \in \mathcal{T}; \tag{1q}$$
$$\underline{S}_i \le s_{i,t} \le \overline{S}_i, \forall t \in \mathcal{T}; \tag{1r}$$
$$s_{i,t+1} = s_{i,t} + p_{i,t}^{S,c} \eta_t^c \frac{\Delta}{E} - \frac{p_{i,t}^{S,d} \Delta}{\eta_t^d E}, \forall i \in \mathcal{S}, \forall t \in \mathcal{T}. \tag{1s}$$

III. Algorithm

In this section, we present a decentralized consensus algorithm to solve the CCM problem.

We first present a algorithm to solve the CCM problem without BESS, and then we present a algorithm to solve the CCM problem with BESS by replicating the algorithm for the CCM problem without BESS. We first decompose the CCM problem into local problems of the DSO and the MGs.

Subproblem for DSO:

$$\min \sum_{t \in \mathcal{T}} \Big(\sum_{i \in \mathcal{G}^{(DSO)}} c_{it}^G(p_{it}^G) - \sum_{b \in \mathcal{B}^{(DSO)}} u_{b,t}^D(p_{b,t}^D) + \lambda_t(p_{1,t}^{root}) \Big) \tag{2a}$$

$$\text{s.t.} \quad f_{1,2,t}^P = p_{1,t}^{\text{root}} - p_{1,t}^D, \forall t \in \mathcal{T}; \tag{2b}$$
$$f_{1,2,t}^Q = q_{1,t}^{\text{root}} - q_{1,t}^D, \forall t \in \mathcal{T}; \tag{2c}$$
$$\sum_{(n,m)\in\mathcal{L}} f_{n,m,t}^P - \sum_{(m,n)\in\mathcal{L}} f_{m,n,t}^P = p_{n,t}^G - p_{n,t}^D, \quad \forall n \in N \setminus (J \cup \{1\}), \forall t \in \mathcal{T}; \tag{2d}$$
$$\sum_{(n,m)\in\mathcal{L}} f_{n,m,t}^Q - \sum_{(m,n)\in\mathcal{L}} f_{m,n,t}^Q = q_{n,t}^G - q_{n,t}^D, \quad \forall n \in N \setminus (J \cup \{1\}), \forall t \in \mathcal{T}; \tag{2e}$$
$$\sum_{(n,m)\in\mathcal{L}} f_{n,m,t}^P + f_{n,j(n),t}^P - \sum_{(m,n)\in\mathcal{L}} f_{m,n,t}^P = p_{n,t}^G - p_{n,t}^D, \quad \forall n \in J, \forall t \in \mathcal{T}; \tag{2f}$$
$$\sum_{(n,m)\in\mathcal{L}} f_{n,m,t}^Q + f_{n,j(n),t}^Q - \sum_{(m,n)\in\mathcal{L}} f_{m,n,t}^Q = q_{n,t}^G - q_{n,t}^D, \quad \forall n \in J, \forall t \in \mathcal{T}; \tag{2g}$$
$$u_{m,t} - u_{n,t} = 2\left(r_{m,n} \cdot f_{m,n,t}^P + x_{m,n} \cdot f_{m,n,t}^Q\right) - (r_{m,n}^2 + x_{m,n}^2) \cdot l_{m,n,t}, \forall (m,n) \in \mathcal{L}, \forall t \in \mathcal{T}; \tag{2h}$$
$$l_{m,n,t} u_{m,t} = (f_{m,n,t}^P)^2 + (f_{m,n,t}^Q)^2, \quad \forall (m,n) \in \mathcal{L}, \forall t \in \mathcal{T}; \tag{2i}$$
$$f_{m,n,t}^{P2} + f_{m,n,t}^{Q2} \le S_{m,n}, \forall (m,n) \in \mathcal{L}, \forall t \in \mathcal{T}. \tag{2j}$$

Subproblem for MG g:

$$\min \sum_{t \in \mathcal{T}} \Big(\sum_{i \in \mathcal{W}} c_{it}^W(p_{it}^W) + \sum_{i \in \mathcal{G}} c_{it}^G(p_{it}^G) - \sum_{b \in \mathcal{B}} u_{b,t}^D(p_{b,t}^D) \Big) \tag{3a}$$

$$\text{s.t.} \quad \sum_{(n,m)\in\mathcal{L}} f_{n,m,t}^P - \sum_{(m,n)\in\mathcal{L}} f_{m,n,t}^P = \sum_{i \in \mathcal{W}_n} p_{i,t}^W + \sum_{i \in \mathcal{G}_n} p_{i,t}^G - p_{n,t}^D, \quad \forall n \in \mathcal{M}_g, \forall t \in \mathcal{T}; \tag{3b}$$
$$\sum_{(n,m)\in\mathcal{L}} f_{n,m,t}^Q - \sum_{(m,n)\in\mathcal{L}} f_{m,n,t}^Q = \sum_{i \in \mathcal{W}_n} q_{i,t}^W + \sum_{i \in \mathcal{G}_n} q_{i,t}^G - q_{n,t}^D, \quad \forall n \in \mathcal{M}_g, \forall t \in \mathcal{T}; \tag{3c}$$
$$u_{m,t} - u_{n,t} = 2\left(r_{m,n} \cdot f_{m,n,t}^P + x_{m,n} \cdot f_{m,n,t}^Q\right) - (r_{m,n}^2 + x_{m,n}^2) \cdot l_{m,n,t}, \forall (m,n) \in \mathcal{L}, \forall t \in \mathcal{T}; \tag{3d}$$
$$l_{m,n,t} u_{m,t} = (f_{m,n,t}^P)^2 + (f_{m,n,t}^Q)^2, \quad \forall (m,n) \in \mathcal{L}, \forall t \in \mathcal{T}; \tag{3e}$$
$$f_{m,n,t}^{P2} + f_{m,n,t}^{Q2} \le S_{m,n}, \forall (m,n) \in \mathcal{L}, \forall t \in \mathcal{T}. \tag{3f}$$

Now we are ready to present the proposed algorithm. In our algorithm, we assume DSO and each MG have a copy of all the variables of the CCM problem 1. In order to distinguish the variables of the DSO and the MG, we use the superscript (DSO) and (MG) to denote the variables of the DSO and the MG, respectively. We apply the ADMM method to solve them. We add a regularization term to (2a) and (3a). Assume λ is the Lagrange multiplier of the constraint $x_i^{(DSO)} = x_i^{(MG)}, \forall i \in \mathcal{X}$, where $\mathcal{X}$ is the set of all variables of the CCM problem that DSO and MG share in common. In particular, in this algorithm, $\mathcal{X}$ includes $f_{n,j(n),t}^P, f_{n,j(n),t}^Q, u_{j(n),t}$, where $j(n)$ is the connection node of the connected MG. The augmented Lagrangian function of the DSO problem is given by

$$\begin{aligned}
\min \sum_{t \in \mathcal{T}} \Big(&\sum_{i \in \mathcal{G}^{(DSO)}} c_{it}^G(p_{it}^G) - \sum_{b \in \mathcal{B}^{(DSO)}} u_{b,t}^D(p_{b,t}^D) + \lambda_t(p_{1,t}^{root}) \Big) \\
&+ (\lambda_{n,j(n)}^P)((f_{n,j(n)}^P)^{(DSO)} - (f_{n,j(n)}^P)^{(MG)}) \\
&+ \frac{\rho}{2}((f_{n,j(n)}^P)^{(DSO)} - (f_{n,j(n)}^P)^{(MG)})^2 \\
&+ (\lambda_{n,j(n)}^Q)((f_{n,j(n)}^Q)^{(DSO)} - (f_{n,j(n)}^Q)^{(MG)}) \\
&+ \frac{\rho}{2}((f_{n,j(n)}^Q)^{(DSO)} - (f_{n,j(n)}^Q)^{(MG)})^2 \\
&+ (\lambda_{n,j(n)}^u)((u_{n,j(n)})^{(DSO)} - (u_{n,j(n)})^{(MG)}) \\
&+ \frac{\rho}{2}((u_{n,j(n)})^{(DSO)} - (u_{n,j(n)})^{(MG)})^2
\end{aligned} \tag{4}$$

The augmented Lagrangian function of the MG problem is given by

$$\begin{aligned}
\min \sum_{t \in \mathcal{T}} \Big(&\sum_{i \in \mathcal{W}} c_{it}^W(p_{it}^W) + \sum_{i \in \mathcal{G}} c_{it}^G(p_{it}^G) - \sum_{b \in \mathcal{B}} u_{b,t}^D(p_{b,t}^D) \Big) \\
&+ (\lambda_{n,j(n)}^P)((f_{n,j(n)}^P)^{(DSO)} - (f_{n,j(n)}^P)^{(MG)}) \\
&+ \frac{\rho}{2}((f_{n,j(n)}^P)^{(DSO)} - (f_{n,j(n)}^P)^{(MG)})^2 \\
&+ (\lambda_{n,j(n)}^Q)((f_{n,j(n)}^Q)^{(DSO)} - (f_{n,j(n)}^Q)^{(MG)}) \\
&+ \frac{\rho}{2}((f_{n,j(n)}^Q)^{(DSO)} - (f_{n,j(n)}^Q)^{(MG)})^2 \\
&+ (\lambda_{n,j(n)}^u)((u_{n,j(n)})^{(DSO)} - (u_{n,j(n)})^{(MG)})
\end{aligned}$$

$$+\frac{\rho}{2}((u_{n,j(n)})^{(DSO)}-(u_{n,j(n)})^{(MG)})^2 \quad (5)$$

Algorithm 1 Consensus Algorithm

Begin

DSO solves the subproblem (2).

DSO broadcasts $(f^P_{n,j(n)})^{(DSO)}$ and $(f^Q_{n,j(n)})^{(DSO)}$ and $(u_{n,j(n)})^{(DSO)}$ to all MGs;

Each MG solves the subproblem (3) with $(f^P_{n,j(n)})^{(DSO)}$ and $(f^Q_{n,j(n)})^{(DSO)}$ and $(u_{n,j(n)})^{(DSO)}$;

while Not Converged **do**

Update ρ as described in [10].

MG sends $(f^P_{n,j(n)})^{(MG)}$ and $(f^Q_{n,j(n)})^{(MG)}$ and $(u_{n,j(n)})^{(MG)}$ and λ to DSO;

DSO solves the subproblem (2) with $(f^P_{n,j(n)})^{(MG)}$ and $(f^Q_{n,j(n)})^{(MG)}$ and $(u_{n,j(n)})^{(MG)}$ and λ with subgradient method;

DSO broadcasts $(f^P_{n,j(n)})^{(DSO)}$ and $(f^Q_{n,j(n)})^{(DSO)}$ and $(u_{n,j(n)})^{(DSO)}$ to all MGs;

Each MG solves the subproblem (3) with $(f^P_{n,j(n)})^{(DSO)}$ and $(f^Q_{n,j(n)})^{(DSO)}$ and $(u_{n,j(n)})^{(DSO)}$;

end while

End

We use the adaptive penalty parameter update scheme proposed in [10].

In order to generalize the proposed algorithm to the case of including BESSs, assume the schedule period of BESSs is T_{BESS}, it suffices to solve the subproblems (2) and (3) for T_{BESS} time periods. In addition, the information shared between the DSO and the MGs should be replicated as a vector of length T_{BESS}.

IV. Numerical Experiments

We test proposed algorithms on the IEEE 33-bus and IEEE 123-bus distribution systems. The performance of both decentralized and centralized approaches are evaluated to demonstrate the advantages of proposed approach. All optimization problems are solving by IPOPT with i7-8750H core and 32GB RAM. To study a system with renewable energy, we modified the IEEE 33-bus and 123-bus systems. Several solar stations are connected to provide renewable energy, and several BESSs are connected to the system for peak shaving.

Table I-II compare the computing efficiency and communication cost of the centralized and decentralized algorithms on the 33-bus and 123-bus test systems, respectively. We use different numbers of solar stations and BESSs to test the scalability of the algorithms. Moreover, we use high and low wholesale electricity price volatility scenarios to test the robustness of the algorithms, which is denoted by PV-H and PV-L, respectively. The tables show that the decentralized algorithm can solve the CCM problem as the centralized algorithm with much lower computing time and limited communication resources. Moreover, higher price volatility can reduce the computing efficiency of the centralized algorithm, but has less impact on the computing efficiency of the decentralized algorithm.

TABLE I
COMPUTING EFFICIENCY AND COMMUNICATION INDICES OF IEEE 33-BUS SYSTEM

Model		Centralized		Decentralized			
#PV	#BESS	CPU Time (s)		CPU Time (s)		Communication (KB)	
		PV-H	PV-L	PV-H	PV-L	PV-H	PV-L
3	0	98.15	92.74	53.57	58.21	10.6	10.5
3	3	174.35	168.24	72.23	71.69	11.5	11.7
3	5	272.37	266.08	115.52	110.26	13.1	12.9
4	0	103.36	109.87	70.12	69.97	11.5	11.2
4	3	185.83	182.24	77.84	76.56	12.4	12.6
4	5	249.50	262.63	123.57	119.95	14.2	13.6
5	0	115.49	128.69	79.54	68.11	11.5	11.6
5	3	203.95	205.24	98.61	86.59	12.3	12.2
5	5	303.69	278.31	152.46	132.24	14.1	13.8

TABLE II
COMPUTING EFFICIENCY AND COMMUNICATION INDICES OF IEEE 123-BUS SYSTEM

Model		Centralized		Decentralized			
#PV	#BESS	CPU Time (s)		CPU Time (s)		Communication (KB)	
		PV-H	PV-L	PV-H	PV-L	PV-H	PV-L
3	0	269.04	241.00	146.28	155.46	30.54	31.62
3	3	438.12	435.63	185.08	198.40	35.51	34.70
3	5	699.66	705.23	279.42	299.12	38.93	39.75
4	0	286.47	250.31	166.30	168.33	32.66	32.31
4	3	460.12	446.25	183.91	183.86	35.70	37.65
4	5	776.56	726.84	294.88	297.38	40.21	38.15
5	0	290.22	274.59	187.38	172.13	36.49	35.32
5	3	501.23	498.61	239.36	231.48	36.32	34.77
5	5	790.58	789.01	347.39	334.47	39.84	39.51

Figure 1 shows the computational time of the centralized and decentralized algorithms on the 33-bus and 123-bus test systems with different BESS penetration levels. Thicker lines represent the 123-bus system, and thinner lines represent the 33-bus system. Solid lines represent the centralized algorithm, and dashed lines represent the decentralized algorithm. The computational time increases with the increasing BESS penetration, since the BESSs need to be scheduled in a whole time horizon. The figure shows that the computational efficiency of the decentralized algorithm is higher than the centralized algorithm on each test system and BESS penetration level. Moreover, the computational time of the decentralized algorithm is much shorter than the centralized algorithm when the BESS penetration is high.

Similar to Figure 1, Figure 2 shows the computational time of the centralized and decentralized algorithms on the 33-bus and 123-bus test systems with different solar stations penetration levels. From the figure, we can observe that the impact of the increasing solar stations penetration on the computational efficiency is smaller than the impact of the BESS penetration. From both Figures 1 and 2, we can observe that the computational costs on the 123-bus system are higher than the 33-bus system, since larger test systems have more buses and microgrids and hence require more iterations to converge. Both figures also show that the computational efficiency of the decentralized algorithm is higher than the centralized algorithm, and spends less time to solve the cases

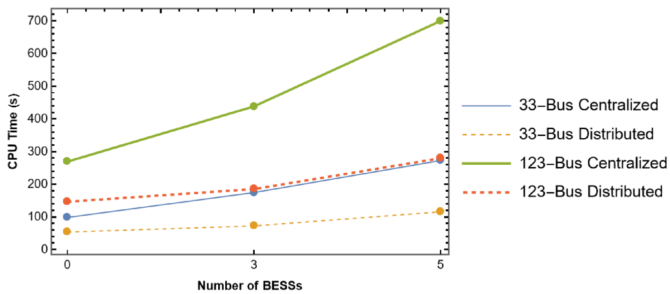

Fig. 1. Impact of the BESS Penetration on the Algorithm Efficiency

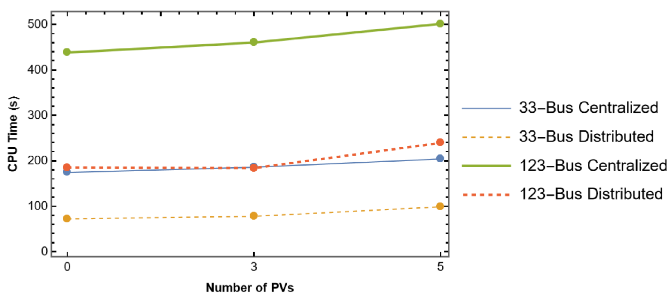

Fig. 2. Impact of the Solar Stations Penetration on the Algorithm Efficiency

with high solar stations penetration and BESS penetration.

Figure 3 and Figure 4 show the communication cost of the decentralized algorithms on the 33-bus and 123-bus test systems with different solar stations and BESS penetration levels, respectively. We use two bulk power system electricity price scenarios to test the robustness of the algorithms. The first scenario is the high wholesale electricity price volatility scenario, which is denoted by High PV. The second scenario is the low wholesale electricity price volatility scenario, which is denoted by Low PV. Figure 3 shows that the communication cost remains the same when the solar stations penetration increases. While Figure 4 shows that the communication cost increases slightly when the BESS penetration increases. As the communication cost is proportional to the number of iterations, larger test systems require more iterations to converge and hence have higher communication cost.

V. Conclusion

To address the communication efficiency and privacy concerns of power distributed systems, this paper proposed a decentralized algorithm for the operations of distribution power systems and networked microgrids. Our simulation results demonstrated that, with limited communication resources, the proposed approach can maintain the same level of system performance as the centralized approach. Our future work will focus on designing asynchronous algorithms to further improve the computational and communicational efficiency of the decentralized approach.

VI. Acknowledgment

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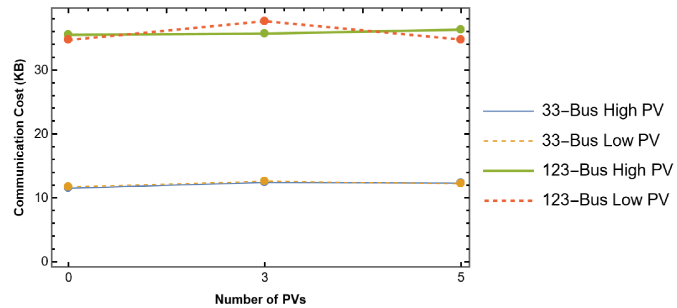

Fig. 3. Impact of the Solar Stations Penetration on the Algorithm Communication Cost

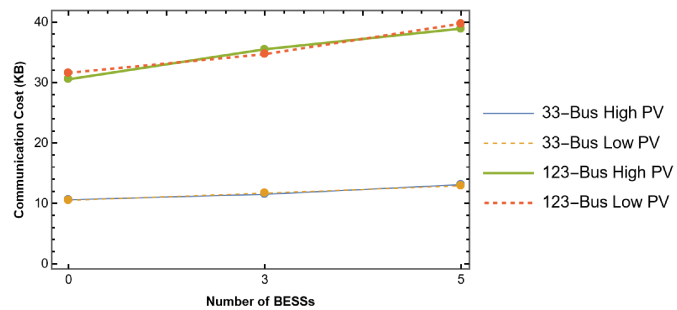

Fig. 4. Impact of the BESS Penetration on the Algorithm Communication Cost

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