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# A Novel Communication-less Approach to Economic Dispatch for Microgrids

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***Abstract*—This letter proposes a fully decentralized approach to economic dispatch in microgrids with a novel communication-less strategy. It is aimed to overcome the limitations on strong dependency of center node and nodal communication in the conventional approaches. Comparative case studies based on a 14-bus microgrid demonstrate that the proposed approach can achieve a global consensus in a mesh network and the overall communication burden can be significantly reduced.**

***Index Terms*—Economic dispatch, communication-less, decentralized optimization, communication cost reduction, microgrid.**

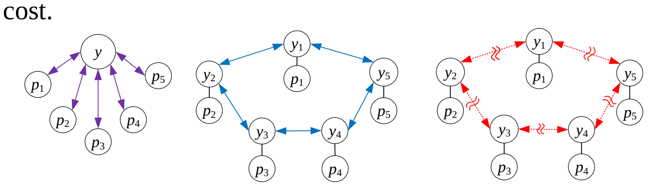
## I. Introduction

THE TREND of microgrid development is to expand its operating scenarios by incorporating more distributed system components covering generation sources, energy storage system (ESS) and controllable loads [1]. To locally accommodate such emerging power-balancing resources, various stakeholders (ESS hub, load aggregator, etc.) have come to light and played roles in system economic dispatch (ED) [2]. Towards this end, decentralized algorithms preserving information privacy become more desirable in achieving microgrid ED in the concerned scenarios.

In the literature, authors in [3] make the pioneering attempts and lay out significant foundations on decentralized approaches to ED of islanded microgrids. The authors in [2] propose a faster decentralized algorithm which twice utilizes the gradient information. In these consensus-based distributed algorithms, the incremental cost in each agent is treated as the consensus variable. To realize a distributed optimization manner, [4] extends alternating direction method of multipliers (ADMM) to ED of microgrids, in which communication concerns are preliminarily discussed. However, it is assumed that the information communication is executed at each iteration [2-4], which needs high-cost communication cables equipment and may incur communication congestion. To the best of our knowledge, dependency reduction of local network communication for microgrid energy management is rarely investigated.

Inspired by the decentralized mechanisms reported in [5], this paper devises a fully decentralized algorithm of ED for a self-sufficient microgrid based on dual-consensus ADMM method. Moreover, to improve the overall communication performance, we take a big step forward by devising a conditional communication strategy so that the communication burden can be reduced. This suggests a promising solution to islanded microgrid equipped with low-cost communication network.

As illustrated in Fig. 1, the technical contribution and novelty of the proposed approach are basically twofold. Firstly, a fully decentralized dual-consensus ADMM approach to ED is proposed, where dual variables are only exchanged with the neighborhoods. Without centric coordinators governing the microgrid operation, the information privacy of the agents can be greatly preserved. Secondly, a conditional communication strategy is newly devised to reduce the communication burden during the whole iteration process. Comparative case studies demonstrate that the proposed approach is fairly promising for practical application with considerably less communication cost.




(a) (b) (c)

Fig. 1. Different optimization manners with five agents. (a) classical ADMM (b) pure dual-consensus ADMM with full communication (c) dual-consensus ADMM with conditional communication.

## II. Problem Formulation

### A. Microgrid Network Model

In this paper, we investigate a typical islanded microgrid with $N$ buses (agents) connected with dispatchable generators, flexible load, wind turbine, or ESS. The microgrid network can be represented by a graph $\mathcal{G}=(\mathcal{N},\mathcal{E})$, where $\mathcal{N}=\{1,2,\ldots,N\}$ denotes the bus set and $\mathcal{E}$ denotes the undirected branch set.

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Two buses $i$ and $j$ are termed as neighbors if the branch $(i,j)\in\mathcal{E}$. The set of all neighbors of bus $i$ is denoted as $\mathcal{N}_i$, of which the degree is denoted by $d_i=|\mathcal{N}_i|$.

## B. Economic Dispatch Model

We consider a quadratic cost function to each agent $i$ in a microgrid given by:

$$f_i(p_i)=\frac{1}{2}a_i p_i^2+b_i p_i+c_i \qquad i=1,2,\ldots,N \tag{1}$$

where $a_i$, $b_i$, $c_i\ge 0$ are local cost parameters; $p_i>0$ if the agent $i$ injects power to the system, and $p_i<0$ if it consumes power from the system. The detailed formulation of the quadratic function models can be referred to [3]. For each agent, the power injection or consumption is subject to:

$$\underline{p}_i\le p_i\le \overline{p}_i \qquad i=1,2,\ldots,N \tag{2}$$

where $\underline{p}_i,\overline{p}_i\ge 0$ for generators; $\underline{p}_i,\overline{p}_i\le 0$ for flexible loads; and $\underline{p}_i\le 0$, $\overline{p}_i\ge 0$ for ESS.

For the energy management system of the microgrid, the objective is to determine the power settings that minimize the social fare, i.e., the total cost of all agents.

$$\text{Cost}=\sum_{i=1}^{N} f_i(p_i) \tag{3}$$

which is subject to the power balance constraint:

$$\sum_{n=1}^{N} p_i=0 \tag{4}$$

# III. Proposed Methodology

Note that in the cost function (1), $p_i$ is a local control variable attained only by agent $i$; $f_i$ is a local convex function with locally known parameters; and equation (4) is a global constraint which couples all $p_i$.

## A. Classical ADMM Method

According to [6], to solve this problem, the classical ADMM method performs updates through (5)-(6) at iteration step $k$:

$$p_i^k=\underset{p_i}{\text{argmin}}\ f_i(p_i)+y^{k-1}\ p_i+\tfrac{\rho}{2}\left\|p_i-(p_i^{k-1}-\overline{p}^{k-1})\right\|_2^2 \tag{5}$$

$$y^k=y^{k-1}+\rho\overline{p}^k \tag{6}$$

where $y$ is the global dual variable associated with the constraint (4), $\overline{p}^k=\frac{1}{N}\sum_{i=1}^{N}p_i^k$ is the average power imbalance and $\rho$ denotes the penalty or step size. As shown in Fig.1 (a), this distributed algorithm enables each agent to update local variables in parallel but requires a "coordinator" to gather and scatter global information at each iteration, e.g., current power imbalance $\overline{p}^k$ and the dual variable $y^k$.

## B. Dual-Consensus ADMM with Conditional Communication

Based on the aforementioned ADMM method, we devise a decentralized dual-consensus-based strategy with conditional communication for microgrid dispatch. For all agents, the dispatch strategy is summarized in Table I.

In the proposed algorithm, we assign the updates of primal, dual and auxiliary variables to each agent in step 2.1 and 2.4. Equation (7) corresponds to the optimal solution of each agent; equation (8) projects the resultant solution onto the local feasible set defined by (2), where $\mathcal{P}_i(\cdot)$ denotes the projection operator; equations (9) and (10) update local dual variables and auxiliary variables, alternately. In steps 2.2 and 2.3, we newly devise a conditional communication strategy in the algorithm to make the information exchange occur only in the case that the considerable difference exists between consecutive iterations. Otherwise, the dual variable holds as the previous iteration in each agent. In this sense, the communication process is called "conditional" since unnecessary information exchange can be avoided.

TABLE I Proposed Algorithm on Dual-consensus ADMM with Conditional Communication

**Algorithm**: **Dual-Consensus ADMM with Conditional Communication**

**Given** $p_i^0, y_i^0$ and $z_i^0=0$; sequence $\{\delta^k\}$.

1: **Set** iteration $k\leftarrow 1$, **do**

2: **For** all $i\in\mathcal{N}$ (in parallel)

2.1: Update primal and dual variables:

$$p_i^k=\arg\min_{p_i}\ \Big\{f_i(p_i)+\tfrac{\rho}{4d_i}\Big\|\tfrac{1}{\rho}p_i-\tfrac{1}{\rho}z_i^{k-1}+\textstyle\sum_{j\in\mathcal{N}_i}(y_i^{k-1}+y_j^{k-1})\Big\|^2\Big\} \tag{7}$$

$$p_i^k=\mathcal{P}_i(p_i^k) \tag{8}$$

$$y_i^k=\tfrac{1}{2d_i}\Big(\textstyle\sum_{j\in\mathcal{N}_i}(y_i^{k-1}+y_j^{k-1})-\tfrac{1}{\rho}(z_i^{k-1}-p_i^k)\Big); \tag{9}$$

2.2: **If** $|y_i^k-y_i^{k-1}|>\delta^k$, exchange $y_i^k$ to neighbors,

**Else** do not exchange;

2.3: Update $y_j^k\ (j\in N_i)$ if received, else set $y_j^k\leftarrow y_j^{k-1}$;

2.4: Update the auxiliary variable:

$$z_i^k=z_i^{k-1}+\rho\textstyle\sum_{j\in\mathcal{N}_i}(y_i^k-y_j^k) \tag{10}$$

3: **Set** $k\leftarrow k+1$, until the stopping criteria: $k\le k_{\max}$

4: **End for**

One can also observe from Fig. 1(c) that in the proposed strategy, each agent $i$ is allowed to have a local copy of the global dual variable $y$, while enforcing the distributed $y_i$ to reach a consensus. Every agent only transmits local dual variable $y_i$ to its neighbors, maintaining the local primal variable in privacy. Thus, the proposed ED approach is privacy-preserving and implemented in a fully decentralized manner.

## C. Communication Time Delay Remarks

In this paper, we investigate the synchronous communication network as deployed by the classical distributed methods for ED [2-5], where the agents are typically equipped with individual GPS to ensure the identical control cycle for each step. Between two executive iterations, the communication time is generally predefined as e.g. 6.3363ms with 10% probability of time-delay (as referred to [7]). Specifically, take a 5-agent system for instance, the computation time for every agent is assumed to be the same. Fig. 2 presents the timing diagram. In every iteration, there are two stages namely computation stage (i.e., steps 2.1, 2.3 and 2.4) and communication stage (i.e., step 2.3). By deploying the proposed algorithm, each agent executes one simple if-else command through the computation stage 2.1, which usually takes several microseconds. It is worth noting that the additional computation burden due to the if-else command (e.g., several microseconds) is much less than the original amount in step 2.1. Therefore, the impacts caused by the delay of the optimization process can be negligible, and the convergence of the synchronous algorithm shall hold. At each dispatching time slot, only the convergent results of the algorithm shall be executed, and thus the stability of microgrids would not be affected, as discussed in [4].

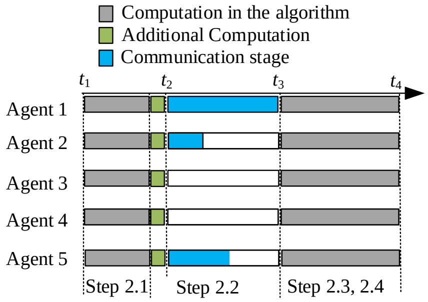



Fig. 2. Illustration of the timing diagram at one iteration of the proposed algorithm. With the proposed conditional communication strategy, an additional computation step is added after step 2.1, while the communication burdens of agents 3 and 4 decrease to 0.

## IV. Case Study

The studied microgrid system consists of 14 buses, five generators, one wind turbine, one ESS [2]. The conditional communication network shares the same topology with the physical power network. Dispatchable generators are located at buses 1-3, 6, and 8. Buses 7 and 9 are allocated with a ESS and a wind generator, respectively. Other buses are load buses. Component parameters are list in [2]. Table II summarizes values of parameters in the algorithm.

TABLE II Values of Parameters

| Parameter | $p_i^0$ | $y_i^0$ | $z_i^0$ | $\rho$ | $k_{\max}$ |
|---|---|---|---|---|---|
| Value | 0 | -5 | 0 | 4.5 | 90 |

To test the performance of the proposed strategy, we compare two options regarding the values of the threshold sequence $\{\delta^k\}$:

- Option 1: $\{\delta^k\}=\{0.9\times 0.75^k\}$;
- Option 2: $\{\delta^k\}=\{0.5\times 0.8^k\}$.

In addition, the pure algorithm with full communication strategy can be considered as a basic case for the proposed algorithm, where $\{\delta^k\}=\{0\}$. We name it as 'Option 0' for clarity when making comparisons in the following discussion.

As illustrated in Fig. 1(c), only dual variables are exchanged in the dual-consensus ADMM. To evaluate the convergence performance of the proposed strategy, we investigate the evolutional process of local dual variables. The simulation results are summarized in in Table II and Fig.3, with stopping criterion $\|y^k - y^{k-1}\| < 0.001$. As compared to option 0, the other two conditional communication cases converge in almost similar manner. Numerically, all three cases with the proposed neighbor-consensus ADMM algorithm possess the same global consensus $y$=-5.618. This also suggests that the conditional communication strategy would not defer the global consensus. Specifically, we look into the insight at the convergence of the local primal variables for 'option 2', as shown in Fig. 4. It is noted that the local primal variables can also converge to the optimal value, even though there is no primal variable exchange during iterative process.

TABLE III Dual Residual Convergence

| Case | Optimal $y$ | Dual residual | iteration |
|---|---|---|---|
| Option 0 | -5.618 | 0.00094 | 44 |
| Option 1 | -5.618 | 0.00088 | 45 |
| Option 2 | -5.618 | 0.00096 | 44 |

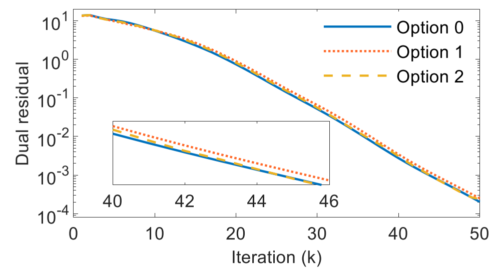



Fig. 3. Convergence of the dual variables. Option 0: a basic case with full communication; Option 1 and Option 2: with proposed conditional communication.

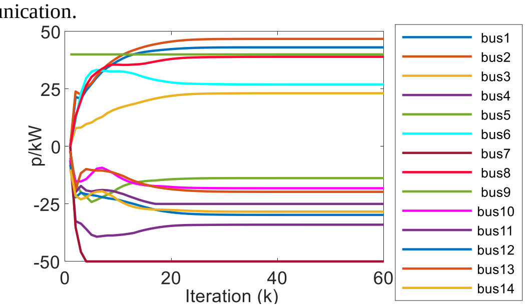
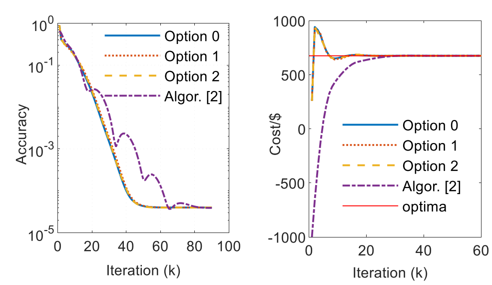



Fig. 4. Convergence of the primal variables (power output at buses) in the case with proposed conditional communication Option 2.

To verify the accuracy and optimality of the proposed approach, we compare the proposed algorithm with that in [2] in terms of accuracy metric, which is defined as $\|p^k - p^*\|/\|p^*\|$. The optimal solution $p$* and optimal objective value (optima) is obtained offline by interior point method in a centralized manner. The stopping criteria is set as maximal iteration of 90. One can see from Fig. 5 that the proposed method (regardless of options on conditional communication threshold) has a competitive convergence behavior to optimal solution and optima. For instance, the iteration number is 34 and 48 for the proposed algorithm and that in [2], given a required accuracy of $10^{-3}$.




(a) (b)

Fig. 5. Accuracy curves and social fare curves of proposed method with various options and comparison with algorithm in [2]. (a) accuracy to iteration; (b) total cost to iteration.

In order to quantitatively reflect the communication efficiency, a metric communication burden is developed in terms of the total number of information exchanging within all agents. The stopping criteria is set as $\|p^k - p^{k-1}\| < 10^{-8}$ so as to evaluate the effectiveness of communication reduction. As illustrated in Fig. 6, the communication burden can be significantly reduced by around 44.3-63.2% with the proposed conditional communication strategy, as compared to the algorithm in [2]. Specifically, as shown in Fig. 7, the communication states of each agent are explicitly presented with individual iteration. The horizontal axis indicates the iteration steps; and the vertical axis indicates the corresponding agents. In particular, a blue dot means that, the corresponding agent $i$ is required to transmit information to neighboring agents at current iteration, thus resulting in a communication burden of $d_i$. The vacant means that the information exchange at this iteration is not necessary. The prolonged convergence iteration number is little even at an extremely strict stopping criterion (i.e., primal residual of $10^{-8}$ ). However, the communication burden can be significantly reduced, as shown in Fig. 6.

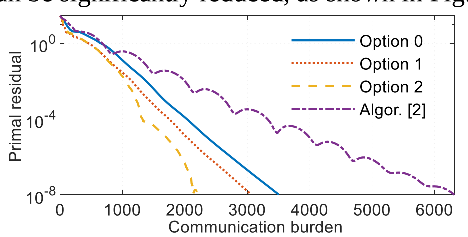



Fig. 6. The communication burden decrease performance with proposed conditional communication strategy.

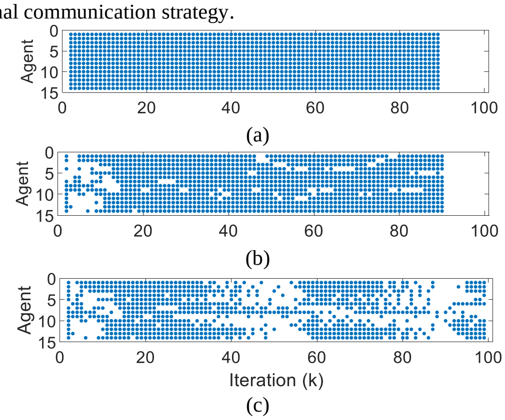



Fig. 7. Communication states of each agent during the iterations with proposed dual-consensus ADMM algorithm. (a) a basic case with full communication: Option 0; (b) with conditional communication: Option 1; (c) with conditional communication: Option 2.

## V. Conclusion

A novel communication-less approach to microgrid economic dispatch based on dual-consensus ADMM is proposed in this letter. Distinguished from the classical distributed approaches, it has merits on 1) a fully decentralized manner without assigning any leaders; 2) privacy preserving and less communication burden (i.e., only dual variables are exchanged with neighborhoods and more than 60% communication burden can be reduced).

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