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Distributed Event-triggered Scheme for Economic Dispatch in Smart Grids

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***Abstract*—To reduce information exchange requirements in smart grids, an event-triggered communication based distributed optimization is proposed for economic dispatch. In this work, the θ-*logarithmic* barrier based method is employed to reformulate the economic dispatch problem and the consensus based approach is considered for developing fully distributed technology-enabled algorithms. Specifically, a novel distributed algorithm utilizes the minimum connected dominating set which efficiently allocates the task of balancing supply and demand for the entire power network at the beginning of economic dispatch. Further, an event-triggered communication based method for the incremental cost of each generator is able to reach a consensus, coinciding with the global optimality of the objective function. In addition, a fast gradient based distributed optimization method is also designed to accelerate the convergence rate of the event-triggered distributed optimization. Simulations based on the IEEE 57-bus test system demonstrate the effectiveness and good performance of proposed algorithms.**

***Index Terms*—economic dispatch, event-triggered, distributed optimization, minimum connected dominating set, fast gradient**

I. INTRODUCTION

SMART grid technologies enable power network operators and electric utilities to dispatch generation resources in the most economical way [1]. The goal of economic dispatch is to optimize the consumption of electric energy under security constraints, which results in financial saving and potentially avoiding building expensive power infrastructure to augment peak demand.

The economic dispatch is formulated as an optimization problem [2] with constraints which could be either convex or non-convex. Various methods have been developed to solve the problem. Convex optimization techniques including the Newton method and dual variable maximization are studied in [3]. Heuristic algorithms involving genetic algorithms and particle swarm optimization are successfully designed to solve the non-convex cases. However, these two categories of methodologies involve an intense centralized computation that requires global information over the entire power grid. Undoubtedly, robustness and scalability of the centralized methods would fail to meet the increasing demand in our modern society. A distributed methodology can provide power operators with many benefits. For instance, the plug and play operation of new generators can be added or removed easily and individual generator failures have no negative impact on economic dispatch. Therefore, it is necessary to develop a new methodology to tackle this problem in a distributed way which only utilizes local information to update itself.

Regarding the distributed approach for solving the economic dispatch problem, communication between spatial connected generators is utilized and computations are locally performed. A distributed dynamical programming based method is developed in [4], where dynamical constraints of the ramp rate limits are considered. By considering the valve-point loading effect and prohibited operating zones, a distributed auction based algorithm and a heuristic technique for searching a better solution [5] are designed to address the non-convex case. Consensus based distributed approaches for economic dispatch are investigated in [6], [7] and [8]. The authors of [6] formulate the economic dispatch as an incremental cost consensus problem, where a penalty-like method is used to update the Lagrange multiplier. The updating rule needs global information about the incremental cost of each generator. In [7], a similar upgrade rule is developed for economic dispatch with transmission losses. It is worth noting that, after the projection operation on box constraints, the Lagrange multiplier may converge to a stable state which does not yield an optimal solution.

Concerning the large scale deployment of IT infrastructure in smart grids, the tremendous data exchange would rapidly make the network load imbalanced and exhaust the network resources [9]. The power network operators have to face the communication bottlenecks which lead to unreliable operations, especially for energy dispatch. If the communication network is congested, the distributed consensus based optimization of economic dispatch would fail to converge. To address this issue, an event-triggered methodology is an option providing good potential to reduce the message passing complexity over a network environment [10], where distributed optimization is studied for the problem of network utility maximization. An event-triggered control scheme for sampled data

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control systems and the multi-agent systems are investigated in [11], [12] and [13]. For the networked control system, the optimization technique is used to balance the performance-security trade-off in [14] and a generalized predictive control with actuator deadband is applied to an event based control structure in [15]. Different triggering communications are considered in [16], where Zeno behaviour of event-triggered communication is eliminated. Note that Zeno behaviour may invalidate these distributed optimization algorithms and deteriorate the communication network. Concerning on the event-triggered asynchronous communication, the synchronization problem of complex dynamical networks is studied in [17]. In the smart grid scenario, event triggering load frequency control is developed for multi area power systems with communication delays in [18]. To further reduce the communication burden, self-triggered communication enabled control is employed to synchronize distributed generation in micro-grids.

Previous work on economic dispatch fails to take the communication issue into account which has the risk of producing a unreliable solution once the link is congested, see [4], [5], [6] and [7]. In light of economic dispatch over a network environment, it is necessary to develop an event-triggered scheme to solve the problem while reducing the communication burden. To achieve the goal, we reformulate the problem via the *θ-logarithmic* barrier which is able to guarantee all the outputs under their capacity as well as exchange information about incremental cost in a completely distributed way. Then, we divide the reformulated problem into two procedures. In the first procedure, the output of all generators is initialized in accordance with the predicted demand. A minimum connected dominating set based distributed algorithm is applied to allocate the task at the initial stage of economic dispatch through the generators in different levels. By this algorithm, the supply-demand balance can always be satisfied. In the next procedure, a distributed consensus based optimization algorithm is proposed and the corresponding event-triggered distributed optimization is derived with the event-triggering criteria. Our event-triggering criteria are based on asynchronous communication that plays a significant role in reducing the requirements of data exchange in smart grids. Self-triggered and event-triggered mechanisms can be developed to avoid the continuous communication amongst neighbour generators. As pointed out in [10] and [16], event-triggered mechanisms could have a negative impact on the convergence rate, where the longer time intermittence between two events leads to a slower convergence. Therefore, a fast gradient based method is designed to accelerate the convergence rate of event-triggered distributed optimization. It is noticeable that even though the unexpected link failure appears, the result produced by the proposed approach is still a feasible solution. Besides, the accuracy of the solution is adjustable according to the network resource condition.

This paper is organized as follows. In Section II, the preliminary of the communication network is introduced and the problem of economic dispatch is reformulated. Meanwhile, the distributed consensus based algorithm is proposed to optimize the problem. Section III introduces an event-triggered distributed optimization scheme to solve the problem of economic dispatch. The event-triggering conditions are derived. The convergence rate of the event-triggered scheme is accelerated by the fast gradient method. The IEEE 57-bus is used as a case study in Section IV. Conclusions are drawn in the last section.

II. Problem Formulation

In this section, some preliminaries about algebraic graph theory of communication network are introduced in advance. Afterwards, the economic dispatch problem is described and reformulated to derive a fully distributed computational model through the distributed consensus method.

A. Algebraic Graph Representation of Network

Denote a weighted undirected communication network as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with the set of vertices $\mathcal{V} = v_1, v_2, \cdots, v_N$ and the set of undirected edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. Define $\mathcal{N} = \{1, 2, ..., N\}$. If there is a communication link between v_i and $v_j (i, j \in \mathcal{N})$, an undirected edge $\mathcal{E}_{i,j}$ is defined by the elements of adjacency matrixes $\mathcal{A}$, i.e. $a_{ij} = a_{ji} > 0$. The degree of vertex v_i is $d_i = \sum_{j=1, j\neq i}^{N} a_{ij}$, which is the total of the weights between this vertex and all the other vertices. An undirected graph $\mathcal{G}$ is connected if an undirected path between vertices v_i and $v_j (i, j \in \mathcal{N})$ exists.

Assume that the communication network is always connected. The elements of a graph Laplacian W associated with the graph $\mathcal{G}$ are defined by $w_{ij} = -a_{ij}, , i \neq j; w_{ii} = d_i$, which implies $\sum_{j=1}^{N} w_{ij} = 0 (i \in \mathcal{N})$.

A connected dominating set of a graph $\mathcal{G}$ is a set $\mathcal{D}$ of vertices, such that,

- Any node in $\mathcal{D}$ can reach any other node in $\mathcal{D}$ by a route that stays entirely within $\mathcal{D}$. $\mathcal{D}$ induces a connected subgraph of $\mathcal{G}$.
- Every vertex in $\mathcal{G}$ either belongs to $\mathcal{D}$ or is adjacent to a vertex in $\mathcal{D}$.

B. Economic Dispatch Problem

Economic dispatch is about short-term power system operation of a number of electricity generation facilities, to meet the predicted total loads at the lowest cost, subject to the operational constraints [2]. In a power grid, the cost function of power generation is modelled by

$$c_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i, \tag{1}$$

where P_i is the output of the i-th power generator. α_i, β_i and γ_i are parameters for the i-th power generator. By assuming a N-generator power grid, the goal of optimal power output dispatch is to minimize the entire cost of the power grid,

$$\begin{aligned} \min_{P_i} \quad & \sum_{i=1}^{N} c_i(P_i), && (2) \\ \text{s.t.} \quad & \sum_{i=1}^{N} P_i = P_D, \\ & P_{i,m} \leq P_i \leq P_{i,M}, \end{aligned}$$

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where P_D is the predicted total power demand of load in this power grid. $P_{i,m}$ and $P_{i,M}$ correspond to the minimal and maximal capacities of the i-th power generator. Intrinsically, each power generator should be operated under its capacity constraint, i.e. $P_i \in \mathcal{P}_i$, where $\mathcal{P}_i$ denotes $[P_{i,m}, P_{i,M}]$.

Before we propose the event-triggered optimization scheme, the problem (2) is reformulated by the θ-*logarithmic* barrier. Specifically, for a parameter $\theta > 0$, we consider the primal problem as follow

$$\min_{P_i \in \mathcal{P}_i} \quad \Phi(P) = \sum_{i=1}^{N} \phi_i(P_i), \tag{3}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} P_i = P_D, \tag{4}$$

where $P = (P_1, P_2, ..., P_N)$. Denote

$$\begin{aligned} \phi_i(P_i) &= \theta_i c_i(P_i) - \sum_{r=1}^{2} \log(h_{i,r}(P_i)), \\ h_{i,1}(P_i) &= P_i - P_{i,m}, \quad h_{i,2}(P_i) = -P_i + P_{i,M}. \end{aligned}$$

Note that this function is available only for the box constraints strictly satisfied, which implies the trajectory of each P_i lies in the feasible domain, and refers to the interior point method. The interior point method is initialized within a feasible domain and a sufficiently large parameter θ_i, where the approximation error of the objective function (3) is upper bounded by $\sum_{i=1}^{N} \frac{2}{\theta_i}$. It indicates that when θ_i goes to infinity, the optimal solution $P_i^\star$ of problem (3) converges to the global minimizer P_i^* of the original problem (2).

C. Distributed Optimization For Economic Dispatch

The Lagrange function of problem (3) is defined by

$$\mathfrak{L}(P, \lambda) = \sum_{i=1}^{N} \phi_i(P_i) + \lambda(\sum_{i=1}^{N} P_i - P_D), \tag{5}$$

where λ is the Lagrange multiplier. A centralized optimization method can simply employ the gradient of the Lagrange function with respective to $P_i (i \in \mathcal{N})$ and λ, respectively.

In order to achieve a global optimal dispatch, the distributed gradient algorithm is developed to locally update the state by considering the communication topology $\mathcal{G}$, such that

$$\dot{P}_i(t) = -\sum_{j=1}^{N} w_{ij} \frac{\partial \phi_j(P_j)}{\partial P_j}, \tag{6}$$

where w_{ij} is the element of the weight matrix W, the graph Laplacian, corresponds to the topology of the underlying information exchange graph $\mathcal{G}$. t is the time. It is noticeable that if the initial values $P_i(i \in \mathcal{N})$ are properly chosen to satisfy the equality constraint (4), the updating of λ is not necessary. Because W is symmetric and zero row-sum, i.e. $\mathbf{1}_N^T W = \mathbf{0}_N$, where $\mathbf{1}_N$ and $\mathbf{0}_N$ are the vector of N ones and zeros, respectively then

$$\frac{1}{N} \sum_{i=1}^{N} \dot{P}_i(t) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \frac{\partial \phi_j(P_j)}{\partial P_j} = 0$$

which indicates, for any $t \in [0, \infty)$,

$$\frac{1}{N} \sum_{i=1}^{N} P_i(t) = 0, \quad \frac{1}{N} \sum_{i=1}^{N} P_i(0) = 0, \tag{7}$$

always holds. As known, when θ_i is large, $\nabla \phi_i(P_i)$ is highly nonlinear due to the variety of Hessian near the boundary of the feasible domain. Consequently, it is difficult to minimize the original problem. However, the problem can be solved in a stepwise way. The dynamics of the whole process can be considered as a switching system with respect to P_i and a switching parameter μ. Provided a desired accuracy ϵ_d and initial $\theta_i(0)$, θ_i will gradually switch for a sufficient large number, which promotes the gradient $\nabla \phi_i(P_i)$ reaching a consensus. Hence, a distributed consensus based optimization algorithm can be proposed in Algorithm 1. ζ is a sufficiently

Algorithm 1 Economic Dispatch by Distributed Consensus

procedure DISTRIBUTEDCONSENSUS(P_0)
  Initialize $\zeta_i (i \in \mathcal{N}),\ P_i(0), K = 1, \mu > 1$;
  $\theta_i(K) = \theta_i(0) > 0,\ \epsilon(K) = \epsilon(0),\ \epsilon_d$;
  repeat
    /*Approximately minimize $\sum_{i=1}^{N} \phi_i(P_i)$*/
    $k = 1, t_k = T_K^\theta$;
    repeat
      /*Computing P_i in parallel*/
      $P_i(t_{k+1}) = P_i(t_k) - \zeta_i \sum_{j=1}^{N} w_{ij} \nabla \phi_j(P_j(t_k))$;
      $k = k + 1$;
    until $\parallel P(t_{k+1}) - P(t_k) \parallel \leq \epsilon[K]$
    $\theta_i(K+1) = \mu \theta_i(K), \epsilon(K+1) = \mu^{-1} \epsilon(K)$;
    $K = K + 1$;
  until $\sum_{i=1}^{N} \frac{2}{\theta_i} \leq \epsilon_d$
  return $P_i^*(i \in \mathcal{N})$;
end procedure

small stepsize. Denote the time interval between two state switching by $t \in [T_K^\theta, T_{K+1}^\theta)$. At each subsequent iteration, $\frac{1}{\theta_i}$ adaptively decreases in a way that the resultant problem is ready to solve if the global minimum of its immediate predecessor $P_i^\star = P_i(t)$ can be available as the new initial point. Mathematically, the sequence of solution P_i will converge to the global minimum of the problem in (2).

III. EVENT-TRIGGERED DISTRIBUTED OPTIMIZATION SCHEME

As aforementioned, the optimization technique requires the interior points to be the initial values. Thus, a feasible start point can be guaranteed by a distributed algorithm to allocate the task of each generator at the beginning of economic dispatch. And then, the distributed optimization in (6) can be implemented successfully to attain the global optimizer.

Considering the nature of economic dispatch, it is executed about every 15 minutes [19] in accordance with the predicted demand, which can be recognized as a periodic event-triggered task distribution. We divide an economic dispatch period into two parts, see Fig. 1. As shown, economic dispatch is triggered by the predictive demand event. The period $T1$ initializes

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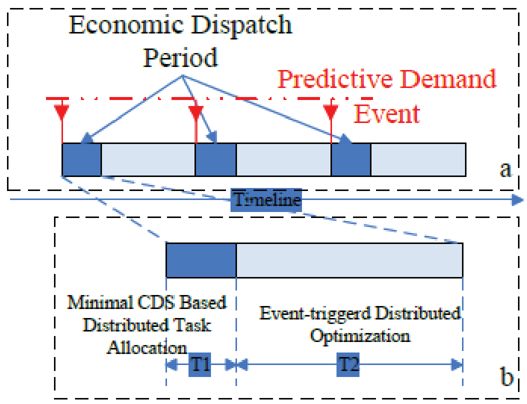

Fig. 1: Event-triggered distributed optimization scheme of economic dispatch

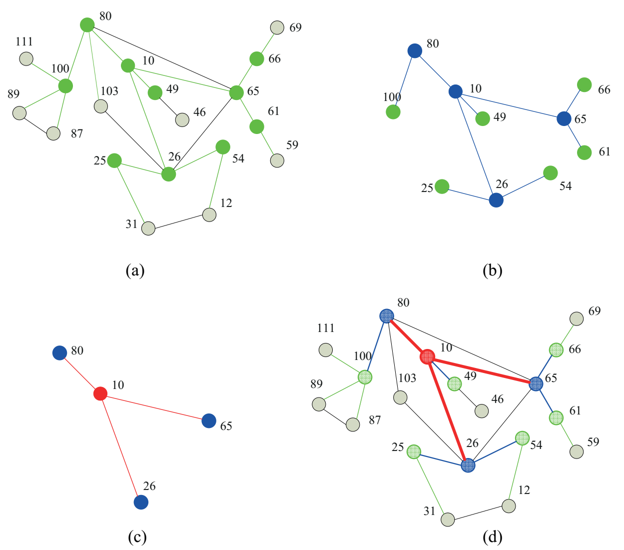

Fig. 2: (a) The minimal connected dominating set $\mathcal{D}_G$ in $\mathcal{L}_1$. (b) The minimal connected dominating set $\mathcal{D}_B$ in $\mathcal{L}_2$. (c) The minimal connected dominating set $\mathcal{D}_R$ in $\mathcal{L}_3$. (d) The entire topology of different levels.

the feasible starting points of each power generator in a distributed way, which has to guarantee the equality constraint (8) satisfied at the beginning. The period $T2$ runs an event-triggered iterative algorithm that enables local information exchange amongst neighbour generators. In the meantime, the accumulative sequence $P_i(t)$ generated by this algorithm will converge to the optimal solution of the problem.

A. Event-triggered Distributed Task Allocation Toward Feasible Initialization

Technically, a fully distributed algorithm for economic dispatch requires that a technology-enabled strategy provides a distributed way of matching supply to demand over the entire time horizon in the power network, such that

$$\sum_{i=1}^{N} P_i(t) = P_D, \quad \forall t \in [0, \infty). \tag{8}$$

As known, the minimum connected dominating set of a graph provides the least cost for information exchange and routing in a network environment, which helps operators making an economic decision to allocate a task. We sketch a minimum connected dominating set based procedure [20] to allocate the initial output of each generator as follows:

- **Step 1.** Given a connected topology of power network $\mathcal{G}$, it can be recursively divided into different connected dominating sets $\mathcal{D}$ in terms of different levels $\mathcal{L}$.
- **Step 2.** From the top level to the bottom level, task allocation of each power generator is executed among adjacent nodes at the same level, where event messages of information exchange are delivered by immediate nodes in the predecessor level.
- **Step 3.** If there are some new nodes of power generation that join into the network, then they are connected in the bottom level and the corresponding nodes of the predecessor level are notified by event messages, which does not have any impact on the previous steps. However, if some nodes in a higher level want to quit from the network, it is necessary to restart **Step 1** and **Step 2**. The event messages are then passed to all nodes to reconstruct all minimum connected dominating sets and corresponding levels.

We employ the distributed minimum connected dominating set(CDS) searching algorithm in [21] as a part of our algorithm, such that

$$(N_{\mathcal{L}}, \mathcal{D}) = DistrMiniCDS(\mathcal{G}),$$

where $\mathcal{D}$, $\mathcal{G}$ are all minimum connected dominating sets in terms of different levels and the graph of a power network. Denote $N_{\mathcal{L}}$ is the number of total levels in a power network. $Sum\mathcal{L}_{j,MIN}$ and $Sum\mathcal{L}_{j,MAX}$(j=1,2,...$N_{\mathcal{L}}$) are the summation of minimal and that of maximal output capacity at j level, respectively, which can be easily obtained by message routing. Now, we are ready to introduce Algorithm 2.

To illustrate our algorithms, we take the topology of IEEE 118-bus test system [22] as an example. There are 54 generators spatially connected into 118-buses. In fact, it only needs to run 19 generators to meet the load demand over 24 hours. Assume that 19 dispatchable generators are connected by a cyber network. First, we use the minimum CDS searching algorithm to obtain $\mathcal{L}_1$, as shown in Fig. 2(a), where green nodes are connected into a minimal connected dominating set $\mathcal{D}_G = \{10, 25, 26, 49, 54, 61, 65, 66, 80, 100\}$. Note that gray nodes in $\mathcal{L}_1$ can communicate with green nodes directly. Second, by removing the gray nodes, a new minimum connected dominating set $\mathcal{D}_B = \{10, 26, 65, 80\}$ is organized by blue nodes into $\mathcal{L}_2$, see Fig. 2(b). Likewise, by taking away green nodes, the set $\mathcal{D}_R = \{10\}$ is found as $\mathcal{L}_3$ in Fig. 2(c). Finally, the entire topology of different levels and the minimum connected dominating set of each level can be obtained in Fig. 2(d).

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Algorithm 2 Minimal CDS Based Distributed Task Allocation

procedure DISTRIBUTEDTASKALLOCATION($\mathcal{G}$, P_D)
  Initialize $P_i = P_{i,m}, \forall i \in \mathcal{G}$,
  $(N_{\mathcal{L}}, \mathcal{D}) = DistrMiniCDS(\mathcal{G})$;
  $k = N_{\mathcal{L}}$;   /*the number of levels*/
  $P_D = P_D - \{Sum\mathcal{L}_{1,MIN} + ...Sum\mathcal{L}_{k,MIN}\}$;
  repeat
    $P_{\text{temp}} = P_D - \{Sum\mathcal{L}_{k,MAX} - Sum\mathcal{L}_{k,MIN}\}$;
    if $P_{\text{temp}} > 0$ **then**
      $P_i = P_{i,M} \quad \forall i \in \mathcal{D}_k$;
      $P_D = P_{\text{temp}}$;
      $k = k - 1$;
    else
      for $i \in \mathcal{D}_k$ **do**
        if $P_{\text{temp}} > P_{i,M} - P_{i,m}$ **then**
          $P_i = x_i + \{P_{i,M} - P_{i,m}\}$;
          $P_{\text{temp}} = P_{\text{temp}} - \{P_{i,M} - P_{i,m}\}$;
        else
          $P_i = P_i + P_{\text{temp}}$;
          Break;
        end if
      end for
    end if
  until $k > 0$
  return P;
end procedure

Each minimal connected dominating set supplies computational service in each level. At beginning, each node of power generator P_i is initialized by its minimal power capacity $P_{i,m}$. From $\mathcal{L}_3$, Node 10 of $\mathcal{D}_R$ is able to check the rest of mismatched output. If the demand could be satisfied and completed in this level, Node 10 would communicate with the other nodes except in $\mathcal{D}_R$ and allocate the task for them by event message. Otherwise, all nodes in $\mathcal{L}_3$ take their maximal capacity and pass the rest of the task to $\mathcal{L}_2$. Recursively, the task would be completed by some levels in this distributed way. Note that if the demand is overloading, the task could not be executed and the warning message will return.

B. Event-triggered Distributed Optimization

Due to the fact that the communication service amongst different generators is only available in discrete time instants, the economic dispatch procedure is involved in continuous-time optimization and discrete-time communication. To avoid continuously communicating with neighbours, self-triggered mechanism for each generator and an event-triggered mechanisms for information exchange over the network are designed.

We define $\tilde{P}_i(i \in \mathcal{N})$ as the last known state of the i-th generator that transmits to the neighbours. Let $\{T_s^i\}(s = 1, 2, ..., \infty)$ denote the time instants of self-triggered mechanism when the generator i broadcasts its incremental cost to the neighbours, i.e., for $t \in [T_s^j, T_{s+1}^j)$, $\tilde{P}_i = P_i(T_s^i)$. Let $\{T_e^i\}(e = 1, 2, ..., \infty)$ denote the time instants of event-triggered mechanism when the generator i broadcasts its incremental cost to the neighbours, i.e., for $t \in [T_e^j, T_{e+1}^j)$, $\tilde{P}_j = P_j(T_e^j)$.

According to the dynamical system in (6), we define the corresponding discrete dynamical system as follow

$$\begin{aligned} P_i(t_{k+1}) &= P_i(t_k) - \zeta_i w_{ii} \nabla \phi_i(P_i(t_k)) \\ &\quad - \zeta_i \sum_{j=1; j \neq i}^{N} w_{ij} \nabla \phi_j(\tilde{P}_j), \end{aligned} \tag{9}$$

where $t_k \geq 0 (k = 1, 2, ..., \infty)$. This means that each generator can sample its own state P_i at time instant t_k and can only update the state by using its neighbours' state $\tilde{P}_j(j \in \mathcal{N})$ received by the last communication. $\zeta_i(i \in \mathcal{N})$ is the stepsize regarding the i-th generator, which is able to avoid Zeno behaviour.

To derive the event trigger criteria for the system (9), define

$$z_i(k) = -[w_{ii} \nabla \phi_i(P_i(t_k)) + \sum_{j=1; j \neq i}^{N} w_{ij} \nabla \phi_j(\tilde{P}_j)],$$

$$\tilde{z}_i(k) = -[w_{ii} \nabla \phi_i(\tilde{P}_i) + \sum_{j=1; j \neq i}^{N} w_{ij} \nabla \phi_j(\tilde{P}_j)],$$

$$\nabla \Phi(P(t_k)) = \sum_{i=1}^{N} \{-z_i(k) + \sum_{j=1; j \neq i}^{N} w_{ij} (\nabla \phi_j(P_j(t_k)) - \nabla \phi_j(\tilde{P}_j))\}.$$

Due to the fact that $\phi_i(P_i)(i \in \mathcal{N})$ is strongly convex, it yields that $l_i \leq \nabla^2 \phi_i(P_i) \leq u_i$, where l_i and u_i are the lower bound and the upper bound, respectively. Let $M = \max_{i \in \mathcal{N}} \{u_i\}$. It gives lower bound and the upper bound as following

$$\Phi(P^\star) \leq \Phi(P) - \frac{1}{2M} \|\nabla \Phi(P)\|^2, \tag{10}$$

where $P^\star$ is the optimal solution of (3). Thus, one has

$$\begin{aligned} \Phi(P(t_{k+1})) &\leq \Phi(P_i(t_k)) + \nabla \Phi(P_i(t_k))(\zeta \cdot z(k)) \\ &\quad + \frac{\lambda_{\max}(W) M}{2} \|\zeta z(k)\|_2^2, \end{aligned} \tag{11}$$

where $\lambda_{\max}(W)$ is the maximal eigenvalue of W.

Define Lyapunov function $V(P(t_k)) = \Phi(P(t_k)) - \Phi(P^*)$, it gives

$$\begin{aligned} \Delta V(P) &= \Phi(P(t_{k+1})) - \Phi(P(t_k)) \\ &\leq \sum_{i=1}^{N} \{\zeta_i z_i(k)[-z_i(k) \\ &\quad + \sum_{j=1; j \neq i}^{N} w_{ij} (\nabla \phi_j(P_j(t_k)) - \nabla \phi_j(\tilde{P}_j))] \\ &\quad + \frac{\lambda_{\max}(W) M}{2} (\zeta_i z_i(k))^2\}. \end{aligned} \tag{12}$$

Note that, for some positive scalar ε_i,

$$\begin{aligned} & z_i(k) \sum_{j=1; j \neq i}^{N} w_{ij} (\nabla \phi_j(P_j(t_k)) - \nabla \phi_j(\tilde{P}_j)) \\ \leq \; & \frac{\varepsilon_i}{2} z_i^2(k) + \frac{[\sum_{j=1; j \neq i}^{N} w_{ij} (\nabla \phi_j(P_j(k)) - \nabla \phi_j(\tilde{P}_j))]^2}{2\varepsilon_i}. \end{aligned}$$

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We have, for the constant $\rho_i \in (0,1)$,

$$\begin{aligned}\Delta V(P) \le & \sum_{i=1}^{N}\{-\zeta_i(1-\frac{\varepsilon_i}{2}-\frac{\lambda_{\max}(W)M\zeta_i}{2})z_i^2(k)\\ &+\frac{\zeta_i}{2\varepsilon_i}[\sum_{j=1;j\neq i}^{N} w_{ij}(\nabla\phi_j(P_j(t_k))-\nabla\phi_j(\tilde{P}_j))]^2\}\\ \le & \sum_{i=1}^{N}\{\frac{w_{ii}\zeta_i}{2\varepsilon_i}\sum_{j=1;j\neq i}^{N} w_{ij}^2(\nabla\phi_j(P_j(t_k))-\nabla\phi_j(\tilde{P}_j))^2\\ &-\zeta_i(1-\frac{\varepsilon_i}{2}-\frac{\lambda_{\max}(W)M\zeta_i}{2})z_i^2(k)\}\\ \le & \sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\{\frac{w_{ij}^2 w_{ii}\zeta_i}{2\varepsilon_i}(\nabla\phi_j(P_j(t_k))-\nabla\phi_j(\tilde{P}_j))^2\\ &-\frac{w_{ij}^2\zeta_i\rho_i}{w_{ii}}(1-\frac{\varepsilon_i+\lambda_{\max}(W)M\zeta_i}{2})\tilde{z}_i^2(k)\}\\ &-\sum_{i=1}^{N}\{\zeta_i(1-\frac{\varepsilon_i}{2}-\frac{\lambda_{\max}(W)M\zeta_i}{2})\\ &\cdot(z_i^2(k)-\rho_i\tilde{z}_i^2(k))\}. \end{aligned} \tag{13}$$

By considering of the strong convexity $\Phi(P)$, it yields

$$\begin{aligned}\Delta V(P) \le & \sum_{j=1,j\neq i}^{N}\sum_{i=1}^{N}\{\frac{w_{ij}^2 w_{ii}\zeta_i M^2}{2\varepsilon_i}(P_j(t_k)-\tilde{P}_j)^2\\ &-\frac{w_{ij}^2\zeta_i\rho_i}{w_{ii}}(1-\frac{\varepsilon_i+\lambda_{\max}(W)M\zeta_i}{2})\tilde{z}_i^2(k)\}\\ &-\sum_{i=1}^{N}\{\zeta_i(1-\frac{\varepsilon_i+\lambda_{\max}(W)M\zeta_i}{2})\\ &\cdot(z_i^2(k)-\rho_i\tilde{z}_i^2(k))\}. \end{aligned} \tag{14}$$

If the inequalities

$$\begin{aligned}&(P_j(t_k)-\tilde{P}_j)^2 \le\\ &\frac{\sum_{i=1}^{N} w_{ji}^2\zeta_i\rho_i w_{ii}^{-1}(2-\varepsilon_i-\lambda_{\max}(W)M\zeta_i)\tilde{z}_i^2}{M^2\sum_{i=1}^{N} w_{ji}^2\zeta_i w_{ii}\varepsilon_i^{-1}}, \end{aligned} \tag{15}$$

$$z_i^2(k)-\rho_i\tilde{z}_i^2 \ge 0, \tag{16}$$

hold with the stepsize $\zeta_i \in (0, \frac{2-\varepsilon_i}{\lambda_{\max}(W)M})$, then $\Delta V(P) \le 0$ which implies the system (9) asymptotically converges to the global minimizer of problem (3).

Therefore, for $t_k \in [t_e^j, t_{e+1}^j)(e=1,2,...,\infty)$, the generator j monitors $P_j(t_k)$, the communication events are triggered at

$$\begin{aligned}t_{e+1}^j = &\inf\{\, t\in[t_e^j+\zeta_j,\infty)\,|\,(P_j(t_k)-\tilde{P}_j)^2 \ge\\ &\frac{\sum_{i=1}^{N} w_{ji}^2\zeta_i\rho_i w_{ii}^{-1}(2-\varepsilon_i-\lambda_{\max}(W)M\zeta_i)\tilde{z}_i^2}{M^2\sum_{i=1}^{N} w_{ji}^2\zeta_i w_{ii}\varepsilon_i^{-1}}\}. \end{aligned} \tag{17}$$

For $t_k \in [t_s^i, t_{s+1}^i)(s=1,2,...,\infty)$, the generator i monitors $z_i(k)$, the communication events are triggered at

$$t_{s+1}^i = \inf\{\, t\in[t_s^i+\zeta_i,\infty)\,|\,z_i^2(k)\le\rho_i\tilde{z}_i^2\}. \tag{18}$$

By considering the update of the θ_i-*logarithmic* barriers and the accuracy ϵ, for $t_k \in [T_K^\theta, T_{K+1}^\theta)(K=1,2,...,\infty)$, the updates occurred at

$$T_{K+1}^\theta = \inf\{t\in[T_K^\theta,\infty)|(P_i(t_{k+1})-P_i(t_k))^2 \le \epsilon[K]\}. \tag{19}$$

We remark that condition (18) only relies on the neighbour generators' information and their states, which implies it is a self-triggered mechanism. Each generator executes its own event-triggering criteria and broadcasts information individually. Hence, an asynchronous communication can be implemented by the proposed event-triggered scheme to prevent an undesirably high demand on the communication resources in smart grids.

C. Accelerated Event-triggered Optimization

When the networked system is large, the convergence rate of the ordinary first-order gradient method tends to be slow. In fact, the event-triggered optimization method in (9) may further degrade the convergence rate. Note that the objective function (3) is strongly convex with twice differentiable gradient. Intrinsically, a fast distributed gradient method enabling a better convergence rate of event-triggered optimization is desired, which searches the minimizer P_i^* with the additional momentum term $\xi(P_i(t_k)-P_i(t_{k-1}))$.

For $t_k \ge 0(k=1,2,...,\infty)$, the fast gradient based event-triggered optimization is introduced, such that

$$\begin{cases} Q_i(k) = P_i(t_k)-P_i(t_{k-1}),\\ P_i(t_{k+1}) = \xi Q_i(k)+P_i(t_k)-\zeta w_{ii}\nabla\phi_i(P_i(t_k))\\ \qquad -\zeta\sum_{j=1;j\neq i}^{N} w_{ij}\nabla\phi_j(\tilde{P}_j), \end{cases} \tag{20}$$

where the parameters of momentum ξ and stepsize ζ are determined by

$$\xi = \left(\frac{\sqrt{\max_{i\in\mathcal{N}}\lambda_i(WH^*)}-\sqrt{\lambda_2(WH^*)}}{\sqrt{\max_{i\in\mathcal{N}}\lambda_i(WH^*)}+\sqrt{\lambda_2(WH^*)}}\right)^2, \tag{21}$$

$$\zeta = \left(\frac{2}{\sqrt{\max_{i\in\mathcal{N}}\lambda_i(WH^*)}+\sqrt{\lambda_2(WH^*)}}\right)^2. \tag{22}$$

H^* is the Hessian matrix of the objective function (3) at the optimal solution. By the result in [23], the convergence rate of the new event-triggered optimization is $\mathcal{O}(\frac{1}{k^2})$ which approximately minimizes the objective function (3). The conditions of the event-triggered optimization are presented in (17), (18) and (19). The proof is the same procedure as Section III-B and omitted here.

IV. Case Study

The IEEE 54-bus test system with 7 generators is considered in a numerical simulation. The parameters of each generation are given in Table (I) and the topology of the entire power networks is assumed in Fig. 3(d).

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TABLE I: Parameters of 7 generators in IEEE 57-bus

Generator No.	α	β	γ	$P_{\min}$	$P_{\max}$
1	0.0775795	20	0	0	78.78
2	0.01	40	0	0	38
3	0.25	20	0	0	33
6	0.01	40	0	0	45
8	0.0222222	20	0	0	56.5
9	0.01	40	0	0	30.5
12	0.0322581	20	0	0	45

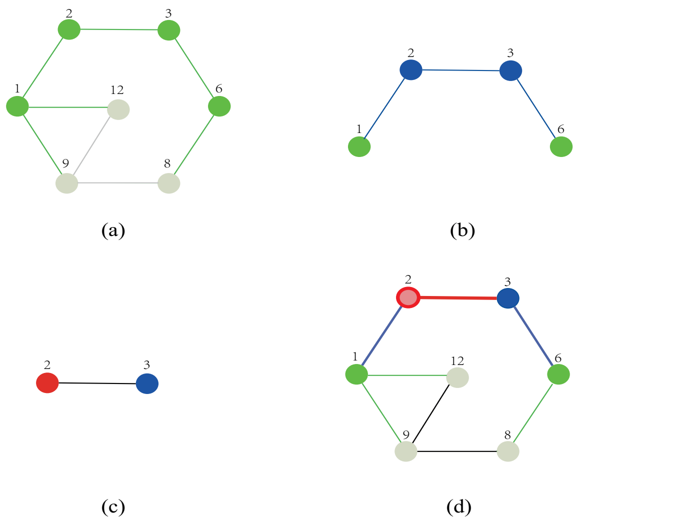

Fig. 3: (a) Green nodes in $\mathcal{L}_1$. (b) Blue nodes in $\mathcal{L}_2$. (c) One red node in $\mathcal{L}_3$. (d) The entire topology of different levels.

A. Minimal CDS Based Distributed Task Allocation Test

To verify the event-triggered distributed optimization method, the generators of IEEE 57-bus system are initialized by the minimal CDS based distributed task allocation algorithm, where the predicted demand is 235.26 MW and the minimal cost is \$6036.40. The distributed CDS searching algorithm produces the minimal connected dominating set in each level as shown in Fig. 3(a)-(c). Specifically, the sets of $\mathcal{L}_1$, $\mathcal{L}_2$, and $\mathcal{L}_3$ are $\{1, 2, 3, 6\}$, $\{2, 3\}$, $\{2\}$, respectively.Thus, the initial value of the task is $P(0) = \{78.78, 38, 33, 45, 9.98, 30.5, 0\}$. Note that each node in the upper level could communicate with the nodes in the lower level in one hop, which significantly reduce the cost of information exchange and routing. Meanwhile, some generators are already operated at the optimal solution, i.e. $P_1^* = 78.78$ MW and $P_3^* = 33$ MW.

B. Performance Evaluation

The performance evaluation on event-triggered distributed optimization is set up as follows. First, the results of event-triggered scheme are compared with the classic gradient based method in Algorithm 1. Let $\theta = 10$, $\epsilon = 1$, $\epsilon_d = 10^{-4}$ and $\mu = 10$. Set the stepsize $\zeta = 0.0003$ and randomly choose $\rho_i \in [0.85, 1)(i = 1, 2, ..., 7)$ for each generator. The topology parameters $\lambda_2 = 0.753$ and $\lambda_{\max} = 4.5321$. Also, the period of communication is $\Delta T = 0.0003s$. The existing algorithms for economic dispatch, [5] and [6] referred as the periodic communication based algorithms, are used to compare the performance.

First, the effectiveness of our proposed algorithm is verified. To initialize all generators with $P(0) = \{58.78, 23, 22, 35, 46.5, 18, 31.98\}$, the results of the event-triggered communication based algorithm are shown in Fig. 4 while those of the periodic communication based algorithm are given in Fig. 5. As shown, the trajectories of active power and the incremental cost are similar, which implies the event-triggered communication based algorithm has a similar performance to reach the optimal solution. During the evolution, all values about the active power always lay in their bounds, which implies the solutions by the θ-*logarithmic* barrier method are always feasible. After 5 seconds, the minimal costs of the event-triggered communication based algorithm and the periodic communication based algorithm are \$6039 and \$6037, respectively. The number of communications by the event-triggered communication based algorithm is 7625 while this number by the periodic communication based algorithm is 1.1667×10^5. Noticeably, the number by the event-triggered communication based algorithm is much less than the counterpart by the periodic communication based algorithm. The communication by the event-triggered based algorithm makes up only a small proportion (6.54%) of the communication by the periodic one, see the details in Figs. 4(c) and 5(c).

Second, to clearly illustrate the good performance in terms of reducing the number of communications, we define the relative error

$$e(t_k) = \frac{\Phi(P(t_k)) - \Phi(P^*)}{\Phi(P^*)}, k = 1, 2, ... \tag{23}$$

which measures the accuracy of two algorithms regarding the optimal solution. All parameters are kept unchanged. The trade-off between the accuracy of the optimal solution and the number of communications obtained by two algorithms is illustrated by Fig . 6 (a). Generally, for both algorithms, the more number of communications used, the better accuracy achieved. However, in comparison with the periodic communication based algorithm, the event-triggered algorithm has a remarkable less number of communications to achieve the same accuracy. To achieve the accuracy of $e(t) = 10^{-1}$, $e(t) = 10^{-2}$ and $e(t) = 10^{-3}$, the numbers of communications by the event-triggered algorithm merely are 15, 4237 and 6098, respectively. For the same accuracy requirements, the numbers of communications by the periodic one needs 1190, 24860 and 37776, respectively. In Fig. 6 (b), the trade-off between the accuracy and the computational time is given, where we use a logarithmic scale for the accuracy of the computational values. Until t =1.648s, two algorithms almost has the same performance to reach the same accuracy from $e(0) = 1.126 \times 10^{-1}$ to $e(1.648) = 4.828 \times 10^{-4}$. After this time, compared with the periodic algorithm, the event-triggered algorithm requires more time to achieve the same accuracy. To converge at $e(t) = 4 \times 10^{-4}$, the event-triggered algorithm needs 4.918s whereas the periodic one only requires 1.655s. This implies if we anticipate an extreme high accuracy,

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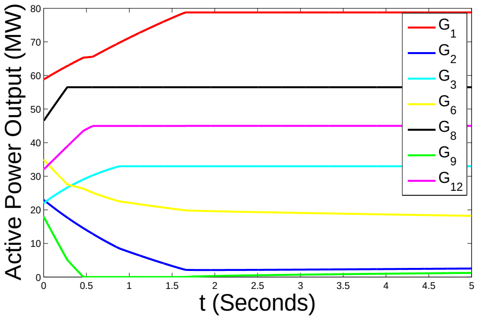
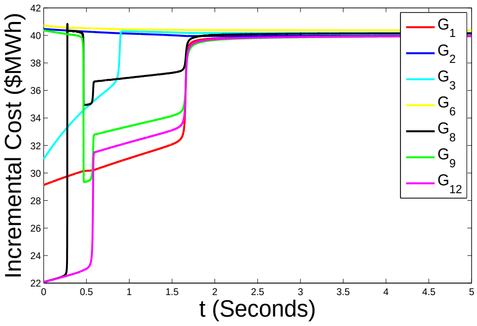


(a)



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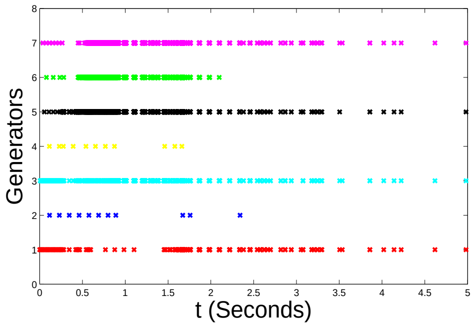
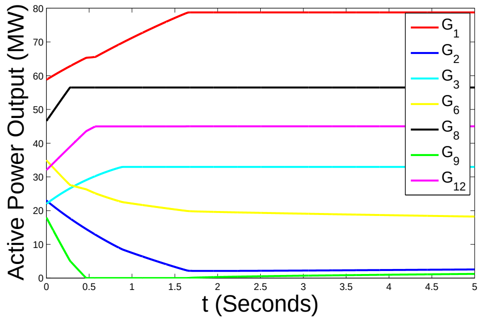
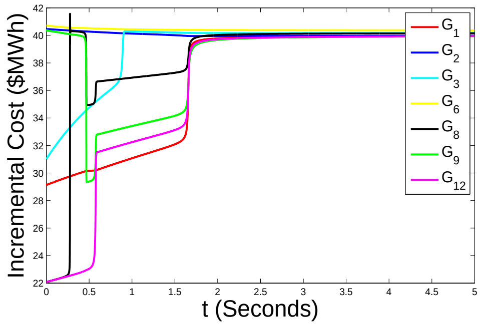


(c)

Fig. 4: (a) Active power output by the event-triggered communication based algorithm. (b) Incremental costs of 7 generators by the event-triggered communication based algorithm. (c) The time instants of an event with respect to 7 generators by the event-triggered communication based algorithm.



(a)



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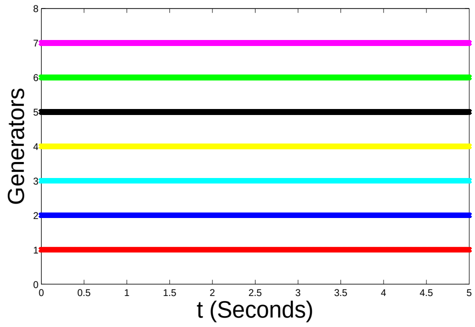

(c)

Fig. 5: (a) Active power output by the periodic communication based algorithm. (b) Incremental costs of 7 generators by the periodic communication based algorithm. (c) The time instants of an event with respect to 7 generators by the periodic communication based algorithm.

the event-trigged scheme, i.e. in this case less than 10^{-4}, is not superior to the periodic one in the sense of the computational time. However, if we only require an acceptable accuracy of the minimal cost, i.e. 10^{-3}, the event-triggered scheme has significant benefits over the periodic scheme.

Third, the switching parameter ϵ plays a significant role in reducing the number of communications. We consider the effect of different ϵ on the trade-off between the accuracy of the optimal solution and the number of communications. Let $\epsilon = \{0.1, 1, 10, 30\}$, $\mu = 12$ and keep other parameters unchanged. Overall, there is a tendency that, with the increase of the value ϵ, the number of the event-triggered communications will grow up. The numbers of the event-triggered communications with respect to $\epsilon = \{0.1, 1, 10\}$ have a slight difference to achieve the accuracy of $e(t) = 0.02$, which are 1257, 1710 and 2186, respectively. To reach this accuracy, the number with respect to $\epsilon = 30$ dramatically increases to 3649. As aforementioned for the interior point method, the switching parameter ϵ has an impact on the number of iterations regarding to the central path. When ϵ increases, the iterations of the θ-*logarithmic* barrier algorithm will prematurely switch to the next stage from the boundaries of the feasible domain, which finally increases the number of the event-triggered communication.

C. Accelerated Event-triggered Economic Dispatch

To verify the advantage of accelerated event-triggered economic dispatch, let the total energy demand be 235.26 MW

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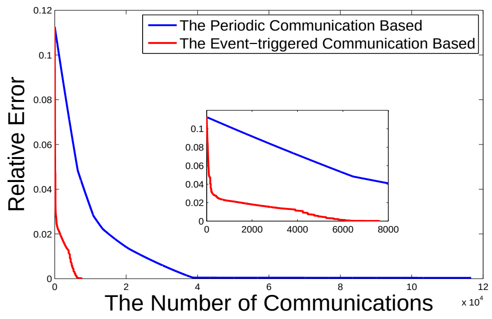
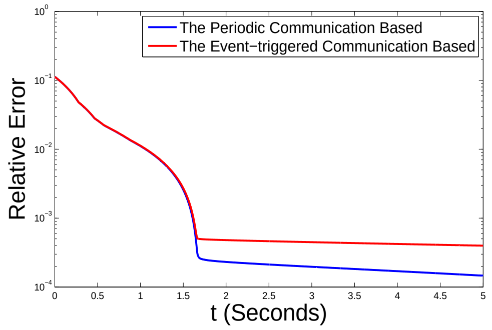


(a)



(b)

Fig. 6: (a) The trade-off between the relative errors and the number of communications. (b) The trade-off between the relative errors and the computational time t.

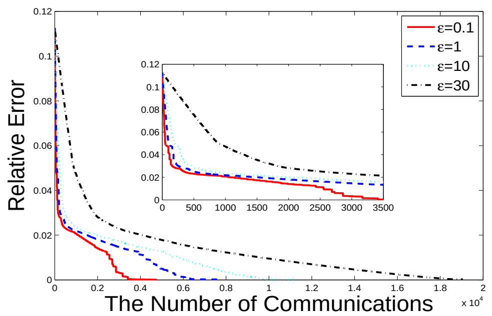
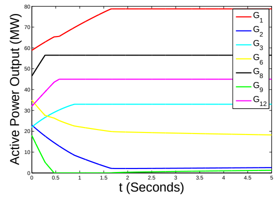


Fig. 7: The trade-off between the relative errors and the number of communications in terms of different ϵ.

and all generators will run to meet the demand. Thus, the 7 generators cooperatively generate active power until they reach a consensus, which is the optimal status of power output for the entire power network. Let $\theta = 10$, $\epsilon = 1$, $\epsilon_d = 10^{-4}$ and $\mu = 10$. We randomly choose $\rho_i \in [0.9, 1)(i = 1, 2, ..., 7)$ for each generator. The topology parameters $\lambda_2 = 0.753$ and $\lambda_{\max} = 4.5321$. The parameters of the momentum term are computed by (21), i.e. $\xi = 0.6703$ and $\zeta = 0.0002$. As shown in Fig. 8, the results by accelerated event-triggered economic dispatch is significantly faster than that by the periodic counterpart with the same stepsize and the same event triggering parameter $\rho_i(i = 1, 2, ..., 7)$, where the optimal solution is $P^* = \{78.78, 7.3267, 33, 7.3266, 56.5, 7.3267, 45\}$. The convergent time of the incremental cost by the event-triggered



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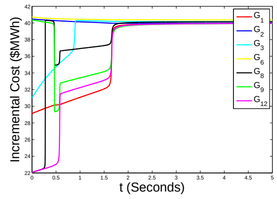

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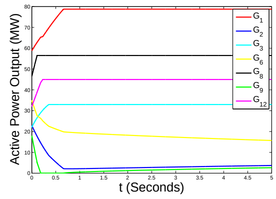

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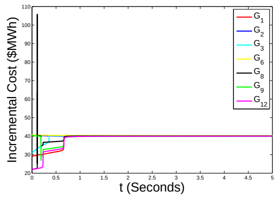

(d)

Fig. 8: (a) Active power output by event-triggered economic dispatch. (b) Incremental cost by event-triggered economic dispatch. (c) Active power output by accelerated event-triggered economic dispatch. (d) Incremental cost by accelerated event-triggered economic dispatch.

communication based economic dispatch is less than 0.7s while this time of the incremental cost by the periodic communication based economic dispatch is more than 2s.

D. Plug and Play Test

Plug and play is critical for modern power networks. This is because the renewable energy may participate into or leave from the economic dispatch arbitrarily. We will illustrate this characteristics of our accelerated event-triggered economic dispatch by a three-phase experiment. Similarly, the demand is 235.26 MW and all other parameters are kept unchanged. In the first phase, G_{12} is disconnected in the time interval $[0, 2)$. Afterward, it participates in the entire network in the second phase. In final phase, G_6 is deleted from the entire network. The minimal CDS based distributed task allocation algorithm is used to reallocate the initial values at the beginning of each stage. As depicted in Fig. 9, the incremental cost of the generators could reach a consensus in all stages while the supply-demand balance is always guaranteed within this three-phase running.

V. Conclusion

In this paper, the event-triggered communication based scheme for economic dispatch has been investigated. The interior point method has been employed where the *θ-logarithmic* barrier is used to reformulate the cost function. A distributed algorithm has been designed to allocate the task of supply-demand balance for the whole power networks in advance. Hybrid event-triggered communication mechanisms are developed to minimize the objective function in a distributed way. Moreover, the fast gradient method has been utilized to accelerate the convergence rate of the distributed optimization. This method provides a safety technique that all the generators are running below their capacity with lower communication

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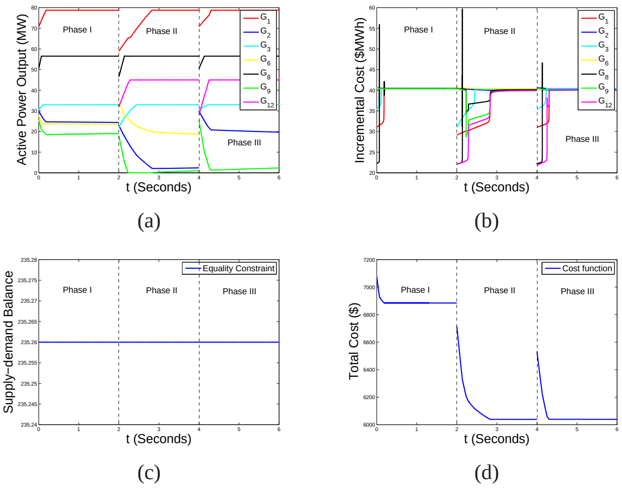

Fig. 9: (a) Active power output in plug and play. (b) Accelerated event-triggered economic dispatch of incremental cost in plug and play. (c) Supply-demand balance in plug and play. (d) The total cost in plug and play.

requirements. Meanwhile, the perfect supply-demand balance is always guaranteed over the entire time horizon in the electricity market by the proposed event-triggered distributed optimization. The results show that there is a trade-off between the accuracy of the optimal solution and the number of communications. The power operators of economic dispatch can balance the trade-off depending on the network resource condition. Further research will concentrate on a more complicated economic dispatch problem, i.e. power losses and non-convex cost functions. Also, the corresponding event-triggered communication mechanisms will be studied.

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