The following publication X. Gao, X. Lu, K. W. Chan, J. Hu, S. Xia and D. Xu, "Distributed Coordinated Management for Multiple Distributed Energy Resources Optimal Operation with Security Constrains," 2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), 2019, pp. 1-5 is available at https://doi.org/10.1109/ISGT.2019.8791673

Distributed Coordinated Management for Multiple Distributed Energy Resources' Optimal Operation with Security Constrains

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***Abstract*—Grid connection of large-scale distributed energy resources (DERs) brings not only many benefits to the power systems including the improvement of system reliability and security but also challenges in their control and operation. Aiming at overcoming the disadvantages of existing centralized methods for solving the corrective security-constrained DC optimal power flow (OPF) problem in transmission systems, this paper presents a fully distributed control algorithm which requires only variables in adjacent buses of the faulty line to update the control signals of DERs so as to allow them to respond quickly to maintain the dynamic power balance in grid after a line contingency. A case study on a modified 6-bus system shows the validity and effectiveness of the proposed algorithm.**

***Index Terms*--contingency, distributed optimization, distributed energy resources, transmission lines**

I. Introduction

It is a great challenge for the power grid to support the growing demand and unexpected outage of generators or transmission lines. As a remedy in recent years, an increasing number of DERs are connected to the grid as shown in Fig.1 [1]. Examples of DERs include battery storage, vehicle-to-grid energy storage, fuel cells storage, solar PV storage, large-scale solar power plants storage, pumped hydro storage, compressed air storage, underground heat storage, thermal energy storage, flywheel storage and so on. Meanwhile, a large number of DERs integrated to the grid also poses new issues, and how to quickly and accurately dispatch DERs for sudden system interruption so as to maintain the dynamic power balance is a subject well worth to investigate.

In case of a line contingency, sensors located in line detect the fault and send signals back to the control center. The system conditions will be analyzed to calculate the optimal power flow for system reconfiguration and optimization. For systems without DERs connected, the power source would consist of traditional generators only, and the system respond time will be longer because of the large system inertia. Power flow on transmission lines may exceed their limits in over short period of time before generator actions could be taken to redirect the power transmission, and cascaded line outages could be caused as a result. On the contrary, grid-connected DERs could be controlled to act as fast-response power supply sources. Since renewable energy resources do not have any rotational inertia, they could have much faster response than traditional generators [2]. After a contingency, energy stored in them could be allocated to inject power into the grid even before generators could respond.

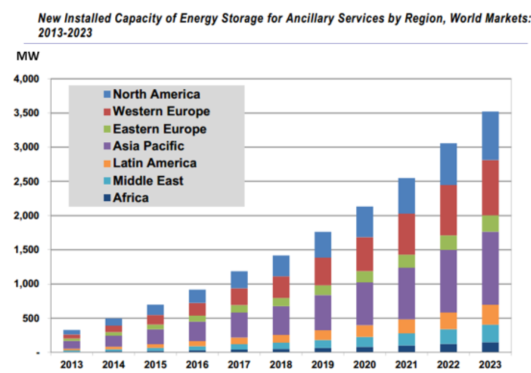

Fig 1. Forecasting development trend of DER capacities [1]

Power system contingency analysis and optimal power flow (OPF) calculation are essential for the planning and operation of the power systems. OPF aims to find the optimal operating point to minimize the given objective function(s) without violating any physical and control constraints [3]. The total power loss and generation cost are the most common objective functions. OPF problem with post-contingency security constraints is referred to security constrained OPF (SC-OPF). Preventive security constrained model (PSC-OPF) and corrective security-constrained model (CSC-OPF) are two existing SC-OPF models. PSC-OPF considers both normal operating state and all contingency states. For a large-scale power system with a large set of possible contingencies, it requires a huge memory space and a long time to compute. However, lots of the contingencies are of little chance to occur

The authors gratefully acknowledge the support of the Hong Kong Polytechnic University.

but incur high operating costs due to the conservativeness of the system settings to ensure the security of all the possible contingencies. Different from PSC-OPF, CSC-OPF model only considers the contingencies when they really occur and fast post-fault corrective control actions are applied to stabilize the system. Although the cost of the post-fault corrective actions could be relatively high, the long-term running cost and the overall total cost are low [4]. Nevertheless, CSC-OPF model needs extra real-time decision variables and limit constraints, as well as fast rescheduling for every contingency [3].

There are three representative algorithms on CSC-OPF model. The first one is a centralized control algorithm, which is the earliest and therefore referred as the traditional method. Centralized mechanism relies on a central controller to collect all the required information and complete all the optimization calculations. As a result, centralized control algorithms need to collect massive data from the power grid over a complex and strong information communication infrastructure, and would have longer time delay to process the data. Meanwhile, high dependency on the centralized controller would impose huge computational demand and pose to single point failure. In addition, it is not as flexible to cater for any changes or interruptions in the system communication topology [5]. The second one is the decentralized control algorithm, which is often applied in multi-area (MA) interconnected systems with a hierarchical structure. Specifically, there exists a virtual central controller, which collects all the information but does not complete any calculation. All optimization calculations are completed in individual nodes relying on data delivered from the virtual central controller [6]. Although decentralized algorithm is less computational demanding, further research is still needed to reduce the impact of communication loss and shorten communication and data processing time. As a better alternative, distributed control algorithm is therefore proposed.

Multi-agent system (MAS) is one of the most popular distributed control methods and has been widely used to settle issues such as active power control, reactive power control, and power management [7]-[9]. A fully distributed MAS-based algorithm applied in electrical market is presented in [10]. Agents negotiate to adjust electricity price by communicating with neighboring agents. Similar, a fully distributed social welfare optimization considering both economy dispatch and demand response is described in [11]. It has been demonstrated to better meet load requirements and encourage great customer participation. Compared to centralized and decentralized control algorithms, fully distributed algorithms have obvious advantages to solve CSC-OPF problem. It does not have any central controller, data are obtained locally relying on simple information exchange with neighbors while optimization calculations are completed in individual nodes [12]. As a result, complex information network is not required and the processing speed is fast such that line constraints can be effectively addressed to avoid cascaded line failures. Meanwhile, it is flexible to changes in system topology caused by line outages [13].

For practical implementation, it is necessary for the power system to rapidly recalculate and dispatch power after line contingencies while satisfying security power flow constraints. However, few works have been focused on line flow constraints in a fully distributed manner. This paper proposes a fully distributed algorithm to dispatch DERs to respond quickly to solve the CSC-OPF problem with the objective function of minimizing the adjustment of grid-connected DERs. The main contributions of this paper are:

(1) Proposed a distributed algorithm to effectively dispatch fast-respond DERs to ensure supply and demand balance.

(2) Constraints of transmission lines are ensured by the proposed distributed method to avoid cascaded failures.

(3) Proposed a flexible algorithm suitable for use with topology changes caused by line contingencies.

The rest of the paper is introduced as follows. Section II presents the problem formulation and Section III details the proposed algorithm. Part IV shows corresponding case study and the last section presents the conclusion and future work.

II. Formulation of Problem

Formulation of CSC-OPF problem is to minimize a given objective function while satisfying for relevant equality and inequality constraints in the post-contingency state. When a line contingency occurs, the objective function in this paper aims to reduce the adjustment of DERs and can be formulated as (1). P_n^{DER} refers to power adjustment of charging or discharging after contingency, and Ω^{DER} is set of DERs. Equality constraints (2) and (3) define bus angle and OPF balance, where P_n^L , P_n^G , P_n^{DER} represent the power of loads, generators and DERs, respectively. Inequality constraints (4) and (5) show limits of line capacities and P_n^{DER} .

$$Min \sum_{n\in\Omega^{DER}} \frac{1}{2}\left(P_n^{DER}\right)^2 \tag{1}$$

subject to

$$\delta_1 = 0 \tag{2}$$

$$P_n^L - P_n^G - P_n^{DER} + \sum_{m=1}^{N} \frac{\delta_n - \delta_m}{X_{nm}} = 0, \forall n \in \Omega^N \tag{3}$$

$$-\overline{P_{nm}} \le \frac{\delta_n - \delta_m}{X_{nm}} \le \overline{P_{nm}}, \forall nm \in \Omega^{NM} \tag{4}$$

$$\underline{P_n^{DER}} \le P_n^{DER} \le \overline{P_n^{DER}}, n \in \Omega^{DER} \tag{5}$$

The Lagrange function for optimization problem (1) can be written as (6) [14]. λ_0 and λ_n are Lagrange multipliers corresponding to equality constraints (2) and (3). μ_{nm}^+ , μ_{nm}^- , μ_n^{DER+}, μ_n^{DER-} relate to nonnegative Lagrange multipliers for inequality constraints (4) and (5).

The first order conditions of Lagrange function (6) are listed as (7). Any solution satisfies all of followed first order optimal conditions is the optimal solution of this CSC-OPF problem [13].

$$
\begin{aligned}
L = & \sum_{n\in\Omega^{DER}} \frac{1}{2}\left(P_n^{DER}\right)^2 + \lambda_0\delta_1 \\
& + \sum_{n\in\Omega^{N}} \lambda_n \left(P_n^L - P_n^G - P_n^{DER} + \sum_{m=1}^{N} \frac{\delta_n-\delta_m}{X_{nm}}\right) \\
& + \sum_{nm\in\Omega^{NM}} \mu_{nm}^{+}\left(\overline{P_{nm}} + \frac{\delta_n-\delta_m}{X_{nm}}\right) + \sum_{nm\in\Omega^{NM}} \mu_{nm}^{-}\left(\overline{P_{nm}} - \frac{\delta_n-\delta_m}{X_{nm}}\right) \\
& + \sum_{n\in\Omega^{DER}} \mu_n^{DER+}\left(P_n^{DER} - \underline{P_n^{DER}}\right) + \sum_{n\in\Omega^{DER}} \mu_n^{DER-}\left(\overline{P_n^{DER}} - P_n^{DER}\right)
\end{aligned}
\tag{6}
$$

$$
\begin{cases}
\dfrac{\partial L}{\partial P_n^{DER}} = P_n^{DER} - \lambda_n + u_n^{DER+} - u_n^{DER-} = 0 \\
\dfrac{\partial L}{\partial \lambda_0} = \delta_1 = 0 \\
\dfrac{\partial L}{\partial \lambda_n} = P_n^L - P_n^G - P_n^{DER} + \displaystyle\sum_{m=1}^{N} \frac{\delta_n-\delta_m}{X_{nm}} = 0 \\
\dfrac{\partial L}{\partial \delta_n} = \lambda_n \displaystyle\sum_{m\in Nn} \frac{1}{X_{nm}} - \sum_{m\in Nn} \lambda_m \frac{1}{X_{nm}} + \sum_{m\in Nn} \frac{\mu_{nm}^{+} - \mu_{nm}^{-}}{X_{nm}} = 0 \\
\mu_{\mathrm{nm}}^{+} \dfrac{\partial \mathrm{L}}{\partial \mu_{\mathrm{nm}}^{+}} = \mu_{\mathrm{nm}}^{+}\left(\overline{P_{nm}} + \dfrac{\delta_n-\delta_m}{X_{nm}}\right) = 0 \\
\mu_{\mathrm{nm}}^{-} \dfrac{\partial \mathrm{L}}{\partial \mu_{\mathrm{nm}}^{-}} = \mu_{\mathrm{nm}}^{-}\left(\overline{P_{nm}} - \dfrac{\delta_n-\delta_m}{X_{nm}}\right) = 0 \\
\mu_n^{DER+} \dfrac{\partial \mathrm{L}}{\partial \mu_n^{DER+}} = \mu_n^{DER+}\left(P_n^{DER} - \underline{P_n^{DER}}\right) = 0 \\
\mu_n^{DER+} \dfrac{\partial \mathrm{L}}{\partial \mu_n^{DER+}} = \mu_n^{DER+}\left(\overline{P_n^{DER}} - P_n^{DER}\right) = 0
\end{cases}
\tag{7}
$$

III. PROPOSED ALGORITHM

To solve the optimization problem in Section II, methods such as the projected gradient method are applied iteratively [15]. In the proposed fully distributed approach, optimization problem (7) is written as the following iterative equations (8)-(12), with Lagrange multipliers λ_n and δ_n found in a fully distributed way. Equation (8) and (10) imply that the updating rule of λ_n and δ_n will converge when the supply demand balance is achieved. In other words, the unique optimal solution of (7) corresponds to unique Lagrange multipliers λ_n and δ_n [16].

$$
\begin{aligned}
\lambda_n(k+1) &= \sum_{m=1}^{N} D_{nm}\lambda_n(k) - \tau\frac{\partial L}{\partial \lambda_n} - \tau\frac{\partial L}{\partial \delta_n} \\
&= \sum_{m=1}^{N} D_{nm}\lambda_n(k) - \tau\left(P_n^L - P_n^G - P_n^{DER} + \sum_{m=1}^{N}\frac{\delta_n-\delta_m}{X_{nm}}\right) \\
&\quad -\sigma\left(\lambda_n \sum_{m\in Nn}\frac{1}{X_{nm}} - \sum_{m\in Nn}\lambda_m\frac{1}{X_{nm}} + \sum_{m\in Nn}\frac{\mu_{nm}^{+}-\mu_{nm}^{-}}{X_{nm}}\right)
\end{aligned}
\tag{8}
$$

$$
D_{nm} = \begin{cases}
2/(n_n + n_m + \varepsilon), m \in N_n, m \neq n \\
1 - \sum 2/(n_n + n_m + \varepsilon), m = n \\
0, otherwise
\end{cases}
\tag{9}
$$

$$
\begin{aligned}
\delta_n(k+1) &= \delta_n(k) - \tau\frac{\partial L}{\partial \lambda_n} \\
&= \delta_n(k) - \tau\left(P_n^L - P_n^G - P_n^{DER} + \sum_{m=1}^{N}\frac{\delta_n-\delta_m}{X_{nm}}\right)
\end{aligned}
\tag{10}
$$

$$
\mu_{nm}^{+}(k+1) = \mu_{nm}^{+}(k) - \xi\left(\frac{\partial \mathrm{L}}{\partial \mu_{\mathrm{nm}}^{+}}\right), \quad \mu_{nm}^{+} >= 0 \tag{11}
$$

$$
\mu_{nm}^{-}(k+1) = \mu_{nm}^{-}(k) - \xi\left(\frac{\partial \mathrm{L}}{\partial \mu_{\mathrm{nm}}^{-}}\right), \quad \mu_{nm}^{-} <= 0 \tag{12}
$$

In above equations (8)-(12), k is iteration index, τ and σ are positive parameters. D_{nm} in equation (8) represents communication coefficients between two neighboring buses and be calculated as equation (9) [13]. N_n in equation (9) is neighboring buses set of bus n, n_n and n_m are numbers of buses connected to bus n and m, respectively. D_{nm} is determined to accommodate for changing of communication network topology as the mean metropolis algorithm proposed in [17]. For Lagrange multiplier λ_n, the first term makes all λ to be the same value, the second term enforces supply-demand balance at each bus and the third part keeps information exchange with neighboring Lagrange multipliers, which leads to updating makes sense. Similarity, power mismatch incentive is used to update the phase angle in (10). μ_{nm}^{+} and μ_{nm}^{-} in equation (11)-(12) are variables required in updating of λ_n in equation (8). Once loads are not fully supplied, proposed updates will result in reductions of δ_n and λ_n until local power balance. Finally, optimal P_n^{DER} is clearly updated to constant values from convergence procedures of proposed algorithm relying on its own and its neighbors' previous iterates at bus n.

The complete algorithm consists of two main steps: The first step is to calculate P_n^L and P_n^G by off-line optimization in pre-contingency state and is given in this paper. The second step is accurately dispatching fast-response DERs to respond line contingency by using the proposed fully distributed algorithm, which is the focus of this paper.

IV. CASE STUDY

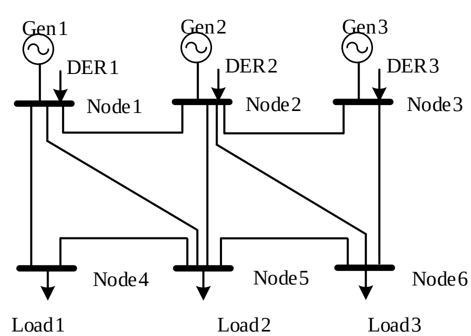

Fig 2. Modified 6-bus system

The proposed algorithm is implemented in MATLAB with a modified 6-bus system as shown in Fig.2, which contains three generators locating at buses 1-3, three loads connecting to buses 4-6, and nine transmission lines. Three sets of fast-respond DERs are separately connected to buses 1-3. Some parameters required in the proposed algorithm are shown in Table I [13]. Variables calculated in the pre-contingency state are listed as follows: real power output of the traditional generators connected to buses 1-3 are 5.07 MW, 3.32 MW and 1.61 MW, respectively; loads connected to buses 4-6 are 4 MW, 3 MW and 3 MW, respectively. Power limits of DERs are individually set to 4.5 MW, 4.5 MW and 4 MW.

TABLE I. TRANSMISSION LINE PARAMETERS IN MODIFIED 6-BUS SYSTEM

Line	X_{nm} *(pu)*	D_{nm}	$\overline{P_{nm}}$ *(MW)*	Line	X_{nm} *(pu)*	D_{nm}	$\overline{P_{nm}}$ *(MW)*
1-2	0.044	0.28	3	2-6	0.070	0.25	3
1-4	0.057	0.33	4	3-6	0.065	0.33	3
1-5	0.074	0.28	3	4-5	0.038	0.28	3
2-3	0.060	0.33	3	5-6	0.048	0.25	3
2-5	0.042	0.25	3				

In a line contingency, traditional generators may not need to change their outputs when the power flow in the remaining lines has not exceeded the line capacities. But once there is any line exceeding its limit, traditional generators should be rescheduled to redirect the power flow, relief the overloaded transmission line(s) and maintain the supply and demand balance. However, time is needed to allow the generators to fully execute the rescheduling due to their large inertias and ramping limits. As a remedy, the proposed fully distributed control algorithm would dispatch the fast-respond DERs to timely provide the necessary power.

For example, when line 1-5 was tripped, power flow in the remaining transmission lines are listed in the third column of Table II. Comparing with the line capacity $\overline{P_{nm}}$ given in Table I, it could be seen that line 2-5 exceeds its capacity. Once this was detected online, the proposed distributed rescheduling algorithm would be applied.

TABLE II. POWER FLOW OF THE 6-BUS SYSTEM

line	*Pre-contingency (MW)*	*Line 1-5 tripped (MW)*	*With DERs (MW)*
1-2	0.5	1.45	1.68
1-4	2.9	3.62	3.61
2-3	0.03	0.07	1.04
2-5	2.42	**3.07**	2.79
2-6	1.44	1.63	1.27
3-6	1.58	1.68	2.33
4-5	1.1	0.38	0.39
5-6	0.02	0.31	0.59
1-5	1.67	-	-

Fig. 3 plots the scheduled power output of the 3 DERs with zero initial power output after the contingency in a time step of 0.1s. It shows that their output power would settle down in about 20s and eventually stabilized at 0.2065 MW, -1.9626 MW and 1.7561 MW, where positive output power refers to power injection to the grid and negative output power means absorbing the excess power from the traditional generators. The total net power, i.e. the sum of all positive and negative power, shall basically be zero if there is no generation change by the traditional generators. In this line contingency with the outage of line 2-5, DER1 and DER3 provide the power to meet load demands while DER2 stores the excess energy produced in bus 2. Post-contingency power production and consumption are balanced as a result.

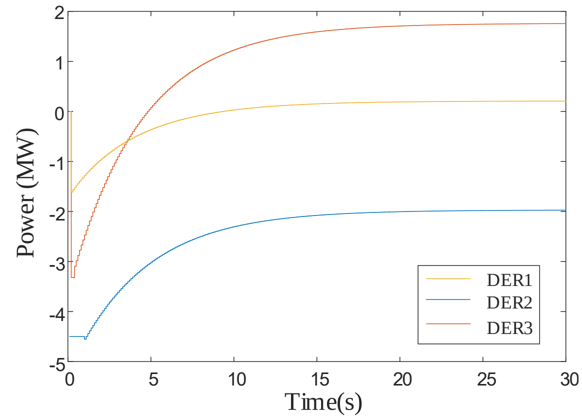

Fig 3. The power change of grid-connected DERs

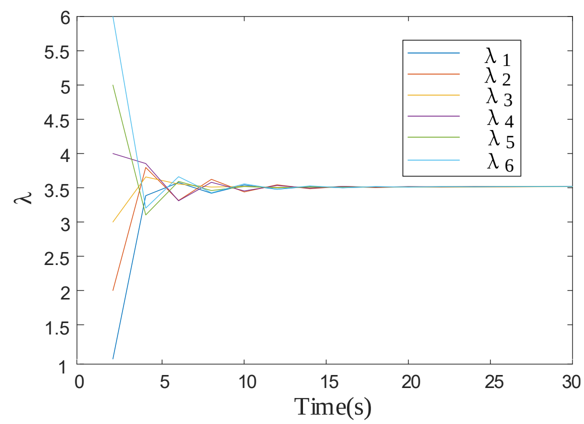

Fig 4. Updates of local information λ during the communication

The last column in Table II shows the final power flow with the rescheduled grid-connected DERs to ensure no transmission line constraint being violated. Fig.4 plots the corresponding Lagrange multiplier λ_n over the period. The optimal solution P_n^{DER} is achieved as the unique Lagrange multipliers λ_n converges using only the information from the adjacent buses. This implies the proposed distributed algorithm is flexible and adaptive to the change of network topology. The simulation results in above shows the proposed distributed algorithm can effectively dispatch DERs for solving the CSC-OPF problem.

V. CONCLUSION

This paper introduced a fully distributed algorithm to dispatch the DERs as the corrective measures to solve the CSC-OPF problem. Different from traditional centralized and decentralized algorithms, the proposed algorithm controls the DERs to balance the supply and demand only relying on local computation and data communication with the adjacent buses. It is therefore cost effective and scalable to large-scale power systems with high flexibility to adapt for network topology change. The proposed algorithm has been tested in a modified 6-bus system, and the results demonstrated that the proposed algorithm can effectivity dispatch DERs to balance the supply and demand without violating any transmission line constraints after a line contingency.

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