Improving Power System Resilience through Decentralized Decision-Making

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***Abstract*—Natural disasters has been causing an increasing amount of economic losses in the past two decades. Natural disasters, such as hurricanes, winter storms, and wildfires, can cause severe damages to power systems, significantly impacting industrial, commercial, and residential activities, leading to not only economic losses but also inconveniences to people's day-to-day life. Improving the resilience of power systems can lead to a reduced number of power outages during extreme events and is a critical goal in today's power system operations. This paper presents a model for decentralized decision-making in power systems based on distributed optimization and implemented it on a modified RTS-96 test system, discusses the convergence of the problem, and compares the impact of decision-making mechanisms on power system resilience. Results show that a decentralized decision-making algorithm can significantly reduce power outages when part of the system is islanded during severe transmission contingencies.**

Keywords—Contingencies, distributed optimization, islanded power systems, power system operations, power system resilience.

I. NOMENCLATURE

Indices

b	Bus.
g	Generator.
k	Iteration number.
l	Transmission line.
seg	Segments for piece-wise linear cost function.

Sets

σ_b^+	Transmission lines with their "to" bus connected to bus b.
σ_b^-	Transmission lines with their "from" bus connected to bus b.
g_b	Generators connected to bus b.

Variables

θ_b	Voltage angle of bus.
$\theta_{fr,l}$	Voltage angle at the "from" bus of line l.
$\theta_{to,l}$	Voltage angle at the "to" bus of line l.
P_g	Real power generation of generator g.
P_g^{seg}	Real power generation of generator g in segment seg.
P_b^{LC}	Flexible load curtailment of bus b.
F_l	Real power flow through transmission line l

Parameters

θ_k^{min}	Minimum voltage angle difference at line l.
θ_k^{max}	Maximum voltage angle difference at line l.
θ_1	Voltage angle at the slack bus at time t.
B	Total number of buses.
B_b	The set of indices for subproblems that include θ_b.
B_e	The set of indices for the buses that are connected to tie lines in subproblem e.
B_i	The total number of buses in subproblem i.
b_l	Susceptance of transmission line l.
G	Total number of generators.
G_i	Total number of generators in area i.
P_b^L	Load at bus b.
F_l^{max}	Upper real power flow limit of transmission line l.
F_l^{min}	Lower real power flow limit of transmission line l.
N	Number of piece-wise linear segments for the generators.
P_g^{max}	Upper generation limit of generator g.
P_g^{min}	Lower generation limit of generator g.
$P_g^{seg,max}$	Upper generation limit of generator g in segment seg.
θ_b^a	The average value of θ_b from all the distributed optimization problems that include θ_b.
μ_g^{seg}	Linear cost of generator g in segment seg.
μ_b^{LC}	Flexible load curtailment compensation rate for bus b.
ρ	The ADMM step size.
λ_b^k	Penalty value for θ_b at iteration k.
ε	Optimality gap.

II. INTRODUCTION

Natural disasters have caused significant economic losses throughout the history, and the power outages caused by natural disasters is one of the leading causes of economic losses [1]. The economic losses caused by power outages including the revenue lost for utility companies, direct or indirect losses from electricity customers, such as the interruption of industrial and commercial activities, and inconvenience in the electricity

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customer's daily life [2]. In recent years, natural disasters have caused significant power outages throughout the U.S. In 2017, Hurricanes Harvey, Irma, and Maria caused significant damages to power systems in multiple states, including Texas, Florida, and Puerto Rico, and led to long-lasting power outages, especially in Puerto Rico, which lasted for several months [3]-[6]. In 2018, Hurricanes Florence and Michael made U.S. landfalls and affected more than 1 million electricity customers [7], [8]. In 2019, Hurricanes Dorian and Barry caused power outages to at least half a million electricity customers [9], [10], and in 2020, Hurricanes Isaias, Laura, Sally caused power outages to millions of electricity customers in multiple states, including New York, New Jersey, Connecticut, Louisiana, Alabama, Georgia, and Florida [11]-[13]. In 2021, a winter storm hit Texas, in which 4.5 million homes lost power, causing billions of dollars of losses and the death of 57 people [14]. History has shown the significant impact of power outages on the society, and, thus, it is critical to improve the resilience of power systems.

Different natural disasters can cause damages to different parts of power systems. Hurricanes can cause damages to transmission and distribution lines and flooding in power plants [3]-[13]. Winter storms can freeze transmission and distribution lines, fuel pipes for power plants, or wind turbines [14]. Wildfires can damage power plants, transmission, and distribution lines. Thus, different measures need to be taken to cope with different natural disasters [15]. In this study, we specifically focus on damages caused to transmission lines, especially severe damages of transmission systems that island part of the power system. This is because transmission lines can be damaged by different types of natural disasters and are one of the most commonly seen components damaged by natural disasters, and unlike the damage of distribution lines, which usually causes local power outages, the damage of transmission systems can cause widespread outages in the system.

There are a number of methods that can be used to improve power system resilience by addressing transmission system failures. From a time-scope perspective, the methods can be divided into three categories [16], [17]. The first category includes preventive measures taken during the planning process, which happens years before the system is committed. This mainly includes system hardening, such as building strong transmission poles or use underground lines [18]. The second category is preventive operational decision-making, which happens from months to minutes before the extreme events. This includes preparing enough onsite fuel storage at certain power plants, pre-allocating the maintenance crew to vulnerable locations, and decide the unit commitment and generation dispatch during the extreme event [16], [19]-[24]. The third category of methods are for the restoration after the extreme events. This mainly includes the dispatch of restoration crew, the sequence of component restoration, etc. [25]-[30].

The U.S. has an aging transmission system and upgrading the transmission system is an extremely capital-intensive and time-consuming process. To reduce power outages during natural disasters, the second category of methods, preventive operation, plays an important role. Reference [19] proposes a method to pre-allocate resources for restoration, which can be considered as a preventive measure. Reference [16] proposed a preventive operation method which considers possible contingency scenarios based on weather forecast. This method can reduce power outages and over generation without over committing generation resources, and this method works well for interconnected systems. However, some natural disasters cause such severe damage that part of the power system is islanded from the rest. In such cases, damaged were not only the transmission lines but also the communication equipment. Due to this reason, control signals cannot be sent from the control center to the islanded area, and the control center cannot remotely monitor the conditions of the components in the islanded area, causing difficulties in operating system in islanded area and resulting in severe power outages. To fill this gap, this paper proposes a decentralized decision-making method based on distributed optimization. This method enables decentralized decision-making in different areas of power systems. When the areas are interconnected, a consensus will be achieved by all the participating areas. When one or more areas are islanded, the islanded area will be able to make decisions on their own while the remaining interconnected areas make decisions by achieving a consensus. The method was implemented on a modified RTS-96 test system, and results show that the decentralized decision-making method can significantly reduce power outages compared to a centralized decision-making method.

The remaining sections of the paper are organized as follows. Section III presents the distributed optimization model used in this study. A case study is discussed in Section IV, and conclusions are drawn in Section V.

III. Mathematical Model

In this paper, we used both the centralized and decentralized decision-making methods to decide generation dispatch in case of severe contingencies caused by natural disasters. The two decision-making models are presented as follows.

A. Centralized Decision-Making

The centralized decision-making model is based on a DCOPF model [31] and presented by Equations (1)-(10). Using this model, only one control center is needed for a power system, and control signals can be sent to different components in the system that need to be operated. The advantage of this method is that it is easy to implement, and the disadvantage of this method is that, when one area in the power system is islanded due to severe contingencies, the load in this area will be completely lost because control signals cannot be sent to the area. The model allows load loss, but the load loss is penalized with a high cost in the objective function, as Equation (1) shows. Besides the penalty for the load loss, the generation dispatch cost is also included in the objective function, and a piece-wise linear generation cost is adopted. Equation (2) is the nodal power balance constraint, which allows load loss. Equations (3)-(5) are the generation constraints considering the piece-wise linear segments. Equations (6) and (7) are the power flow constraints. The maximum load loss cannot exceed the maximum load at the bus, as Equation (8) shows. Since the DCOPF model can only be applied when the differences between bus voltages angles are small, Equation (9) sets a limit for the bus voltage angle differences between the two ends of each transmission line, and Equation (10) sets Bus 1 as the reference bus.

$$\min\left\{\sum_{g=1}^{G}\sum_{seg=1}^{N}\mu_g^{seg}P_{g,t}^{seg}+\sum_{b=1}^{B}\mu^{LC}P_b^{LC}\right\} \quad (1)$$

$$\sum_{g\in g_b}P_g+\sum_{l\in\sigma_b^+}F_l-\sum_{l\in\sigma_b^-}F_l=P_b^L-P_b^{LC} \quad (2)$$

$$P_{g,t}=\sum_{seg=1}^{N}P_{g,t}^{seg} \quad (3)$$

$$0\le P_{g,t}\le P_g^{max} \quad (4)$$

$$0\le P_{g,t}^{seg}\le P_g^{seg,max} \quad (5)$$

$$-b_l\left(\theta_{fr,l}-\theta_{to,l}\right)=F_l \quad (6)$$

$$F_l^{min}\le F_l\le F_l^{max} \quad (7)$$

$$0\le P_b^{LC}\le P_b^L \quad (8)$$

$$\theta_l^{min}\le\theta_{fr,l}-\theta_{to,l}\le\theta_l^{max} \quad (9)$$

$$\theta_1=0 \quad (10)$$

B. *Decentralized Decision-Making Based on ADMM*

The decentralized decision-making algorithm is based on a distributed DCOPF, which is developed using the alternating direction method of multipliers (ADMM) [32], [33]. ADMM is adopted in study because it is suitable for parallelize the power system optimization problem based on sub-areas of the power system. The decentralized decision-making algorithm allows us to divide the power system into multiple areas and make generation dispatch decisions in a decentralized manner based on areas. Using this algorithm, each area needs to have a control center, and the control centers communicate with each other to reach a consensus on generation dispatch decisions. In this way, globally optimal generation dispatch decisions can be made. When one of the areas is islanded, the area will operate independently and make locally optimal decisions for the area, while the interconnected areas could still communicate and make globally optimal decisions. When one area of the system is islanded, the area could still make sure at least some of the load in this area being met, thus reducing load loss caused by such islanding events. To implement this algorithm, each area needs to implement a distributed optimization problem, or subproblem. For these subproblems, only the bus voltage angles at the two ends of the tie lines between different areas need to reach a consensus. Other variables in the optimization problems are internal to each area and does not need to be agreed on by other areas. The objective function of the distributed optimization problem is shown in Equation (11). It minimizes the total generation dispatch cost in the area, penalizes load loss in the area, and includes two ADMM terms that facilitates the consensus-reaching process of certain variables. Constraints (2)-(10) will be included in each distributed optimization problem, however, the constraints in each problem will only consider the generators, transmission lines, and buses in each area. The global optimal solution will be achieved in an iterative manner. In each iteration, all the subproblems need to be solved, and then the bus voltage angles at the ends of tie lines will be exchanged between different subproblems. An average of each variable that needs to be agreed on is calculated by Equation (12), and then the Lagrangian multipliers will be updated using Equation (13). A flow chart for the solution process is shown in Fig. 1.

$$\begin{aligned}\min_{P^{k+1},\theta^{k+1}}\Bigg\{&\sum_{g=1}^{G_i}\sum_{seg=1}^{N}\mu_g^{seg}P_{g,t}^{seg,k+1}\\&+\sum_{b=1}^{B_i}\mu^{LC}P^{LC}\\&+\sum_{b=1}^{B_e}\lambda_b^k(\theta_b-\theta_b^a)\\&+\sum_{b=1}^{B_e}\frac{\rho}{2}\|\theta_b-\theta_b^a\|_2^2\Bigg\}\end{aligned} \quad (11)$$

$$\theta_b^a=\frac{1}{B}\sum_{b=1}^{B_b}\theta_b \quad (12)$$

$$\lambda_b^{k+1}=\lambda_b^k+\rho(\theta_b-\theta_b^a) \quad (13)$$

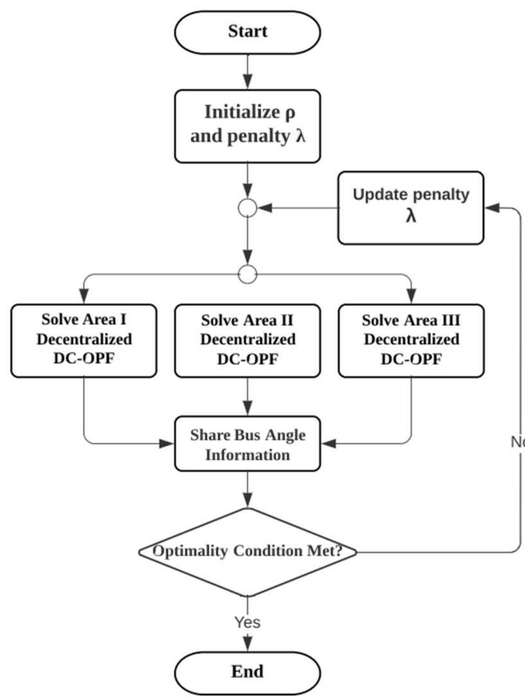

Fig. 1. Decentraliced Consensus-ADMM Algorithm Flowchart

IV. Case Studies and Results Discussion

A. *Simulation Setup*

A modified version of the RTS-96 test system [34] was used to implement the case studies of the proposed simulations, and each case study is implemented in single-period manner. For case study purposes, the mentioned 24-bus system was divided into three sub-regions or areas as presented in TABLE I. In this case study, the areas were divided in a way that minimizes the number of tie-lines between regions and consequently reduce the computational time for the decentralized model. The area division and node clustering can be optimally performed with assistance of graph theory clustering methods [35].

This case study was implemented assuming Area III is islanded from the other areas due to the outage of all the tie lines that connects Area III to other areas. The resilience study evaluates load-loss results under this condition when the system was operating in centralized and decentralized cases. In the centralized case, the control center was assumed to be in Area I, and in the decentralized case, there was a sub-control center in each area.

TABLE I. RTS-96 CASE STUDY AREAS

	Buses	***Available Generation Capacity (MW)***	***Load (MW)***
Area I	1 – 7, 24	684	791
Area II	8 – 13	591	1286
Area III	14 – 23	2130	773

B. *Centralized Decision-Making Results*

The centralized decision making was implemented using the model shown in Section III-A, when the control center was located in Area I and Area III was islanded. When Area III was islanded, no power lines or communication wires were connecting Area I and Area II with Area III, and thus neither power nor control signals could be delivered to Area III. Results from the centralized decision-making algorithm are shown in TABLE II.

TABLE II. LOAD LOSS IN CENTRALIZED DECISION-MAKING

	Load (MW)	***Generation (MW)***	***Load Loss (MW)***
Area I & II	2,077	1,275	802
Area III	773	0	773
Total Load Loss	-		**1,575**

As the results show, with no control signal from the centralized control center and all the tie lines out, Area III could neither generate power for itself nor receiving power from other areas, and this resulted in a significant amount of load loss, which totals 1,575 MW. Islanding Area III can be considered as the worst islanding contingency scenario, due to the inability of Area I and Area II to fulfill its demand. Areas I and II had a total load loss of 802 MW because of a lack of generation capacity. The importance of implementing distributed control can be noted in this scenario, where although enough generation was present to meet the local area demand in Area III, the control signals could not be sent properly due to communication failures, resulting in a complete load loss in Area III.

C. *Decentralized Decision-Making Results*

To overcome the problems caused by a single centralized control center, the distributed algorithm shown in section III-B was implemented to simulate distributed control centers in each area. This case allowed Area I and Area II to exchange power and bus voltage angle information, with the advantage that the islanded Area III could make its own generation dispatch decisions. Area I and II shared bus voltage angle information to reach a consensus, while Area III operates independently. The results are provided in TABLE III.

TABLE III. LOAD LOSS IN DECENTRALIZED DECISION-MAKING

	Load (MW)	***Generation (MW)***	***Load Loss (MW)***
Area I & II	2,077	1,275	802
Area III	773	773	0
Total Load Loss	-		**802**

Results from Area I and Area II remain consistent with the centralized algorithm, however, since Area III could perform decision-making independently in this case, load loss in Area III is eliminated since Area III has enough generation capacity. Since Area III is able to meet its total load demand through independent decision-making, the total load loss reduced by 51% compared to case with centralized decision-making.

D. *Computational Efficiency*

Both centralized and decentralized algorithms were implemented using Python and Gurobipy on a Computer with an Apple M1 Pro CPU and 16 GB of RAM. The computational time for the centralized algorithm was 0.28 seconds, compared to the decentralized algorithm taking 41.13 seconds to converge. Although the decentralized version took considerably longer than the centralized version, both solutions could be found within an appropriate operational time frame.

V. CONCLUSIONS

This paper presents an ADMM-based distributed DCOPF model which allows load loss during emergent conditions and studies the importance of decentralized algorithms and the positive effects of decentralized control when severe contingencies island part of the power system. The ADMM-based distributed DCOPF algorithm was implemented on a modified RTS-96 test system when severe contingencies islands one of the three areas. Results show that the decentralized decision-making method can significantly reduce the total load loss under extreme events in which communication and power interconnections are interrupted. In the future work, the decentralized decision-making algorithm will be tuned to speed up its convergence and apply to large-scale power systems with complex operating conditions and different contingency scenarios.

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