Two-Stage Robust Distribution Network Reconfiguration Against Failures of Lines and Renewable Generations

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ABSTRACT Network reconfiguration is a significant strategy to enhance the resiliences of distribution systems against contingencies. This paper proposes a two-stage robust network reconfiguration model to maximize the power supply under the uncertain failures of both lines and renewable generators. In stage 1, before the contingencies are realized, the network topology is reconfigured into several subsystems supplied by conventional generators. Then the contingencies are launched to the reconfigured distribution system, inducing load curtailments. In stage 2, the flexible resources, e.g., conventional and renewable generators, and energy storages, are dispatched to guarantee the maximal power supply under the worst-case contingencies. To solve the two-stage robust model, we develop a column & constraint generation (C&CG) algorithm. The network reconfiguration decision is made in the master problem according to an increasing amount of worst-case scenarios generated by the subproblem. Simulation results demonstrate the performance of the network reconfiguration decision of the two-stage robust model and verify the effectiveness of the C&CG algorithm to deal with the proposed model.

INDEX TERMS Distribution network reconfiguration, resilience, failures of lines, failures of renewable generators, two-stage robust dispatch, column and constraint generation algorithm.

NOMENCLATURE

A. SETS AND GRAPHS

G Directed graph of distribution network.
N Set of real buses.
E Set of real transmission lines.
G+ Augmented directed graph of distribution network.
N+ Set of real and fictitious buses.
E+ Set of real and fictitious transmission lines.
T Set of time intervals.
G Set of conventional generators.
B Set of energy storages.
R Set of renewable generators.
K Set of worst-case scenarios.
U Feasible region of stage 1 decisions.

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B. VARIABLES

x Vector of stage 1 decisions.
fij Fictitious flow through line (i, j).
uij Binary: 1 if line (i, j) is in service.
v Vector of contingency variables.
vij,t Binary: 0 if line (i, j) is damaged at time t.
zij,t Binary: 1 if damage of line (i, j) starts or ends at time t.
vr,i,t Binary: 0 if renewable generator i is damaged at time t.
zr,i,t Binary: 1 if damage of renewable generator i starts or ends at time t.
y Vector of stage 2 decisions.
pri,t / qri,t Active / reactive power output of conventional generator i at time t.

\[ V \]
Uncertainty set of contingencies.
\[ \mathcal{Y}(u, v) \]
Feasible region of stage 2 decisions.

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I. INTRODUCTION

A. MOTIVATION

In recent years, the damages of unexpected disasters in distribution networks have been attracting more and more attention in the power system community. External threats such as meteorological disasters [1] and cyber attacks [2], [3], [4] may lead to large-scale blackouts and secondary disasters. In 2012, hurricane Sandy causes 8 million people lacking power supply for up to 15 days in the U.S. [5]. A survey by the U.S. Energy Information Administration shows that the weather-related blackouts significantly increase from 1992 to 2012 [6]. Therefore, it is significant to enhance the resiliences of distribution networks to alleviate the effects of uncertain contingencies.

In order to alleviate the dependence on fossil energy and reduce the emission of greenhouse gas, renewable energy generation technologies, e.g., wind farms and solar panels, have been heavily promoted in model power systems. However, the reliability of renewable energy is seriously dependent on the meteorological environment. For instance, if hurricanes suddenly attract, solar panels cannot work without sun-light radiations, whereas wind turbines also fail to generate electricity above cut-out wind speed [7]. Hence it is meaningful to consider not only distribution line damages but also failures of renewable generators in the resilience enhancements of distribution networks.

Due to the temporal energy shifting virtue, energy storages have been regarded as a substantial flexible resource to promote the resiliences of distribution networks. Unlike the renewable generators, the reliabilities of energy storages are more committed. Besides, the valid increasing of electric vehicles (EVs) makes it possible to utilize their spacial energy shifting flexibilities [8]. Thus, it is avoidless to consider the ability of energy storages in the distribution network resilience against contingencies.

This work focuses on the network reconfiguration model for distribution networks to deal with the failures of distribution lines and renewable generators with the help of conventional generators and energy storages.

B. LITERATURE REVIEW

It has been a significant research field to enhance the resiliences of distribution networks due to the rapidly increasing flexibility and uncertainty in the demand side. Methods in the existing works can be divided into two categories: 1) equipment side and 2) grid side. The simple structure of the literature review is presented in Fig. 1.

In the equipment side, the allocations of controllable devices are optimized to adequately improve the distribution network resilience. For instance, reference [9] allocates diesel oil and batteries in the pre-hurricane stage so as to serve outage critical loads in the post-hurricane stage. In [10], both the placement of distributed generators and the hardening of distribution lines are utilized to prevent natural disasters in a two-stage robust model.

As a rapidly increasing type of flexible resource on the demand side, energy storages have been widely used in the post-contingency dispatch due to the spatial and temporal energy shifting properties. In [11], a cost minimization problem involving the costs of switching topology, curtailing loads, and operating energy storages is presented, which highlights the effect of energy storages on economy and
resilience. Reference [12] utilizes the particle swarm optimization method to analyze both dynamic and static seasonal reconfigurations jointly with allocating distributed generators and energy storages. Besides the temporal flexibility, many energy storages, e.g., truck-mounted mobile energy storage systems [13], electric buses [14], and LNG tube trailers [15], own the spacial energy shifting virtue. In [13] and [14], the network reconfiguration problem combined with the vehicle routing and scheduling is solved to better promote the resilience. Reference [15] employs LNG tube trailers to build the coupling between the power and gas systems, which immensely broadens the decision space for dispatching.

In the grid side, the methods of resilience enhancement commonly involve hardening distribution lines and changing the network topology. Reference [16] develops a two-stage stochastic mixed-integer linear model to combat the natural disaster uncertainty, where the line hardening and distributed generator installation are employed to prevent uncertain disasters in the pre-event stage. In [17], a tri-level optimization framework is proposed for the resilience enhancement under extreme weather events, where the objectives in these levels are hardening lines, determining worst-case scenarios of out-of-service lines, and minimizing load shedding costs, respectively.

Besides hardening lines, another method to enhance resilience is to change the topology of the distribution network, since the topology indicates the structural vulnerability of power systems [18]. There has been a large amount of literature carried out on utilizing the network reconfiguration method to raise the resilience levels of distribution networks. According to the chronological order of contingencies and reconfigurations, these existing works can be divided into two categories: pre-contingency reconfiguration [13], [19], [20] and post-contingency reconfiguration [21], [22], [23], [24]. For the former, the reconfiguration strategy is made before contingencies so that controllable devices can receive their instructions even if communication links fail. For the latter, as the real contingencies have been observed, the reconfiguration strategy can be contrapuntally made to combat the specific failures. This work focuses on the pre-contingency reconfiguration.

In terms of the pre-contingency reconfiguration, reference [19] proposes a distributionally robust model to find the optimal topology in expectation, given the ambiguity set of the contingency probability distribution. In [13], the distribution network reconfiguration is adopted to coordinate with the placement of mobile power sources by shifting the system into a state less impacted by contingencies. Reference [20] develops a novel two-level network reconfiguration model against extreme weather events. In the first level, the pre-contingency reconfiguration is made according to the predicted wind speed and failed lines, while the post-contingency reconfiguration is carried out to restore the power supply.

In terms of the post-contingency reconfiguration, reference [21] identifies the critical switches for dynamic network reconfiguration by restricting the number of switches and switch-type-dependent operation constraints. In [22], a tri-level defender-attacker-defender model is formulated to find the best hardening location that promotes the resilience considering the network reconfiguration. Reference [23] combines the distributed energy resource scheduling and the network reconfiguration to improve the resilience, where the probability distribution of line disruptions under different wind speeds during hurricanes. In [24], the restoration after blackout is divided into two steps. Firstly, the network reconfiguration is determined based on the minimum diameter spanning tree theory. Then the load restoration is formulated as mixed-integer semidefinite program, which is solved by an iterative algorithm.

When enhancing the resilience of the distribution network, how to describe the uncertainties of contingencies is an important issue. In the above literature, there are mainly three types of models: 1) stochastic programming [16], [25]; 2) distributionally robust optimization [19], [26]; and 3) robust optimization [13], [17], [21], [22]. The stochastic programming model requires information about scenarios of uncertainties and their probability distributions, while the distributionally robust optimization model develops an ambiguity set of the uncertainty distribution. However, there may be no data about the future uncertainties caused by extreme weather events. In this situation, the robust optimization model has better performance, since an uncertainty set describing a possible region of the uncertain variable is sufficient. Thus, the robust optimization model is utilized to formulate the uncertain contingencies of lines and generators failures in this paper.

C. CONTRIBUTIONS

The main contributions of this paper are as follows:

1) The two-stage robust network reconfiguration model is developed in this paper. At stage 1, we make the pre-contingency reconfiguration according to the predicted uncertainty set of distribution line and...
renewable generation failures. Then when the contingency realizes, we dispatch generators and energy storages to maximize the power supply at stage 2.

2) Both the failures of distribution lines and renewable generators are considered in this paper, which matches the resilience requirements of future high-proportion renewable energy power systems. Besides, a novel uncertainty set of contingencies is proposed, which can flexibly describe the time duration of failures of distribution lines and renewable generators.

3) The C&CG algorithm is formulated to solve the two-stage robust network reconfiguration model. The big-M method is utilized to cope with the bilinear nonconvex terms in the subproblem, which makes the whole problem tractable.

D. ORGANIZATION
The rest of this paper is organized as follows. Section II formulates the two-stage robust network reconfiguration model under the unexpected failures of distribution lines and renewable generators. Section III utilizes the C&CG algorithm to deal with this model based on the big-M method. In Section IV, by numerical simulations, the performance of the robust network reconfiguration and the efficiency of the C&CG algorithm is verified. Section V concludes this paper.

Notation: For a set \( \mathcal{A} \), \( |\mathcal{A}| \) stands for its cardinality. For vectors \( \mathbf{x}, \mathbf{y} \in \mathbb{R}^n \), we denote the Hadamard product as \( z = \mathbf{x} \circ \mathbf{y} \) if \( z_i = x_i y_i \), \( \forall i = 1, 2, \ldots, n \).

II. TWO-STAGE ROBUST NETWORK RECONFIGURATION MODEL
In this section, we will develop the two-stage robust network reconfiguration model to deal with the uncertain contingencies, which consists of the failures of distribution lines and renewable generators. At stage 1, before the failures happen, we make the pre-contingency network reconfiguration to enhance the resilience. We firstly forecast the possible contingency and then decompose the distribution network into several subnetworks. Then a set of disruptions is launched to the system, which induces the failures of distribution lines and renewable generators. At stage 2, after we observe the failures, we dispatch the distributed flexible resources, e.g., conventional generators and energy storages, to maximize the power supply.

A. STAGE 1: PRE-CONTINGENCY RECONFIGURATION
Consider a distribution network described by an directed graph \( G := (\mathcal{N}, \mathcal{E}) \), \( \mathcal{N} := \{1, 2, \ldots, |\mathcal{N}|\} \) represents the set of buses in the distribution network, while \( \mathcal{E} \) is the set of distribution lines. Denote by \( (i, j) \in \mathcal{E} \) the distribution line from the bus \( i \in \mathcal{N} \) to the bus \( j \in \mathcal{N} \). To avoid trivial discussions, we define the positive direction of any distribution line is from the bus with the smaller index to the other, i.e., \( i < j \), \( \forall (i, j) \in \mathcal{E} \). Distribution systems are commonly designed as meshed networks but operated radially. Thus there must be \( |\mathcal{N}| - 1 \) in-service distribution lines, while others are not in service. In emergency, not-in-service lines can be utilized to reconfigure the radial network so as to enhance the resilience of the power supply.

After reconfiguration, the distribution network is divided into stand-alone subsystems which also operate radially. Conventional generators in the distribution system are able to support the temporary power supply for nearby loads. Thus, the buses with conventional generators can be the roots of radial subsystems if necessary.

To guarantee the radial structures of subsystems, we utilize the single commodity flow model [19], [27]. Firstly, we introduce a fictitious bus indexed by 0 and fictitious lines from bus 0 to the roots of subsystems. Denote by \( \mathcal{E}^+ \) the set of fictitious and physical distribution lines. Obviously we have \( \mathcal{E} \subseteq \mathcal{E}^+ \). In the meantime, denote by \( \mathcal{N}^+ = \{0\} \cup \mathcal{N} \) and \( \mathcal{G}^+ = (\mathcal{N}^+, \mathcal{E}^+) \) the set of fictitious and physical buses and the augmented graph of the distribution system, respectively. Besides, we assume any bus in \( \mathcal{N} \) owns a unit fictitious load, which must be supplied by the fictitious bus 0 through lines in \( \mathcal{E}^+ \). Denote by \( f_{ij} \) the fictitious flow through the line \((i, j)\). Then we have the following single commodity flow model with respect to \( f_{ij} \)

\[
\sum_{(0, i) \in \mathcal{E}^+} f_{0i} = |\mathcal{N}| \tag{1a}
\]

\[
\sum_{(i, j) \in \mathcal{E}^+} f_{ij} - \sum_{(j, k) \in \mathcal{E}^+} f_{jk} = 1, \forall j \in \mathcal{N} \tag{1b}
\]

\[
-|\mathcal{N}| u_{ij} \leq f_{ij} \leq |\mathcal{N}| u_{ij}, \forall (i, j) \in \mathcal{E}^+ \tag{1c}
\]

Constraint (1a) shows that the fictitious bus 0 supply all fictitious loads of \(|\mathcal{N}|\) buses. Constraint (1b) ensures the connectivity of the augmented graph. In (1c), the binary variable \( u_{ij} \) is zero if the line \((i, j)\) is connected and one if unconnected. Constraint (1c) indicates that the fictitious flow can only go through in-service lines.

In the meantime, we decide which lines are in service according to the following constraints

\[
u_{ij} \in \{0, 1\}, \forall (i, j) \in \mathcal{E}^+ \tag{2a}
\]

\[
\sum_{(i, j) \in \mathcal{E}^+} u_{ij} = 1 \tag{2b}
\]

\[
\sum_{(0, i) \in \mathcal{E}^+} u_{0i} \geq 1. \tag{2c}
\]

Constraint (2b) is a necessary condition of the number of in-service lines, which guarantees the reconfigured network is radial. Constraint (2c) ensures that there is at least one subsystem after reconfiguration.

Example 1: (Single Commodity Flow Model): We use an example of 5 buses in Fig.2 to illustrate the single commodity flow model of the network reconfiguration. The pairs of values around lines are defined as \([u, f]\). In Fig.2 (a), the pair \([1, 5]\) of line \((0, 3)\) means that the line is connected, i.e., \(u_{01} = 1 \) and the fictitious flow through the line is 5, i.e., \(f_{01} = 5\). There are two substations located at buses 0 and 5 that can provide the power supply. After the
network reconfiguration, the original system is divided into 2 subsystems, as can be seen in Fig. 2 (b). It should be noted that the fictitious flow through line (3, 4) is negative since the positive direction is defined from the smaller index 3 to the larger index 4.

In stage 1, we forecast the possible contingency and reconfigure the distribution network in advance. Our decision variable is \( u := \{u_{ij}\} \), whose feasible region \( \mathcal{U} \) is defined as

\[
\mathcal{U} := \left\{ \{u_{ij}\} \mid \exists \{f_{ij}\} \text{ such that (1) and (2) hold.} \right\} \quad (3)
\]

B. UNCERTAINTY SET OF CONTINGENCIES

In this paper, we consider two kinds of uncertain contingencies: 1) the failures of distribution lines; and 2) the failures of renewable generators. A variety of models have been proposed to cope with the uncertainty of the contingency, such as stochastic programming, robust optimization, and distributionally robust optimization. Robust optimization catches the worst-case scenario of the uncertain contingency, which helps us deal better with the possibly most serious situation. Assume that distribution lines suffer from continuous failures lasting for several time intervals during the time horizon. The uncertainties of distribution line failures are modeled as

\[
v_{ij,t} \in [0, 1], \forall (i,j) \in \mathcal{E}, \forall t \in \mathcal{T} \quad (4a)
\]

\[
z_{ij,t} \in [0, 1], \forall (i,j) \in \mathcal{E}, \forall t \in \mathcal{T} \quad (4b)
\]

\[
\sum_{(i,j) \in \mathcal{E}} (1 - v_{ij,t}) \leq \Gamma^l, \forall t \in \mathcal{T} \quad (4c)
\]

\[
\sum_{t \in \mathcal{T}} (1 - v_{ij,t}) \leq \Delta^l_{ij}, \forall (i,j) \in \mathcal{E} \quad (4d)
\]

\[
1 - v_{ij,t} \leq u_{ij}, \forall (i,j) \in \mathcal{E}, \forall t \in \mathcal{T} \quad (4e)
\]

\[
v_{ij,t} - v_{ij,t-1} \leq z_{ij,t} - 2 - v_{ij,t-1} - v_{ij,t}, \forall (i,j) \in \mathcal{E}, \forall t = 2, 3, \ldots, |\mathcal{T}| \quad (4f)
\]

\[
v_{ij,t} - v_{ij,t-1} \leq z_{ij,t} + v_{ij,t}, \forall (i,j) \in \mathcal{E}, \forall t = 2, 3, \ldots, |\mathcal{T}| \quad (4g)
\]

\[
z_{ij,t} = 1 - v_{ij,t}, \forall (i,j) \in \mathcal{E} \quad (4h)
\]

The binary variable \( v_{ij,t} \) is zero if the line \((i,j)\) is damaged and one if intact. The binary variable \( z_{ij,t} \) marks the time intervals when the line failure starts or ends. \( z_{ij,t} \) is one if the line failure starts or ends and zero otherwise. Constraint (4c) describes the scale of the line failure, while constraint (4d) shows the maximal time duration. Constraint (4e) indicates that only the damages of in-service lines needs to be considered. Constraints (4f) - (4j) guarantees that line failures last for several time intervals. A detailed explanation of the continuous line failure constraints is presented in the appendix.

From [19], ignoring (4e) does not influence the optimality of the robust optimization model. Since we aim to find the worst-case scenario of the uncertain contingency, damaging the not-in-service lines is not worst-case obviously. Hence we can ignore the constraint (4e) in the robust model.

Remark 1 (Valuing \( \Gamma^l \)): \( \Gamma^l \) is a budget parameter representing the intensity of line failures in the robust uncertainty model. The value of \( \Gamma^l \) highly impacts the reconfiguration of the system, which mainly depends on two factors: disaster intensity and system resilience. Firstly, the weather bureau will predict the disaster level, which reflects the disaster intensity. Then the distribution system operator can evaluate \( \Gamma^l \) based on historical data. For instance, \( \Gamma^l \) can be set as the number of not-in-service lines under the historical disaster with the same intensity level. In essence, valuing \( \Gamma^l \) belongs to the field of pre-disaster assessment. It is an interesting topic, but far away from our focus in this manuscript: distribution network resilience enhancement. Instead of valuing \( \Gamma^l \), we will analyze the model sensitivity of the budget parameters.

Similarly, the uncertainties of renewable generator failures are formulated as

\[
v_{i,t} \in [0, 1], \forall i \in \mathcal{R}, \forall t \in \mathcal{T} \quad (5a)
\]

\[
v_{i,t} \in [0, 1], \forall i \in \mathcal{R}, \forall t \in \mathcal{T} \quad (5b)
\]

\[|\mathcal{T}| + 1 \]
For constraints (7a) and (7b) are the lower and upper bounds of the renewable generator failure starts or ends and zero otherwise. Constraint (5c) describes the scale of the failures of renewable generators, while constraint (5d) shows the maximal time duration. Constraints (5e) - (5i) guarantees that renewable generator failures last for several time intervals.

By defining the vector variable \( v := \{v_{ij,t}, v_{il,t}\} \), we obtain the compact uncertainty set as follows

\[
V := \left\{ v'_{ij,t}, v'_{il,t} \right\} : \exists \left\{ \bar{z}_{ij,t}, \underline{z}_{ij,t} \right\} \text{ such that (4a)-(4i),(5) hold} \right\}
\]

(6)

C. STAGE 2: POST-CONTINGENCY DISPATCH

In stage 2, given the reconfiguration decision \( u \) in stage 1 and the realization of contingency \( v \), we dispatch flexible resources, e.g., conventional generators and energy storages, to maximize the power supply after contingencies.

1) MODEL OF CONVENTIONAL GENERATOR

For \( i \in G \), we have the following model

\[
\begin{align*}
\sum_{i \in R} (1 - v_{i,t}) & \leq \Gamma, \quad \forall t \in T \\
\sum_{i \in T} (1 - v_{i,t}) & \leq \Delta \gamma, \quad \forall i \in R \\
v'_{i,t} - v_{i,t-1} & \leq \bar{z}_{i,t} \leq 2 - v_{i,t-1} - v_{i,t}, \quad \forall i \in R, \quad \forall t = 2, 3, \ldots, |T| \\
(5c) & \\
v_{i,t} - v_{i,t-1} & \leq \bar{z}_{i,t} \leq v_{i,t-1} + v_{i,t}, \quad \forall i \in R, \quad \forall t = 2, 3, \ldots, |T| \\
(5d) & \\
\bar{z}_{i,1} & = 1 - v_{i,1}, \quad \forall i \in R \\
(5e) & \\
\bar{z}_{i,|T|+1} & = 1 - v_{i,|T|}, \quad \forall i \in R \\
(5f) & \\
\sum_{i = 1}^{T} \bar{z}_{i,t} & \leq 2, \quad \forall i \in R \\
(5i) & 
\end{align*}
\]

The binary variable \( v_{i,t} \) is zero if the renewable generator at bus \( i \) is damaged and one if intact. The binary variable \( v'_{i,t} \) is one if the renewable generator failure starts or ends and zero otherwise.

Constraints (5e) - (5i) guarantees that renewable generator failures last for several time intervals.

By defining the vector variable \( v := \{v_{ij,t}, v_{il,t}\} \), we obtain the compact uncertainty set as follows

\[
V := \left\{ v'_{ij,t}, v'_{il,t} \right\} : \exists \left\{ \bar{z}_{ij,t}, \underline{z}_{ij,t} \right\} \text{ such that (4a)-(4i),(5) hold} \right\}
\]

(6)

C. STAGE 2: POST-CONTINGENCY DISPATCH

In stage 2, given the reconfiguration decision \( u \) in stage 1 and the realization of contingency \( v \), we dispatch flexible resources, e.g., conventional generators and energy storages, to maximize the power supply after contingencies.

1) MODEL OF CONVENTIONAL GENERATOR

For \( i \in G \), we have the following model

\[
\begin{align*}
P^b_i \leq p_{i,t} \leq P^b_i, \quad \forall t \in T \\
(7a) & \\
Q^b_i \leq q_{i,t} \leq Q^b_i, \quad \forall t \in T \\
(7b) & \\
\bar{R}_i \leq p_{i,t} - p_{i,t-1} \leq \bar{R}_i, \quad \forall t = 2, 3, \ldots, |T|. \\
(7c) & 
\end{align*}
\]

Constraints (7a) and (7b) are the lower and upper bounds of the active and reactive power output, respectively. Constraint (7c) shows the ramping limitation of the active power output.

2) MODEL OF ENERGY STORAGE

For \( i \in B \), we have the following model

\[
\begin{align*}
(p_{b,i,t})^2 + (q_{b,i,t})^2 & \leq S_i^b, \quad \forall t \in T \\
(8a) & \\
\bar{P}_i & \leq p_{b,i} \leq \bar{P}_i, \quad \forall t \in T \\
(8b) & \\
\bar{Q}_i & \leq q_{b,i} \leq \bar{Q}_i, \quad \forall t \in T \\
(8c) & \\
E^b_i & \leq E_{b,i,t} \leq \bar{E}_i, \quad \forall t \in T \\
(8d) & 
\end{align*}
\]

Constraint (8a) represents the limitation of the apparent power due to the capacity of the equipped power electronic device. Constraints (8b), (8c) and (8d) are the lower and upper bounds of the active and reactive power output and the stored energy in the battery, respectively. The positive direction of the active power is discharging to the distribution system. Constraint (8e) describes the charging and discharging model of the battery. Constraint (8f) shows that the energy storage is fully charged to combat the contingency.

Note that the inequality (8a) is a second-order conic constraint, which should be solved by second-order conic program (SOCP) solvers. However, SOCP problems is much more difficult to solve than linear problems. Thus we replace the constraint (8a) - (8c) with its inscribed polygon, which is

\[
a^h_{b,i} p_{b,i} + b^h_{b,i} q_{b,i} \leq f^h_{b,i}, \quad \forall h = 1, 2, \ldots, H, \quad \forall t \in T \\
(9)
\]

3) MODELS OF RENEWABLE GENERATION AND LOAD CURTAILMENTS

For \( i \in R \), we have the model of renewable generator as

\[
0 \leq p_{i,t} \leq v_{i,t}^c p_{i,t}^{ac}, \quad \forall t \in T. \\
(10)
\]

If the renewable generator is intact, we can curtail its power output if necessary.

For \( i \in N \), we have the model of load as

\[
\begin{align*}
0 & \leq p_{i,t} \leq \bar{P}_{i,t}, \quad \forall t \in T \\
0 & \leq q_{i,t} \leq \bar{Q}_{i,t}, \quad \forall t \in T \\
q_{i,t} & = p_{i,t} \tan \phi_{i,t}, \quad \forall t \in T \\
(11) & 
\end{align*}
\]

The loads can be shed if necessary. However, our goal is to maximize the power supply as far as possible after contingencies.

4) MODELS OF POWER FLOW

We utilize the linearized distribution flow model [28] to describe the distribution network.

\[
\begin{align*}
\sum_{(i,j) \in E} P_{j,t} - \sum_{(j,k) \in E} P_{k,t} = P_{j,t}, \quad \forall j \in N, \quad \forall t \in T \\
(12a) & \\
\sum_{(i,j) \in E} Q_{j,t} - \sum_{(j,k) \in E} Q_{k,t} = Q_{j,t}, \quad \forall j \in N, \quad \forall t \in T \\
(12b) & \\
m(u_{ij} v_{ij,t} - 1) & \leq V_{i,t} - V_{j,t} - r_{ij} P_{i,t} - x_{ij} Q_{i,t} \\
& \leq M(1 - u_{ij} v_{ij,t}), \quad \forall t \in T \\
(12c) & 
\end{align*}
\]

Constraints (12a) and (12b) are the power balance equations at each bus \( j \in N \). Constraint (12c) shows the relationship of the voltage difference through each line \((i, j)\). If the line is not-in-service or damaged, i.e., \( u_{ij} = 0 \) or \( v_{ij,t} = 0 \), the relationship (12c) is invalid, since \( M \) is a sufficiently large constant.
Net loads of all bus \( i \in \mathcal{N} \) in (12) are defined as
\[
P_{i,t} = p_{i,t}^d - p_{i,t}^g - p_{i,t}^b, \quad \forall t \in \mathcal{T}
\]
\[
Q_{i,t} = q_{i,t}^d - q_{i,t}^g - q_{i,t}^b, \quad \forall t \in \mathcal{T}.
\]  
(13a)

To avoid trivial discussions, we set \( p_{i,t}^g = q_{i,t}^g = 0 \) if there is no conventional generator at bus \( i \). Similar settings are made for energy storage and renewable generators.

In the meantime, the voltage of each bus \( i \in \mathcal{N} \) and the power flow through each line \((i,j) \in \mathcal{E}\) should satisfy the following physical limitations
\[
V_i \leq V_{i,t} \leq \bar{V}_i, \quad \forall t \in \mathcal{T}
\]
\[
-u_i v_{ij}^t P_{ij,t} \leq p_{ij,t} \leq u_i v_{ij}^t P_{ij,t}, \quad \forall t \in \mathcal{T}
\]
\[
-u_i v_{ij}^t Q_{ij,t} \leq q_{ij,t} \leq u_i v_{ij}^t Q_{ij,t}, \quad \forall t \in \mathcal{T}
\]  
(14a)

Our target is to maximize the power supply, which is
\[
\max \sum_{i \in \mathcal{N}} \sum_{t \in \mathcal{T}} p_{i,t}^d
\]
over \( p_{i,t}^g, q_{i,t}^g, p_{i,t}^b, q_{i,t}^b, E_{i,t}, p_{ij,t}^d, q_{ij,t}^d, P_{ij,t}, Q_{ij,t}, V_{i,t}, P_{i,t}, Q_{i,t} \)
\[
s.t. (7), (8d) - (8f), (9) - (14)
\]  
(15b)

By defining the decision variable vector \( y := \{ p_{i,t}^g, q_{i,t}^g, P_{i,t}, q_{ij,t}^d, E_{i,t}, p_{ij,t}^d, Q_{ij,t}, V_{i,t}, P_{i,t}, Q_{i,t} \} \), we obtain the compact form of (15) as
\[
\max_{y} g^T y
\]
\[
s.t. A(Bu \circ v) + Cv + Dy \leq d
\]  
(16a)

where we denote the feasible region of \( y \) as \( \mathcal{Y}(u, v) \).

D. OVERALL ROBUST MODEL

Based on the formulation, we obtain the two-stage robust network reconfiguration model as
\[
\max_{u \in \mathcal{U}} \min_{v \in \mathcal{V}} \max_{y \in \mathcal{Y}(u, v)} g^T y
\]  
(17)

Note that this intractable problem cannot be solved directly.

Remark 2 (Pre-Contingency Reconfiguration): Instead of the post-contingency reconfiguration, the pre-contingency reconfiguration is utilized in this model, which is a proactive method to enhance the resilience. For a given distribution network, different topologies lead to different resilience levels. Before the contingency realizes, the distribution network is reconfigured into the topology with the highest resilience level to withstand the initial shock. Besides, the pre-contingency reconfiguration can better deal with communication failures. Before the contingency, the signal of reconfiguration can be smoothly conveyed to the whole distribution network. After the contingency, the communication in a self-organization subnetwork is much easier to achieve than that in the whole network by means of wireless networks or manual communications.

Remark 3 (Fault Location, Isolation, and Service Restoration): The proposed model does not conflict with the fault location, isolation, and service restoration (FLISR) system. In fact, the fault location and isolation are implicitly included in our model. When an unexpected disaster causes a fault, the FLISR system opens switches of lines. The not-in-service lines are then observed, which correspond to the binary variables \( v_{ij}^t \) in the manuscript. Since we consider an optimization-based model, the fault location and isolation are simplified. Besides, the post-contingency dispatch belongs to a temporary self-organization stage, after which the service restoration is implemented. In summary, the proposed model is complementary to the FLISR system.

III. SOLUTION ALGORITHM

In this section, we will propose a C&CG algorithm to deal with the two-stage robust reconfiguration model (17). In each iteration of the C&CG algorithm, we need to solve two problems successively, which are called the master problem and the subproblem. The key idea of the C&CG algorithm is solving the master problem with restriction to a set of worst-case scenarios, generating a new worst-case scenario by solving the subproblem, and then adding the worst-case scenario into the set.

A. FORMULATION OF MASTER PROBLEM

In the master problem, the reconfiguration decision is made according to the set of worst-case scenarios. Given the latest set of worst-case scenarios indexed by \( \mathcal{K} \), the master problem is formulated as
\[
\max \delta
\]
over \( \delta, u, \{ y_k \} \)
\[
s.t. \delta \leq g^T y_k, \quad \forall k \in \mathcal{K}
\]
\[
A(Bu \circ v_k) + Cv_k + Dy_k \leq d, \quad \forall k \in \mathcal{K}
\]  
(18a)

where \( v_k \) represents the \( k \)-th worst-case scenario of contingencies. By solving the master problem, we obtain the latest reconfiguration decision denoted by \( u_k \) and a upper bound \( UB_k \) of the optimal value of the original problem (17).

B. FORMULATION OF SUBPROBLEM

Given the latest reconfiguration decision \( u_k \), we obtain the worst-case scenario of contingencies by solving the following problem
\[
\min_{v \in \mathcal{V}} \max_{y \in \mathcal{Y}(u_k, v)} g^T y
\]  
(19)

We first focus on the inner maximization problem (16). By defining the Lagrange multiplier \( \lambda \) with respect to the constraint (16b), we have the dual problem of (16) as
\[
\min_{\lambda} \lambda^T d - \lambda^T Cv - \lambda^T A(Bu_k \circ v)
\]
\[
s.t. \lambda \geq 0, \quad D^T \lambda = g
\]  
(20a)
Algorithm 1 C&CG Algorithm for Network Reconfiguration

Initialization: Set $K = \emptyset$, $k = 1$, $UB = +\infty$, $LB = -\infty$, and $\varepsilon > 0$.

S1 (Master problem): Update the reconfiguration decision $u_k$ and the cost $\delta_k$ by solving the master problem (18). Update $UB = \delta_k$.

S2 (Subproblem): Obtain the worst-case scenario of contingencies $v_k$ and the optimal solution $g_k$ by solving the subproblem (23), put the constraints of the worst-case scenario into the master problem, and then set $K \leftarrow K \cup \{k\}$. Update $LB = \max\{LB, g_k\}$.

S3 (Judgment): If $UB - LB \leq \varepsilon$, the algorithm is terminated and the latest reconfiguration decision $u_k$ is outputted. Otherwise, set $k \leftarrow k + 1$ and go to S1.

From [29], the strong duality of the problem (16) holds. Therefore, the dual gap is zero, which means the problems (16) and (20) are equivalent.

Thus the subproblem (19) can be converted into

$$
\begin{align}
\min_{v, \lambda} & \quad \lambda^T d - \lambda^T C v - \lambda^T A(B u_k \circ v) \\
\text{s.t.} & \quad v \in \mathcal{V}, \lambda \geq 0, \; D^T \lambda = g
\end{align}
$$

Note that there exist two bilinear terms in the objective of (21). We turn to employing the big M method [30] to make the problem tractable. Define the auxiliary variables $\mu$ and $\xi$. Their constraints include

$$
\begin{align}
M(v - 1) & \leq \mu - C^T \lambda \leq M(1 - v) \\
-Mv & \leq \mu \leq Mv \\
M(v - 1) & \leq \xi - (Bu_k) \circ (A^T \lambda) \leq M(1 - v) \\
-Mv & \leq \xi \leq Mv
\end{align}
$$

which actually indicates that $\mu = C^T \lambda \circ v$ and $\xi = (A^T \lambda) \circ (Bu_k) \circ v$.

Then we get the tractable subproblem as follows.

$$
\begin{align}
\min_{v, \lambda, \mu, \xi} & \quad d^T \lambda - 1^T \mu - 1^T \xi \\
\text{s.t.} & \quad (21b), (22)
\end{align}
$$

By solving the subproblem, we obtain a worst-case scenario of contingencies $v_k$ and a lower bound $LB_k$ of the optimal value of the original problem (17).

C. OVERALL ALGORITHM

Based on the formulation, we obtain the C&CG algorithm, named Algorithm 1, to solve the two-stage robust network reconfiguration model. The convergence of the C&CG algorithm has been proved in [31]. Both the master problem and the subproblem belong to the mixed-integer linear programming (MILP), which can be solved by commercial solvers.

IV. CASE STUDY

A. SETUP

The simulation results are carried out on the IEEE 33-bus distribution system [32], whose configuration is presented in Fig.3. Five distribution lines are not in service in the original topology. The base power is chosen as 100 MVA. There are 5 substations, 2 energy storage units, and 2 renewable generator units integrated into the system. The parameters of conventional generators and energy storages are presented in Table 1 and Table 2, respectively. The renewable generator unit located at bus 13 is a wind generator of 0.18 MW, while that at bus 26 is a solar panel of 0.2 MW. The profiles of loads, and wind and solar generation outputs are taken from those of the PJM Interconnection, US, at 15:00-16:00 on 2022-04-01 [33]. The time duration of each time interval is set as $\Delta t = 15$ minutes. The maximal failure durations of distribution lines and renewable generators are 30 and 45 minutes, respectively. Set the budget parameters as $\Gamma^l = 4$ and $\Gamma^r = 1$. All case studies are implemented in MATLAB R2021b with Gurobi 9.1.2 on a computer with Intel i5-9300H and 16 GB memory.

B. RESULTS

Firstly, we verify the convergence of the C&CG algorithm for the two-stage robust network reconfiguration model. As can be seen in Fig.(4), the C&CG algorithm converges after 14 iterations. As the number of worst-case scenarios grows, the operation constraints in the master problem also increase. The network reconfiguration decision should cope with more and more contingencies. Thus the overall power supply in the worst case is reduced. In the meantime, the blackout caused by contingencies is alleviated since the resilience is promoted
by updating the network reconfiguration. When the upper and lower bounds are equal to each other, the latest network reconfiguration is recognized as the optimal one. Then the algorithm terminates.

As can be seen in Fig.5, the original distribution system has been decomposed into 5 subsystems supported by conventional generators. The loads are supplied by nearby generators, while energy storages can also provide partial electricity. After the network reconfiguration, the resilience of the 33-bus distribution system is markedly enhanced.

Then we compare the network reconfiguration by the two-stage robust model with the original configuration. 10,000 Monte Carlo simulations are carried out to evaluate the effectiveness of the reconfigured topology. The criterion of comparison is the power supply rate after the contingency.

Denote by \( p_{d,i}^t \) the real load at bus \( i \) at time interval \( t \). The power supply rate is obtained by

\[
\frac{\sum_{t \in T} \sum_{i \in N} p_{d,i}^t \times 100\%}{\sum_{t \in T} \sum_{i \in N} p_{d,i}^t}
\]

Table 3 shows the results of the Monte Carlo simulations. If the network reconfiguration is not implemented, the minimal power supply rate is only 34.59%. By the proposed two-stage robust model, we divided the network into 5 isolated subsystems, as shown in Fig. 5. The minimal power supply rate increases to 48.18% with a relative improvement of 39.26%. Even the average power supply rate by the reconfiguration increases to 68.60% from 61.72%. This numerical result validates the effectiveness of the proposed two-stage robust network reconfiguration model in the distribution network resilience enhancement.

### V. CONCLUSION

In this paper, we have proposed a two-stage robust network reconfiguration model to deal with uncertain contingencies of distribution line and renewable generator failures. In stage 1,
the network reconfiguration decision is made according to the forecast contingencies. In stage 2, after observing the real contingencies, generators and energy storages are dispatched to maximize the power supply. The two-stage robust model is solved by the C&CG method. The main idea is to solve the master problem with restriction to operation constraints of several worst-case scenarios generated by the subproblem. The big-M method is utilized to transform the bilinear terms in the subproblem into linear constraints, which makes the subproblem tractable. The simulation results show that our robust network reconfiguration result performs better in maximizing power supply under contingencies than the nominal topology.

**APPENDIX A**

**EXPLANATION OF UNCERTAINTY SET**

Here is an explanation on how constraints (4f) - (4j) guarantee that line failures are temporally continuous.

Recall that the binary variable \( v_{ij,t} \) is zero if the line \((i, j)\) is damaged at \(t\) and one if intact. The binary variable \( z^l_{ij,t} \) marks the time intervals when the line failure starts or ends.

Inequalities (4f) and (4g) locate the starting and ending time intervals of line failures, which are equivalent to

\[
\begin{align*}
z^l_{ij,t} & = \begin{cases} 
1, & v_{ij,t-1} = 0, v_{ij,t} = 1 \\
0, & v_{ij,t-1} = 0, v_{ij,t} = 0 \\
0, & v_{ij,t-1} = 0, v_{ij,t} = 1, v_{ij,t+1} = 1 \\
1, & v_{ij,t-1} = 1, v_{ij,t+1} = 1
\end{cases}
\end{align*}
\]

\( \forall (i, j) \in E, \forall t = 2, 3, \ldots, |T| \)

The above equation cannot deal with situations when failures start at \(t = 1\) or end at \(t = |T|\). Then constraints (4h) and (4i) are employed to make up these boundary situations. Besides, constraint (4j) restricts the count of failures in a distribution line.

If a distribution line \((i, j)\) fails during \([t_1, t_2]\), then it follows that

\[
z^l_{ij,t} = \begin{cases} 
1, & t = t_1 \text{ or } t_2 + 1 \\
0, & \text{otherwise}
\end{cases}
\]

**FIGURE 6.** Values of \( z^l_{ij,t} \) and \( v_{ij,t} \) in the scenarios of line failures.

Consider an uncertainty set of a distribution line during 5 time intervals, i.e., \(|T| = 5\). Assume that the line failure lasts for 2 time intervals. All possible scenarios of line failures and all feasible values of \( z^l_{ij,t} \) and \( v_{ij,t} \) in the uncertainty set are in one-to-one correspondence, which is presented in Fig. 6.

**REFERENCES**

[1] D. K. Mishra, M. J. Ghadi, A. Azizzibehed, L. Li, and J. Zhang, “A review on resilience studies in active distribution systems,” *Renew. Sustain. Energy Rev.*, vol. 135, Jan. 2021, Art. no. 110201.

[2] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao, and Z. Li, “Power system risk assessment in cyber attacks considering the role of protection systems,” *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 572–580, Mar. 2017.

[3] B. Li, T. Ding, C. Huang, J. Zhao, Y. Yang, and Y. Chen, “Detecting false data injection attacks against power system state estimation with fast go-decomposition approach,” *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 2892–2904, May 2018.

[4] B. Li, Y. Chen, S. Huang, S. Mei, Z. Wang, and J. Li, “Real-time detecting false data injection attacks based on spatial and temporal correlations,” in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2019, pp. 1–5.

[5] Y. Chi, Y. Xu, C. Hu, and S. Feng, “A state-of-the-art literature survey of power distribution system resilience assessment,” in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2018, pp. 1–5.

[6] F. H. Jufri, V. Widiputra, and J. Jung, “State-of-the-art review on power grid resilience to extreme weather events: Definitions, frameworks, quantitative assessment methodologies, and enhancement strategies,” *Appl. Energy*, vol. 239, pp. 1049–1065, Apr. 2019.

[7] V. Petrović and C. L. Bottasso, “Wind turbine envelope protection control over the full wind speed range,” *Renew. Energy*, vol. 111, pp. 836–848, Oct. 2017.

[8] B. Li, Y. Chen, W. Wei, S. Mei, Y. Hou, and S. Shi, “Preallocation of electric buses for resilient restoration of distribution network: A data-driven robust stochastic optimization method,” *IEEE Syst. J.*, vol. 16, no. 2, pp. 2753–2764, Jun. 2022.

[9] H. Gao, Y. Chen, S. Mei, S. Huang, and Y. Xu, “Resilience-oriented pre-hurricane resource allocation in distribution systems considering electric buses,” *Proc. IEEE*, vol. 105, no. 7, pp. 1214–1233, Jul. 2017.

[10] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang, and B. Zeng, “Robust optimization-based resilient distribution network planning against natural disasters,” *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2817–2826, Nov. 2016.

[11] P. Akaber, B. Moussa, M. Debbabi, and C. Assi, “Automated post-failure service restoration in smart grid through network reconfiguration in the presence of energy storage systems,” *IEEE Syst. J.*, vol. 13, no. 3, pp. 3358–3367, Sep. 2019.

[12] B. Mukhopadhyay and D. Das, “Multi-objective dynamic and static reconfiguration with optimized allocation of PV-DG and battery energy storage system,” *Renew. Sustain. Energy Rev.*, vol. 124, May 2020, Art. no. 109777.

[13] S. Lei, C. Chen, H. Zhou, and Y. Hou, “Routing and scheduling of mobile power sources for distribution system resilience enhancement,” *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5650–5662, Sep. 2018.

[14] B. Li, Y. Chen, W. Wei, S. Huang, and S. Mei, “Resilient restoration of distribution systems in coordination with electric bus scheduling,” *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 3314–3325, Jul. 2021.

[15] B. Li, Y. Chen, W. Wei, S. Mei, and C. Wang, “Online coordination of LNG tube trailer dispatch and resilience restoration of integrated power-gas distribution systems,” *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 1938–1951, May 2022.

[16] M. Ghasemi, A. Kazemi, M. A. Gilani, and M. Shafie-Khah, “A stochastic planning model for improving resilience of distribution system considering master-slave distributed generators and network reconfiguration,” *IEEE Access*, vol. 9, pp. 78859–78872, 2021.

[17] S. Ma, B. Chen, and Z. Wang, “Resilience enhancement strategy for distribution systems under extreme weather events,” *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1442–1451, Mar. 2016.

[18] E. Bompad, D. Wu, and F. Xue, “Structural vulnerability of power systems: A topological approach,” *Electr. Power Syst. Res.*, vol. 81, no. 7, pp. 1334–1340, 2011.

[19] S. Babaei, R. Jiang, and C. Zhao, “Distributionally robust distribution network configuration under random contingency,” *IEEE Trans. Power Syst.*, vol. 35, no. 5, pp. 3332–3341, Sep. 2020.

[20] M. S. Khomami, K. Jalilpoor, M. T. Kenari, and M. S. Sepasian, “Bi-level network reconfiguration model to improve the resilience of distribution systems against extreme weather events,” *IET Gener. Transmiss. Distrib.*, vol. 13, no. 15, pp. 3302–3310, May 2019.
[21] S. Lei, Y. Hou, F. Qiu, and J. Yan, “Identification of critical switches for integrating renewable distributed generation by dynamic network reconfiguration,” IEEE Trans. Sustain. Energy, vol. 9, no. 1, pp. 420–432, Jan. 2017.

[22] Y. Lin and Z. Bie, “Tri-level optimal hardening plan for a resilient distribution system considering reconfiguration and DG islanding,” Appl. Energy, vol. 210, pp. 1266–1279, Jan. 2018.

[23] Q. Shi, F. Li, M. Olama, J. Dong, Y. Xue, M. Starke, C. Winstead, and T. Kuruganti, “Network reconfiguration and distributed energy resource scheduling for improved distribution system resilience,” Int. J. Electr. Power Energy Syst., vol. 124, Jan. 2021, Art. no. 106355.

[24] Y. Wang, Y. Xu, J. He, C. Liu, K. P. Schneider, M. Hong, and D. T. Ton, “Coordinating multiple sources for service restoration to enhance resilience of distribution systems,” IEEE Trans. Smart Grid, vol. 10, no. 5, pp. 5781–5793, Sep. 2019.

[25] A. Kavousi-Fard, M. Wang, and W. Su, “Stochastic resilient post-hurricane power system recovery based on mobile emergency resources and reconfigurable networked microgrids,” IEEE Access, vol. 6, pp. 72311–72326, 2018.

[26] W. Zheng, W. Huang, D. J. Hill, and Y. Hou, “An adaptive distributionally robust model for three-phase distribution network reconfiguration,” IEEE Trans. Smart Grid, vol. 12, no. 2, pp. 1224–1237, Mar. 2020.

[27] T. L. Magnanti and L. A. Wolsey, “Optimal trees,” in Handbooks in Operations Research and Management Science, vol. 7. Elsevier, 1995, pp. 503–615.

[28] X. Zhou, M. Farivar, Z. Liu, L. Chen, and S. H. Low, “Reverse and forward engineering of local voltage control in distribution networks,” IEEE Trans. Autom. Control, vol. 66, no. 3, pp. 1116–1128, Mar. 2020.

[29] S. Boyd, S. P. Boyd, and L. Vandenberghe, Convex Optimization, Cambridge, U.K.: Cambridge Univ. Press, 2004.

[30] S. Siddiqui and S. A. Gabriel, “An SOS1-based approach for solving MPECs with a natural gas market application,” Netw. Spatial Econ., vol. 13, pp. 205–227, Jul. 2013.

[31] B. Zeng and L. Zhao, “Solving two-stage robust optimization problems using a column-and-constraint generation method,” Oper. Res. Lett., vol. 41, no. 5, pp. 457–461, 2013.

[32] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Trans. Power Del., vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

[33] (2022). PJM Interconnection LLC. [Online]. Available: https://dataminer2.pjm.com/list

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