Robust Microgrid Scheduling With Resiliency Considerations

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ABSTRACT A new microgrid scheduling model with resiliency guaranteed under the risk of both utility failure and prevailing uncertainties of renewable generation and load is proposed in this article. The proposed model minimizes the overall operating cost of the microgrid by efficiently coordinating the power supply from local distributed energy resources and the main grid. The resiliency is ensured by maintaining certain amount of flexibility in local distributed energy resources, which can be quickly deployed to keep the power supply uninterrupted whenever the utility grid suddenly goes down. In addition, the uncertainties of renewable generation and load are captured with the proposed two-stage robust optimization model. By solving the proposed optimization, the solution not only guarantees the resiliency of the microgrid by supporting possible islanding incidents without load interruption, but also ensures robustness against the randomness of renewable generation and load. Results of case studies on a typical microgrid demonstrate the effectiveness of the presented robust microgrid scheduling model.

INDEX TERMS Distributed generation, microgrid scheduling, resiliency, robust optimization, unintentional islanding.

NOMENCLATURE The term \((k)\) in the upper right position stands for the value of the symbol’s \(k\)-th iteration. A bold symbol stands for its corresponding vector.

INDICES

- \(i\) Index of dispatchable distributed generators, running from 1 to \(N_G\).
- \(d\) Index of demands, running from 1 to \(N_D\).
- \(b\) Index of energy storage systems, running from 1 to \(N_B\).
- \(w\) Index of wind turbines, running from 1 to \(N_W\).
- \(v\) Index of photovoltaic panels, running from 1 to \(N_{PV}\).
- \(t\) Index of time periods, running from 1 to \(N_T\).
- \(k, l\) Index of iterations.

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VARIABLES

BINARY VARIABLES

- \(u_{it}\) 1 if dispatchable distributed generator \(i\) is scheduled on during period \(t\) and 0 otherwise.

CONTINUOUS VARIABLES

- \(P_{it}\) Scheduled power of dispatchable distributed generator \(i\) during period \(t\).
- \(S^U_{it}, S^D_{it}\) Start-up/shut-down cost of dispatchable distributed generator \(i\) during period \(t\).
- \(P_{PCC}^t\) Exchanged power at the point of common coupling (PCC) during period \(t\).
- \(P^C_{bt}, P^D_{bt}\) Charging/discharging power of energy storage system \(b\) during period \(t\).
- \(SOC_{bt}\) State of charge of energy storage system \(b\) during period \(t\).
- \(P_{IS}^t\) Power output of dispatchable distributed generator \(i\) during period \(t\) after islanding.
\( p_{bt} \) Power output of energy storage system \( b \) during period \( t \) after islanding.

\( p_{wt} \) Power output of wind turbine \( w \) during period \( t \).

\( p_{PV} \) Power output of photovoltaic panel \( v \) during period \( t \).

\( p_{dt} \) Scheduled power of demand \( d \) during period \( t \).

\( \bar{p}_{wt}, \mu_{wt} \) Auxiliary variables for uncertainty of wind power \( p_{wt}. \)

\( \bar{p}_{PV}, \mu_{PV} \) Auxiliary variables for uncertainty of photovoltaic panel power \( p_{PV}. \)

\( \bar{p}_{dt}, \mu_{dt} \) Auxiliary variables for uncertainty of demand \( p_{dt}. \)

**CONSTANTS**

\( C_{bt} \) Degradation cost of energy storage system \( b \).

\( \lambda_{it} \) Marginal cost of the energy generated by dispatchable distributed generator \( i \) during period \( t \).

\( \rho_{PCC} \) Price of exchanged power at PCC during period \( t \).

\( p_{i}^{\text{max}} \) Maximum output of dispatchable distributed generator \( i \).

\( p_{i}^{\text{min}} \) Minimum output of dispatchable distributed generator \( i \).

\( r_{i}^{U, \text{max}} \) Maximum ramping up rate of dispatchable distributed generator \( i \).

\( r_{i}^{D, \text{max}} \) Maximum ramping down rate of dispatchable distributed generator \( i \).

\( p_{PCC}^{\text{max}} \) Maximum PCC power during period \( t \).

\( p_{wt} \) Forecast power of wind turbine \( w \) during period \( t \).

\( p_{PV}^{\text{hat}} \) Forecast power of photovoltaic panel \( v \) during period \( t \).

\( p_{dt}^{\text{hat}} \) Forecast power usage of demand \( d \) during period \( t \).

\( p_{b}^{\text{C, max}} \) Maximum charging power of energy storage system \( b \).

\( p_{b}^{\text{D, max}} \) Maximum discharging power of energy storage system \( b \).

\( SOC_{bt}^{\text{max}} \) Maximum state of charge of energy storage system \( b \) during period \( t \).

\( SOC_{bt}^{\text{min}} \) Minimum state of charge of energy storage system \( b \) during period \( t \).

\( \eta_{b}^{C}, \eta_{b}^{D} \) Energy storage system charging/discharging efficiency factor.

\( \delta_{wt}^{\text{W}} \) Maximum deviation from the nominal forecast power of wind turbine \( w \) during period \( t \) (\( p_{wt}^{\hat{w}} \)).

\( \delta_{PV}^{\text{PV}} \) Maximum deviation from the nominal forecast power of photovoltaic panel \( v \) during period \( t \) (\( p_{PV}^{\hat{v}} \)).

\( \delta_{dt}^{L} \) Maximum deviation from the nominal forecast power of demand \( d \) during period \( t \) (\( p_{dt}^{\hat{d}} \)).

\( \Gamma_{t} \) Robust control parameter during period \( t \).

\( \Delta t \) Time duration of each period.

\( \tau \) Fault duration time.

\( \Delta \tau \) Allowed short adjusting time of dispatchable distributed generators after islanding.

\( \varepsilon \) Maximum optimality gap for convergence.

### I. INTRODUCTION

Resilience is the ability of power systems to prepare for and adapt to low-probability, high-impact incidents and withstand and recover rapidly from disruptions. With the aging of electricity transmission and distribution infrastructure and increasing threats of weather-related incidents and natural disasters, the need to effectively enhance the resilience of the power system has become urgent and attracted worldwide attention from both academia and industry [1]. One viable solution for improving power system resiliency is to deploy microgrids, which are groups of interconnected distributed generators (DGs), energy storage systems (ESSs), and collocated loads with the ability to intentionally disconnect from the main grid and continue to supply the isolated portion of the grid without any interruption [2]. By virtue of this particular feature, microgrids enhance the resiliency of the power system through lowering the probability and amount of load shedding, preventing cascading blackouts, and reducing the time of restoration [3]. In addition, microgrids introduce many unique opportunities, such as reducing carbon emissions [4], improving energy efficiency, integrating various renewable energy resources, delaying investment in system expansion, participating in voltage and frequency regulation [5], and encouraging customer interaction [6]. In light of all these advantages, more and more microgrids have been deployed at utilities, university and hospital campuses, military bases, and industrial parks in recent years [7].

Generally, a microgrid central controller (MCC) is equipped to optimize the power from local distributed energy resources (DERs) and imported/exported power from/to the utility network through the point of common coupling (PCC) to meet certain operational objectives. The MCC communicates with all components in the microgrid to collect real-time measurement data and distribute dispatch orders to DERs and controllable loads. A large amount of existing literature focuses on this area [8]. An energy management system (EMS) based on a rolling horizon strategy for a renewable-based microgrid is proposed in [9]. Two-stage stochastic microgrid operation methods considering intermittent renewable energy resources are proposed in [10], [11]. A two-stage stochastic programming model for the joint optimization of investment and operation of a microgrid considering ESSs, renewable generation and demand response is proposed in [12]. The two-stage stochastic energy management is considered for the operation of interconnected microgrids in.
A chance-constrained programming-based scheduling model, which makes full use of ESSs to provide spinning reserve service for isolated microgrids is proposed in [14]. The building thermal dynamics are integrated into the energy management of microgrids in [15], [16]. To resolve the risk of loss of load, conditional value at risk (CVaR) has been incorporated in the objective function in [16]. A risk-averse multi-stage stochastic energy management for a residential microgrid considering multi-energy (i.e., electricity, heating and cooling) is presented in [17]. While the majority of literatures are focused on the uncertainties of renewable generation and load, the uncertainties of day-ahead and real-time energy prices are considered in [18]. In [19], an efficient salp swarm algorithm (ESSA) is proposed to solve the energy management of microgrids considering emission-related objectives. A multi-objective optimization model for microgrid energy management is formulated in [20]. Using global criterion method, the multi-objective model is converted into a single-objective model. In addition, the performance of various evolutionary optimization algorithms in solving the microgrid energy management problem is evaluated and compared. As a distinctive value proposition, a microgrid could help to improve the system resiliency through intentional or unintentional islanding. Specifically, a microgrid could disconnect from the main grid and provide uninterrupted power supply to the loads with required power quality in case of main grid failure. In grid-connected mode, a microgrid usually imports/exports power from/to the utility network, and this power is suddenly interrupted when the microgrid is islanded. Under this situation, the transition of a microgrid from grid-connected to islanded mode often requires quickly adjusting the output of committed DGs and ESSs to mitigate the change of power at the PCC. In other words, during normal operation, when it is connected to the grid, the microgrid should be prepared for a feasible islanding operation. The prevailing uncertainties regarding renewable generation and loads could significantly impact microgrid optimal scheduling, specifically, the imported/exported power at the PCC, the commitment and dispatch of DGs, and the charging/discharging of ESSs, which further affect the success of islanding. In fact, these uncertainties complicate the resilient operation problem considerably by transforming it into a multi-level optimization, which is very challenging to solve. So far, research work on scheduling and dispatch of microgrids with resiliency considerations remains limited. Existing studies can be found in [21]–[30]. The adequacy constraints are included in the economical dispatch model of a microgrid to ensure sufficient operating margin to cover critical loads in case of upstream network faults in [21]. Considering the uncertainty of renewable generation and demand, a probabilistic chance constraint is proposed to guarantee that the microgrid is capable of meeting the local demand with specified probability in [22]. However, this model applies only to uncertainties with normal distribution. A new model of quantifying the spinning reserve requirement in microgrids is presented in [23]. The spinning reserve amount is determined by a trade-off between reliability and economics considering the combinatorial characteristic of unit outage events. A new microgrid scheduling model, with chance-constrained islanding capability to ensure successful islanding of a microgrid with a specified probability, is proposed in [24]. Another two-stage stochastic microgrid scheduling strategy in which the frequency control reserve is incorporated to ensure economic, reliable and stable microgrid operation in a joint energy and ancillary service market environment is proposed in [25]. Nevertheless, [22]–[25] require the probability distributions of uncertainties, which are difficult to obtain in practice. A droop controller for primary frequency control is proposed in [26], [27] to improve microgrid resilience in the moments subsequent to islanding. Nevertheless, the operating cost has been ignored. A resiliency-oriented microgrid optimal scheduling model that considers the main grid supply interruption time and duration was proposed in [28]. The model was extended to consider the prevailing uncertainties of renewable generation and load in [29]. However, the charging/discharging status of ESSs are assumed to be the same as in normal operation after islanding to keep the inner stage of the max-min problem linear. Another robust optimization-based scheduling model for microgrid operation with reserve requirements is proposed in [30]. Nevertheless, the uncertainties of renewable generation and load under normal operation are assumed to be completely handled through PCC, which is not necessarily true in practice.

In this article, a new microgrid scheduling model with resiliency guaranteed under the risk of both utility failure and the uncertainties of renewable generation and load is proposed. Specifically, the resiliency is realized in two aspects. First, the local DGs and ESSs in the microgrid are prepared for disruptions of the utility grid by maintaining certain amount of flexibility. For example, additional DGs are committed to maintain certain amount of spinning reserve. Meanwhile, the state of charge (SOC) of ESSs are kept at a high level. Second, once the utility grid is interrupted the flexibility maintained by the committed local DGs and ESSs can be quickly deployed to support the unintentional islanding of the microgrid, so the local demands could still be supplied continuously. After successfully islanded, the backup generators in the microgrid could be started to restore the flexibility of the committed local DGs and ESSs, so further risks and uncertainties could be handled. With these resiliency constraints, a microgrid is guaranteed to deliver the ability to use local DERs and automatic control to keep uninterrupted power supply when the utility grid is interrupted or goes down. In addition, the uncertainties of renewable generation and load are captured by formulating a two-stage robust optimization model, which optimizes the microgrid under the worst realization of the modeled uncertainties. The formulated two-stage robust optimization model is solved using the column-and-constraint generation (C&CG) algorithm. The solution not only guarantees the resiliency of the microgrid by supporting possible islanding incidents without load interruption, but also ensures robustness against the randomness.
of renewable generation and load. The main contribution of this article are summarized as following:

- A new scheduling model for microgrids is proposed, with resiliency guaranteed under the risk of both utility failure and the uncertainties of renewable generation and load. Resiliency is captured by supporting the unintentional islanding of the microgrid so as to supply the local demand continuously in case of utility failure.
- The effectiveness of the proposed model has been validated by results of case studies. In addition, the effects of fault duration $\tau$ on the operation of batteries have been analyzed.

The reminder of the paper is organized as follows. Section II presents the proposed two-stage robust scheduling model with resiliency constraints. Section III introduces the solution methodology. Results of numerical simulations are shown in Section IV. Finally, the paper is concluded in Section V.

II. MATHEMATICAL FORMULATION FOR MICROGRID SCHEDULING

A. MICROGRID MODELING

Generally, a microgrid includes dispatchable and undispatchable DGs, ESSs, and demand. Dispatchable DGs, such as microturbines, can change their power output according to the dispatch order of the MCC; whereas undispatchable DGs, like wind turbines and photovoltaic (PV) panels, have uncertain power output depending on the meteorological conditions. There is large amount of existing literature focused on the forecasting of wind and PV power [31], [32]. However, the accuracy declines quickly as the lead time increases. Typically, the forecast error of wind power is around 10% for hour-ahead forecasting, over 20% for day-ahead forecasting, and even higher for a longer lead time [33]. The forecast error for PV generation is even higher because the PV power output is greatly affected by cloud coverage with varying random patterns. For this reason, wind and PV generation are usually paired with energy storage facilities to mitigate the intermittency and uncertainty in a microgrid. In this article, renewable generation and demand are modeled as independent, symmetric, and bounded random variables with unknown probability distributions. The models of microgrid components are discussed in detail in [18]. The focus of this article is to enhance the resiliency of the microgrid through readiness to perform seamless islanding, considering the prevailing uncertainties of renewable generation and demand.

B. MICROGRID SCHEDULING WITH RESILIENCY CONSTRAINTS

The deterministic microgrid scheduling model is described in this subsection. The objective is minimizing the operating cost of the microgrid over the scheduling horizon, as shown in Eq. (1). In specific, the operating costs of dispatchable DGs (including fuel cost, start-up and shut-down cost) are presented in the first line; the energy purchasing cost (or benefit of selling energy to the utility) is presented in the second line; the degradation cost of the ESSs is presented in the third line. In general, the degradation cost of ESS can be expressed as a function of the actual ESS cycle life [34]. Detailed ESS degradation is a complex process affected by many factors (e.g., temperature, depth of discharge, state of charge, charging/discharging rate, ESS application, type of ESS, manufacture of ESS, etc.) [35]. Nevertheless, the ESS degradation cost can be approximately formulated as a linear function of the charged and discharged energy [11], [36]. The start-up and shut-down costs of generators $S^U_i$ and $S^D_i$ are functions of $u_i$ and $u_i, t$. Similar to [37], $S^U_i$ and $S^D_i$ could be reformulated into mixed-integer linear form. Generally, the fuel cost function of a DG could be represented by a quadratic [10], [12], [22] or piecewise linear function [6], [18], [24]. Nevertheless, due to the small capacities and limited number of DGs in a microgrid, it is also very common to model the fuel cost of a DG as a linear function [14], [15], [17], [23], [28]. Unlike DGs, the ESSs are always committed except faults or scheduled maintenance due to relatively low idling cost. Therefore, the start-up and shut-down costs of ESSs are ignored.

$$\min_{u, P, P^U_{PCC}, P^D_{PCC}} \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} \left[ \lambda_i P_{U_i} + S^U_i + S^D_i \right] + \sum_{t=1}^{N_T} \sum_{i=1}^{N_B} \left[ \lambda^P_{PCC} P^U_{PCC} + P^D_{PCC} \right]$$

(1)

The following constraints should be considered.

$$P^\min_{U_i} \leq P_{U_i} \leq P^\max_{U_i} \quad \forall i, \forall t$$

(2)

$$-R^D_{i, t} \leq P_{D_i} - P_{U_i, t-1} \leq R^U_{i, t} \quad \forall i, \forall t$$

(3)

$$0 \leq P^U_{C_i} \leq P^U_{C_i, \max} \quad \forall b, \forall t$$

(4)

$$0 \leq P^D_{b_i} \leq P^D_{b_i, \max} \quad \forall b, \forall t$$

(5)

$$SOC_{b_t} = SOC_{b, t-1} + P^C_{b_t} C_{\Delta t} - P^D_{b_t} \frac{1}{\eta_D} \Delta t \quad \forall b, \forall t$$

(6)

$$SOC^\min_{b_t} \leq SOC_{b_t} \leq SOC^\max_{b_t} \quad \forall b, \forall t$$

(7)

$$\sum_{i=1}^{N_G} P_{U_i} + \sum_{w=1}^{N_W} P^W_{W_i} + \sum_{v=1}^{N_PV} P^PV_{PV_i} + P^U_{PCC} + \sum_{b=1}^{N_B} \left[ P^D_{b_i} - \sum_{d=1}^{N_D} P^L_{d_i} \right] \quad \forall t$$

(8)

$$-P^D_{PCC, \max} \leq P^D_{PCC} \leq P^D_{PCC, \max}$$

(9)

Eq. (2) is the minimum and maximum power constraint of a dispatchable DG. The output of a dispatchable DG is also constrained by its ramping rate as in Eq. (3). For ESSs, the maximum charging/discharging power of an ESS is specified by Eqs. (4) and (5). The SOC of an ESS in the current time interval is defined as the SOC in the previous
time interval, plus the energy charged or minus the energy discharged, as in Eq. (6). The SOC of an ESS is limited by Eq. (7). It should be noted that an optimal solution cannot have ESS charging and discharging at the same time due to the unnecessary losses caused by simultaneous charging and discharging. The generation and demand are balanced in grid-connected mode as in Eq. (8). The PCC power is limited by Eq. (9).

Note that Eqs. (1) – (9) constitute a traditional scheduling model for microgrids in normal operation [18]. An optimal solution which satisfies all loads with the least amount of cost could be determined by solving Eqs. (1) – (9). However, this solution is not resilient and very likely subject to load shedding, even microgrid breakdown, when the utility grid is interrupted. Specifically, when the power supply at PCC is interrupted suddenly, the committed dispatchable DGs and ESSs might not have adequate spare capacity and/or high enough ramping speed to mitigate the lost power at PCC in a very short time. Under this situation, emergency load shedding is unavoidable, and the microgrid might even go down.

To enhance the resilience and guarantee the capability of seamless islanding of a microgrid, additional resiliency constraints Eqs. (10) – (14) are proposed to ensure sufficient spare capacity and high enough ramping speed of committed dispatchable DGs and ESSs are maintained to mitigate the change of power at the PCC in case the utility supply is interrupted. By this way, the microgrid is prepared for and could rapidly adapt to the failure of utility grid at any time. The load in the microgrid could be served uninterrupted in the event of main grid failure. Thus, the resilience of power supply is procured.

Specifically, by quickly adjusting the power from dispatchable DGs and ESSs to mitigate the change of power at the PCC, the balance between generation and demand is regained in islanded mode, which is guaranteed by Eq. (10). The commitment statuses of dispatchable DGs in islanded model are forced to be the same as in their normal operation state, and the output power of dispatchable DGs is constrained by the minimum/maximum power limits as in Eq. (11). After islanding, the power balance should be rebuilt in a very short time. Thus, it is necessary that the dispatchable DGs are quickly adjusted to mitigate the imbalance. The outputs of dispatchable DGs in islanded mode are limited by their ramping rates, as in Eq. (12), where \( \tau \) is the allowed short adjustment time of dispatchable DGs after islanding. For ESSs, the power output/input of an ESS in islanded mode is constrained by the maximum charging/discharging power as in Eq. (13). Unlike dispatchable DGs, ESSs can be switched from charging to discharging status instantaneously after islanding, and vice versa. However, an ESS is required to retain its output in islanding mode until it is released by backup generators or the fault is cleared. This requirement is represented by Eq. (14), where \( \tau \) represents the minimum time duration for which a battery needs to retain its output after islanding. Note that \( \tau \) is defined as the minimum of fault duration and startup time of backup generators. In fact, \( \tau \) is in the fault duration when no backup generators are installed in the microgrid.

\[
\begin{align*}
\sum_{i=1}^{N_G} p_{\text{it}}^S + \sum_{w=1}^{N_W} p_{\text{wt}}^W + \sum_{v=1}^{N_V} p_{\text{vt}}^V \\
+ \sum_{b=1}^{N_B} p_{\text{bt}}^S - \sum_{d=1}^{N_D} p_{\text{dt}} \quad \forall t
\end{align*}
\]

where \( p_{\text{it}}^S \) is the ESS power in islanding mode.

\[
P_{\text{it}} - R_{\text{t}} \delta W \leq p_{\text{it}}^W \leq R_{\text{t}} \delta W, \quad \forall t, \forall i
\]

where \( R_{\text{t}} \) is the ramping rate of dispatchable DGs.

\[
P_{\text{bt}}^S + \eta^D_{\text{bt}} (SOC_{\text{bt}} - SOC_{\text{min}}) \leq \frac{\tau}{P_{\text{it}}}
\]

C. ROBUST MICROGRID SCHEDULING WITH RESILIENCY CONSTRAINTS

Probabilistic approaches such as Monte Carlo Simulation (MCS) and Point Estimation Method (PEM) are also popular as options to handle uncertain variables, i.e., renewable generation and load. However, probabilistic approaches require known or assumed probability distributions of renewable generation and load, which are usually not precisely known in practice due to the limited size and relatively concentrated footprint of a microgrid. In contrast, robust optimization-based approaches do not require probability distributions or correlation of renewable power generation and load. Thus, a two-stage robust optimization model is proposed to capture the uncertainties of renewable generation and load in this article.

The robustness counterpart of the deterministic microgrid scheduling is described in this subsection. As mentioned earlier, wind and PV generation cannot be forecast precisely. In this article, the wind power \( P_{\text{wt}}^W \), PV power \( P_{\text{vt}}^V \), and load \( P_{\text{it}} \) are modeled as independent random variables which take value in \([\hat{P}_{\text{wt}}^W - \delta_{\text{wt}}, \hat{P}_{\text{wt}}^W + \delta_{\text{wt}}]\), \([\hat{P}_{\text{vt}}^V - \delta_{\text{vt}}, \hat{P}_{\text{vt}}^V + \delta_{\text{vt}}]\), and \([\hat{P}_{\text{it}} - \delta_{\text{it}}, \hat{P}_{\text{it}} + \delta_{\text{it}}]\), respectively. \( \delta_{\text{wt}}, \delta_{\text{vt}} \) and \( \delta_{\text{it}} \) are the maximum deviations from nominal forecast values, which could be determined based on historical data. In the robust microgrid scheduling model, the commitment status of dispatchable DGs are first-stage decisions; they are determined at the beginning of the scheduling horizon to hedge all possible uncertainties of renewable generation and demand, as well as the failure of the utility network. The PCC power, output of dispatchable DGs, and charging/discharging power of ESSs in both normal operation and islanded mode are second-stage variables, which are determined after the uncertainties are revealed for each time interval. The robustness counterpart is formulated in min-max-min form as shown in Eqs. (15) – (18), which guarantee the solution is feasible for all possible uncertainties and performs well for the worst case.
Mathematically, the proposed two-stage robust microgrid scheduling model is a tri-level “min-max-min” optimization problem. The outer-level “min” problem optimizes first-stage decision variables. The inner-level “min” problem corresponds to the second-stage decision variables. The middle-level “max” problem determines the worst realization of uncertainties in renewable generation and demands, so that the solution will be robust to all possible realization of uncertainties.

The tri-level “min-max-min” optimization problem cannot be solved directly since the three optimization levels impact one another. Nevertheless, decomposition based methods such as BD with dual cutting planes [39] and the C&CG algorithm [40] have been proved to be efficient for solving this kind of problem. Heuristic algorithms such as implicit enumeration, particle swarm optimization, differential evolution, Tabu, and greedy search have also been proposed to solve tri-level “min-max-min” optimization problems. Detailed comparison of different solution algorithms is out of the scope of this article. A comprehensive review on tri-level “min-max-min” optimization from basic principles to both classical and evolutionary solution strategies is presented in [41]. Compared with BD, the C&CG algorithm generates primal cutting planes to accelerate the convergence. It has been proved that the C&CG algorithm requires many fewer iterations to converge [40]. For this reason, the C&CG algorithm has been used in various problems in the power system area, such as security-constrained unit commitment [42], distribution network restoration [43], and DG placement [44]. In this article, the C&CG algorithm is introduced to solve the proposed tri-level “min-max-min” optimization problem. First, the inner “min” problem is transformed into complementary constraints based on the (Karush-Kuhn-Tucker) KKT optimality conditions. As a result, the tri-level “min-max-min” optimization problem is converted into a bi-level “min-max” optimization problem. Then, the resulting bi-level “min-max” optimization problem can be solved using the C&CG algorithm.

The tri-level “min-max-min” optimization problem can be abstracted as follows:

$$\min_{w \in \mathcal{W}} \left\{ A^T_0 u + \max_{w \in \mathcal{W}} \min_{x \in \mathcal{X}(u, w)} B^T_0 w + C^T_0 x \right\}$$

subject to

$$\mathcal{X} = \left\{ x : A^T_1 u + B^T_1 w + C^T_1 x = q_1, A^T_2 u + B^T_2 w + C^T_2 x \leq q_2 \right\} .$$

In the C&CG algorithm, this problem is reformulated into a master problem that optimizes the first- and second-stage decisions based on the identified worst case scenarios, and a subproblem that searches the worst case scenario based on the current value of the first-stage decisions. These two problems are solved iteratively until the gap between the lower bound given by the master problem and the upper bound provided by the subproblem is reduced to an allowed termination threshold, meaning that a robustly optimal solution is obtained.
The master problem for the $k$-th iteration is defined as follows:

$$\min_{u \in U} A^T_k u + \xi.$$ (21)

subject to

$$\xi \geq B^T_l w^l + C^T_l x \quad \forall l \leq k.$$ (22)

$$A^T_k u + B^T_l w + C^T_l x = q_l \quad \forall l \leq k.$$ (23)

$$A^T_k u + B^T_l w + C^T_l x \leq q_l \quad \forall l \leq k.$$ (24)

In the master problem, the decision variables are $u$ and $x^l$. $w^l$ is the worst case scenario identified in the $l$-th iteration, and the primal cutting planes are iteratively introduced by Eqs. (22) – (24). Note that the master problem is based on a partial enumeration of the uncertainty set $W$. Therefore, it is a relaxation of the tri-level “min-max-min” optimization problem and yields a lower bound.

The subproblem for the $k$-th iteration is defined as follows:

$$\max_{w \in W} \min_{x} B^T_0 w + C^T_0 x.$$ (25)

subject to

$$A^T_0 u^{k+1} + B^T_l w + C^T_l x = q_l.$$ (26)

$$A^T_0 u^{k+1} + B^T_l w + C^T_l x \leq q_l.$$ (27)

where $u^{k+1}$ is the solution of the master problem in the $k$-th iteration. Denote the objective value of the subproblem as $Q(u^{k+1})$. If $u^{k+1}$ is not optimal, $A^T_0 u^{k+1} + Q(u^{k+1})$ will be larger than the true optimal value of the “min-max-min” optimization problem. Thus, the subproblem yields an upper bound. Note that the subproblem is still bi-level programming. To solve it, the inner “min” problem is reformulated into complementary constraints using the KKT optimality conditions. The subproblem becomes as follows:

$$\max_{w \in W} B^T_0 w + C^T_0 x.$$ (28)

subject to

$$A^T_0 u^{k+1} + B^T_l w + C^T_l x = q_l.$$ (29)

$$C^T_0 + \beta^T C_1 + \gamma^T C_2 = 0.$$ (30)

$$0 \leq q_l - A^T_0 u^{k+1} - B^T_l w - C^T_l x \perp \gamma \geq 0.$$ (31)

where $\beta$ and $\gamma$ are dual variables of the constraints Eq. (26) and Eq. (27), respectively. The nonlinear complementary constraint Eq. (31) can be further reformulated into mixed-integer linear form as follows:

$$0 \leq q_l - A^T_0 u^{k+1} - B^T_l w - C^T_l x \leq M\delta.$$ (32)

$$0 \leq \gamma \leq M(1 - \delta).$$ (33)

where $M$ is a large number and $\delta$ is a binary variable. Thus, the subproblem is finally reformulated as MILP.

A complete description of the C&CG algorithm for solving the proposed two-stage robust optimization problem can be found in Algorithm 1. As can be seen, for each iteration, the master problem is solved to get an optimal solution $u^{k+1}$ and update the lower bound. Then, the subproblem is solved and the upper bound is updated. Based on the solution of the subproblem, the primal cutting planes Eqs. (34) – (36) are formulated and incorporated into the master problem. The algorithm terminates until the gap between the lower bound given by the master problem and the upper bound provided by the subproblem is reduced under a small threshold, i.e., the algorithm converges to the optimal solution.

### IV. CASE STUDIES

**A. TEST SYSTEM**

The proposed two-stage robust scheduling of microgrids considering resiliency constraints was tested on a modified Oak Ridge National Laboratory (ORNL) Distributed Energy Control and Communication (DECC) microgrid test system as shown in Fig. 1. The system includes various DGs and ESS. The parameters for the dispatchable generators are presented in Table 1. Because of the relatively small capacities of the dispatchable generators, the minimum up and down time was neglected. The maximum ramping up and down rates of a dispatchable DG are assumed the same. The allowed short adjustment time of dispatchable DGs after islanding $\Delta \tau$ was set as 1 minute to allow the response of microgrid secondary control (i.e., automatic generation control) [45], [46].

The forecast wind power and PV power are presented in Table 2 [18]. Forecast errors of $\pm 35\%$ for wind power and $\pm 35\%$ for PV power were considered. The capacity of the battery was 100 kW with a maximum charging/discharging power of 50 kW. The round-trip efficiency of the battery was set to be 0.9. The minimum and maximum SOC were set as 25% and 95%, respectively. The initial SOC and final SOC were both assumed to be 50%. The degradation cost of

| Unit       | Min. Power (kW) | Max. Power (kW) | Startup Cost ($) | Fuel Cost (S/kWh) | Ramping Rate (kW/min) |
|------------|-----------------|-----------------|------------------|-------------------|----------------------|
| Diesel     | 20              | 80              | 3                | 0.4239            | 20                   |
| Microturbine 1 | 10          | 30              | 2                | 0.3507            | 10                   |
| Microturbine 2 | 10          | 30              | 1.5              | 0.2485            | 10                   |
| Fuel Cell  | 10              | 30              | 1.5              | 0.1385            | 10                   |
the battery was assumed to be 0.02 $/kWh [36]. The fault duration τ was set as 10 minutes. The maximum power at the PCC was set as 200 kW.

The analysis was conducted for a 24-hour scheduling horizon with 1-hour resolution. The forecasted total load and energy prices at the PCC are shown in Table 3 [47]. The total demand was equally divided into 2 loads. A forecast error of ±9% was considered for each load.

All numerical simulations were coded in MATLAB and solved using the MILP solver CPLEX 12.6 [48]. With a pre-specified optimality gap of 0.1, it took only a few iterations for the algorithm to converge, and the running time of each case was less than 10 seconds on a 2.66 GHz Windows-based PC with 4 GB of RAM.

B. EFFECTS OF RESILIENCY CONSTRAINTS

For easy illustration, we defined a new parameter robustness level as $\Gamma = \frac{t}{NW + NPV + ND}$ and assumed $\Gamma$ was consistent for all time intervals. Thus, $\Gamma = 0$ means no robustness considered and $\Gamma = 1$ means fully robust. The results of the proposed robust microgrid scheduling with and without the resiliency constraints are compared in this subsection. The power at the PCC is compared in Fig. 2. In general, the power at the PCC is significantly reduced when the resiliency constraints are considered. With resiliency constraints included in Fig. 2a, the power at the PCC was limited to 150 kW, which is the maximum amount of reserve from both dispatchable DGs and ESSs. This limit guaranteed that all load could be served continuously when the utility network was faulted. When resiliency constraints were not considered, as shown in Fig. 2b, the power at the PCC was much higher. This was because the utility rate was relatively low compared with the generation cost of dispatchable DGs.

To validate the effectiveness of the proposed two-stage robustness optimization in improving system resiliency, the total reserves from dispatchable DGs and ESSs are calculated and compared with the power at the PCC in Fig. 3. As can be seen, the total reserves provided by dispatchable DGs and ESSs are always equal to or greater than the power at the PCC as long as the resiliency constraints are considered in the optimization. Thus, the system resiliency is guaranteed. Further consideration of uncertainties of load and renewable generation in Fig. 3b leads to increasing of both the PCC power and total reserve, which could be easily observed from

![FIGURE 1. Modified ORNL DECC microgrid system.](image)

```latex
\begin{table}[h]
\centering
\caption{Forecast wind and PV power.}
\begin{tabular}{|c|c|c|c|c|}
\hline
\textbf{Hour} & \textbf{Wind (kW)} & \textbf{PV (kW)} & \textbf{Hour} & \textbf{Wind (kW)} & \textbf{PV (kW)} \\
\hline
1 & 51.4829 & 0 & 13 & 23.5169 & 35.2199 \\
2 & 38.3711 & 0 & 14 & 39.4794 & 35.4594 \\
3 & 43.5590 & 0 & 15 & 35.7380 & 34.8303 \\
4 & 40.7514 & 0 & 16 & 18.0383 & 23.6244 \\
5 & 27.7421 & 0 & 17 & 24.2732 & 14.1623 \\
6 & 30.1540 & 0 & 18 & 26.5555 & 4.6705 \\
7 & 28.6452 & 0.1617 & 19 & 26.7732 & 0.1834 \\
8 & 23.7867 & 1.7726 & 20 & 26.2159 & 0 \\
9 & 21.7503 & 5.2978 & 21 & 32.8428 & 0 \\
10 & 34.8202 & 11.6044 & 22 & 36.0156 & 0 \\
11 & 27.1748 & 36.6382 & 23 & 37.2312 & 0 \\
12 & 30.1965 & 42.6717 & 24 & 44.1215 & 0 \\
\hline
\end{tabular}
\end{table}
```

```latex
\begin{table}[h]
\centering
\caption{Forecast load and energy prices at PCC.}
\begin{tabular}{|c|c|c|c|c|c|}
\hline
\textbf{Hour} & \textbf{Load (kW)} & \textbf{Price (ct/kWh)} & \textbf{Hour} & \textbf{Load (kW)} & \textbf{Price (ct/kWh)} \\
\hline
1 & 124.7103 & 8.65 & 13 & 189.9998 & 26.82 \\
2 & 123.9769 & 8.11 & 14 & 187.0655 & 27.35 \\
3 & 126.9111 & 8.25 & 15 & 192.2006 & 13.81 \\
4 & 124.7103 & 8.10 & 16 & 194.4014 & 17.31 \\
5 & 128.3739 & 8.14 & 17 & 187.0655 & 16.42 \\
6 & 135.4320 & 8.13 & 18 & 185.5983 & 9.83 \\
7 & 146.7180 & 8.34 & 19 & 183.3975 & 8.63 \\
8 & 178.2624 & 9.35 & 20 & 187.0655 & 8.87 \\
9 & 186.3319 & 12.00 & 21 & 190.7334 & 8.35 \\
10 & 190.7334 & 9.19 & 22 & 181.9303 & 16.44 \\
11 & 195.8685 & 12.30 & 23 & 161.3898 & 16.19 \\
12 & 189.9998 & 20.70 & 24 & 134.9806 & 8.87 \\
\hline
\end{tabular}
\end{table}
```
Fig. 2a. More detailed analysis of the effect of robustness level on the optimal solution is presented in Subsection IV-C.

When resiliency constraints are not considered in the robustness optimization, the total reserves from dispatchable DGs and ESSs are calculated and compared with the power at the PCC in Fig. 4. It can be seen that the total reserves provided by dispatchable DGs and ESSs are less than the power at the PCC under different robustness levels. In these situations, if the utility networked is faulted, the DGs and ESSs cannot supply all loads. Therefore, load shedding will be necessary.

In the case of unexpected utility network failure, a microgrid will disconnect from the main grid through unintentional islanding, followed by quick adjustment of the power output of dispatchable DGs and ESSs. As the last resort, ideal emergency load shedding is assumed to mitigate the remaining power imbalance between local generation and demand after the reserve from dispatchable DGs and ESSs has been deployed at the first time. The amount of load shedding in the case of unintentional islanding is calculated at the PCC minus the total reserve from dispatchable DGs and ESSs. To show the benefit of resiliency under the worst scenario, the amounts of load shedding following unintentional islanding in different cases are compared in Fig. 5. As can be seen, the amounts of load shedding are significantly reduced in unintentional islanding when the resiliency constraints are included in the optimization. However, only considering the resiliency constraints is not enough. Ignoring the uncertainties of renewable generation and load still results in certain amounts of load shedding in unintentional islanding as the blue line indicates. By the proposed robust optimization, load shedding could be completely avoided in the worst scenario as the purple line indicates. Note that the assumed emergency load shedding is still impractical in real-time operation. As a result, the microgrid is very likely to break down when it has resorted to the assumed emergency load shedding.

It should be noted that load shedding is not considered in the optimization, but taken as the last resort to restore the power balance between generation and load after islanding of microgrids. Nevertheless, the model proposed in this work could be easily extended to include load shedding as an option to mitigate the generation deficiency after islanding. To realize this idea, we can simply divide the total load $P_{dt}$ into critical load $P_{dt}^{CL}$ and non-critical load $P_{dt}^{NL}$. By adding another continuous variable $\alpha_{dt}^{NL}$ indicating the percentage of non-critical load shedding after islanding, we could modify Eq. (10) by replacing $P_{dt}$ with $P_{dt}^{CL} + (1 - \alpha_{dt}^{NL})P_{dt}^{NL}$, then
add the cost of non-critical load shedding in the objective (1). In this way, the proposed model is extended to include load shedding as an option to mitigate the generation deficiency after islanding.

As mentioned earlier, the utility rate was relatively low compared with the generation costs of dispatchable DGs. With resiliency constraints considered, the power generated by dispatchable DGs was increased to reduce the power at the PCC. Thus, resiliency was gained at the expense of increasing operating costs. The total operating costs in the cases with and without resiliency constraints are compared in Fig. 6. As can be observed, the operating cost increases significantly with resiliency constraints included. In addition, the operating cost increases monotonically as the robustness level $\Gamma$ increases.

Although the operating costs of microgrids increase significantly with resiliency constraints considered, as shown in Fig. 6, the proposed two-stage robust microgrid scheduling with resiliency constraints still has a practical significance in improving the resilience and reliability of power supply to microgrid customers. First, the resiliency constraints make the microgrid better prepared for possible disruptions of the utility network, so that the microgrid could provide uninterrupted power supply to microgrid customers, especially critical customers, with required power quality. This could lead to significant social benefits in the face of natural disasters. Second, given the low probability of utility network disruptions, the MCC might consider the resiliency constraints only under certain conditions, such as severe weather alerts, standby line/switch maintenance, or specific reliability requests from customers, while choosing to ignore the resiliency constraints during most normal operating conditions.

**C. SENSITIVITY ANALYSIS WITH DIFFERENT ROBUSTNESS LEVELS**

In this subsection, the results for the proposed robust scheduling model under different robustness levels are compared. For the worst case scenario, the power exchanged at the PCC and the total power output of the dispatchable DGs are compared in Fig. 7a and Fig. 7b, respectively. As the robustness level increases, both the power at the PCC and the dispatchable DG output increase, since more of the forecast errors of renewable generation and load are taken into account. Although the utility rate was relatively low compared with generation costs of the dispatchable DGs, the majority of the uncertainties in renewable generation and load were handled by adjusting the dispatchable DG output because the power at the PCC was subject to the resiliency constraints. In other words, a large increase of power at the PCC will compromise the resilience...
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FIGURE 7. Power at PCC, total power output of dispatchable DGs and total capacity of committed dispatchable DGs at different robustness levels.

In an extreme case (e.g., hour 21), the PCC power is 150 kW, which equals the maximum amount of reserve that dispatchable DGs and ESSs could provide. Under this situation, even a tiny increase of the PCC power could compromise the resilience of the system.

To further show the effect of uncertainties on the unit commitment of dispatchable DGs, the total capacity of committed dispatchable DGs at different robustness levels are compared in Fig. 7c. As can be seen, for each time interval, the total capacity of committed dispatchable DGs increase as the robustness level $\Gamma$ increases, i.e., more dispatchable DGs need to be committed with higher robustness level $\Gamma$. The reason is obvious. With increasing robustness level $\Gamma$, more forecast errors will be considered. As a result, additional dispatchable DGs need to be committed to compensate the extra forecast errors.

D. SENSITIVITY ANALYSIS WITH DIFFERENT UNCERTAINTY LEVELS

In this subsection, the results of proposed robust microgrid scheduling under different levels of uncertainties of renewable generation and demand are compared. The original forecast errors of renewable generation and loads are multiplied by an uncertainty scale factor to create various scenarios with different levels of uncertainties. With the robustness...
level $\Gamma$ set as 1, the proposed robust microgrid scheduling under different levels of uncertainties are solved. For the worst scenario, the power exchanged at PCC, total reserve from DGs and ESSs and total power output of dispatchable DGs for the worst scenario are compared in Fig. 8a, Fig. 8b and Fig. 8c, respectively. As the level of uncertainties increases, both power exchanged at PCC and power output of DGs increase due to enlarged forecast errors of renewable generation and loads. Nevertheless, the increase of power exchanged at PCC is limited due to the resiliency constraints. This is particularly obvious when power exchanged at PCC is above 100 kW.

The total operating cost of the microgrid under different uncertainty levels are compared in Fig. 9. As can be observed, the total operating cost increases monotonically as the level of uncertainties increases. Considering the majority of the enlarged forecast errors in renewable generation and loads need to be handled by adjusting the output of dispatchable DGs since the power at PCC is subject to the resiliency constraints, meanwhile, the generation cost of dispatchable DGs is relatively high comparing with the utility rate at PCC, the total operating cost of the microgrid will necessarily rise as as the level of uncertainties increases.

E. EFFECTS OF FAULT DURATION $\tau$

In this subsection, the effect of fault duration $\tau$ on the operation of battery is studied. The SOC and cost savings of the battery under different fault duration $\tau$ are compared in Fig. 10. As can be seen in Fig. 10a, the fault duration $\tau$ has a significant impact on the lower bound of the SOC. In specific, as the fault duration $\tau$ increases, the lower bound of the SOC increases so that the battery can retain its output during the extended fault duration after islanding.

Although the total operating costs of microgrids increase significantly when the resiliency constraints are added into the optimization problem, from the viewpoint of batteries, they might still make a profit by arbitrage under a dynamic utility rate given the relatively low degradation cost. The profits of the battery are calculated and compared under different fault durations $\tau$ in Fig. 10b. As can be seen, the profit of the battery monotonically decreases as the fault duration $\tau$ increases. This is because the battery must maintain a higher SOC over a longer fault duration $\tau$, which greatly reduces the flexibility of the battery. If quick-start backup generators were installed, the battery could be gradually released by the backup generators after islanding. Thus, $\tau$ would be reduced and the profit of the battery would increase. Determining the optimal trade-off between an investment in backup generators and the potential profit of batteries by sizing the backup generators and batteries appropriately is a new, challenging problem that will be investigated in the future. It should be noted that even though the batteries might alleviate the rising total system operating cost by arbitrage, the total system operating cost still increases significantly owing to the resiliency constraints.

V. CONCLUSION

In this article, a new microgrid scheduling model is developed that considers resiliency requirements. A two-stage robust optimization model is formulated and solved using the C&CG algorithm. The solution of the proposed robust optimization model ensures the resiliency by facilitating possible unintentional islanding incidents of the microgrid without
any load interruption, meanwhile, ensures robustness against the randomness of local renewable generation and demand. The effectiveness of proposed microgrid scheduling model is validated by numerical simulations on a typical microgrid. Moreover, the sensitivity analysis under varying robustness levels is presented.

It should be noted that the presented model in this article only considers active power generation and load. Future works include expanding the current model to consider the reactive power balance, voltage limits and distribution power flow model.

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