Robust Scheduling of Microgrids Considering Unintentional Islanding Conditions

Guodong Liu, Max Ferrari, Ben Ollis, Aditya Sundararajan
Grid Component & Controls Group
Oak Ridge National Laboratory
Oak Ridge, USA
Email: {liug, ferrarimagmf, ollistb, sundararajaa}@ornl.gov

Kevin Tomsovic
Dept. of Electrical Engineering and Computer Science
The University of Tennessee
Knoxville, USA
Email: tomsovic@utk.edu

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***Abstract*—This paper proposes a robust scheduling model for microgrids considering the stochastic unintentional islanding conditions. The proposed model minimizes the total operating cost of the microgrid by efficiently coordinating the supply of power from local distributed energy resources and the main grid. To capture the prevailing uncertainties in renewable generation and demand as well as unintentional islanding conditions, a two-stage adaptive robust optimization model is formulated to minimize the total operating cost under the worst realization of the modeled uncertainties. The column and constraint generation (C&CG) method is used to solve the problem in an iterative manner. The solution of the proposed scheduling model ensures robust microgrid operation in consideration of all possible realization of renewable generation, demand and unintentional islanding condition. Numerical simulations on a microgrid consisting of a wind turbine, a PV panel, a fuel cell, two micro-turbines, a diesel generator and a battery demonstrate the effectiveness of the proposed approach.**

***Index Terms*—Robust optimization, microgrid scheduling, uncertainty, islanding, mixed-integer linear programming (MILP)**

NOMENCLATURE

The main symbols used in this paper are defined below. Others will be defined as required in the text. A bold symbol stands for its corresponding vector.

A. Indices

i	Index of dispatchable generators, running from 1 to N_G.
d	Index of demands, running from 1 to N_D.
b	Index of battery storage devices, running from 1 to N_B.
w	Index of wind turbines, running from 1 to N_W
v	Index of PV, running from 1 to N_v
t	Index of time periods, running from 1 to N_T.

B. Variables

1) Binary Variables:

u_{it}	1 if unit i is scheduled on during period t and 0 otherwise.
Z_t^{G}	1 if microgrid is grid-connected and 0 otherwise.

2) Continuous Variables:

P_{it}	Power output scheduled from dispatchable unit i during period t.
P_t^{PCC}	Exchanged power at PCC during period t.
$P_{bt}^{\mathrm{C}}, P_{bt}^{\mathrm{D}}$	Charging/discharging power of battery b during period t.
SOC_{bt}	State of charge of battery b during period t.
P_{wt}^{W}	Power output of wind turbine w during period t.
P_{vt}^{PV}	Power output of PV panel v during period t.
P_{dt}^{L}	Power consumption scheduled for demand d during period t.
P_{dt}^{LS}	Load shedding of demand d during period t.
$\overline{\mu_{wt}}$, $\underline{\mu_{wt}}$	Auxiliary variables for uncertainty of wind power P_{wt}^{W}.
$\overline{\mu_{vt}}$, $\underline{\mu_{vt}}$	Auxiliary variables for uncertainty of PV power P_{wt}^{PV}.
$\overline{\mu_{dt}}$, $\underline{\mu_{dt}}$	Auxiliary variables for uncertainty of demand P_{dt}^{L}.

C. Constants

C_{bt}	Degradation cost of battery b during period t.
C_{it}^{ON}	Fixed operation cost of DG i during period t.
λ_{it}	Generation cost of DG i during period t.
λ_t^{PCC}	Purchasing/selling price of energy from/to distribution grid during period t.
$P_i^{\max}, P_i^{\min}$	Maximum/minimum output of DG i.
$R_{\tilde{i}}^{\max}$	Maximum ramping up/down rate of unit i.
$P_{\tilde{w}t}^{\mathrm{W}}$	Forecasted output of wind turbine w in period t.
$P_{\tilde{v}t}^{\mathrm{PV}}$	Forecasted output of PV panel v in period t.
$P_{\tilde{d}t}^{\mathrm{L}}$	Forecasted consumption of demand d in period t.
$P_b^{\mathrm{C,max}}, P_b^{\mathrm{D,max}}$	Maximum charging/discharging power of battery b.

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$SOC_{bt}^{\max}, SOC_{bt}^{\min}$ Maximum/minimum state of charge of battery b during period t.

$\eta_b^{\mathrm{C}}, \eta_b^{D}$ Battery charging/discharging efficiency factor.

$\delta_{wt}^{\mathrm{W}}, \delta_{vt}^{\mathrm{PV}}, \delta_{dt}^{\mathrm{L}}$ Maximum deviation from the nominal forecast values $\hat{P_{wt}^{\mathrm{W}}}$, $\hat{P_{vt}^{\mathrm{PV}}}$ and $\hat{P_{dt}^{\mathrm{L}}}$.

Γ_t^{P} Robust control parameter of renewable generation and demand during period t.

Γ^{G} Robust control parameter of unintentional islanding conditions.

$\triangle t$ Time duration of each period.

α_{dt} Maximum percentage of load shedding of demand d during period t.

I. Introduction

A microgrid can be defined as a low voltage distribution network comprising various distributed generators (DGs), energy storage systems (ESSs) and loads that can be operated in both grid-connected and islanded modes [1]. From the point of view of the grid, a microgrid can be regarded as a controllable element which is connected to the utility distribution network at the Point of Common Coupling (PCC). A microgrid can not only exchange power with the utility grid, but also provide various ancillary services, e.g., frequency regulation, voltage support, virtual inertia, etc., to the utility grid that a conventional end-user system cannot [2], [3]. From the point of view of customers, a microgrid can reduce carbon emission and improve energy efficiency. More importantly, a microgrid can improve the reliability of local electricity supply by islanding from the distribution grid during an grid disturbance, and continuing to supply its islanded portion [4]. Due to such benefits, microgrids have attracted growing attention from both academia and industry [5].

Comparing with intentional islanding, i.e., a microgrid intentionally separates itself from the utility grid in case of foreseeable utility disturbances, unintentional islanding, i.e., a microgrid unintentionally separates itself from the utility grid driven by unforeseeable utility disturbances, is more important for reliability improvement since the vast majority of utility disturbances are unpredictable. Generally, a microgrid imports/exports power from/to the distribution grid in grid-connected mode, and this power is instantaneously forced to be zero when the microgrid is unintentionally islanded. Under this circumstance, the transition of microgrid from grid-connected to islanded mode often requires quick adjustment of the power output of already committed DGs and ESSs, even load shedding as the last resort to mitigate the power imbalance caused by unintentional islanding. To reduce load shedding and have the microgrid prepared for possible unintentional islanding, certain DGs should be committed and the ESSs should be charged to certain level. However, the occurrence time and duration of the unintentional islanding are uncertain. In addition, the uncertainties in the forecasting of renewable generation and load makes the problem more challenging. Therefore, development of new scheduling methods considering stochastic unintentional islanding conditions of microgrids and probabilistic characteristics of load and renewable generation is necessary for achieving the reliability benefit of microgrids.

So far, research work on scheduling of microgrids considering unintentional islanding conditions could be divided into two categories: stochastic optimization and robust optimization. For the first category, the adequacy constraints are considered to ensure sufficient operating margin to cover critical loads in case of upstream network faults in [6]. A more general microgrid scheduling model with chance-constrained islanding capability is proposed in [7]. However, neither [6] nor [7] considers the islanding duration of microgrids. The islanding duration is modeled as scenarios through enumeration in [8]. Nevertheless, [6], [7], [8] require the probability distributions of uncertainties, which are difficult to obtain in practice. As to the second category, a robust optimization-based microgrid scheduling model with reserve requirements is proposed in [9]. The uncertainties of renewable generation and load are considered in [10]. However, the duration of the unintentional islanding has been neglected. A pre-set islanding duration is considered in [11], [12]. However, the charging/discharging status of ESSs is assumed same as normal operation after islanding in order to keep the inner-stage of the max-min problem linear. In [13], both occurrence time and duration of unintentional islanding are included in the microgrid scheduling problem through a two-stage robust optimization model. However, the load shedding has been ignored.

In view of the shortcomings of the existing literature, a robust optimization model for microgrids scheduling considering the stochastic unintentional islanding conditions is proposed in this paper. The microgrid is guaranteed to supply critical demands continuously through quickly adjusting the output of committed DGs and load shedding when unintentional islanding happens. To capture the uncertainties in renewable generation, demand and the occurrence time and duration of the unintentional islanding, a two-stage robust optimization model is formulated to minimize the total operating cost under the worst realization of the modeled uncertainties. The column and constraint generation (C&CG) algorithm is used to solve the problem. The solution ensures robust microgrid operation in consideration of all possible realization of renewable generation, demand and unintentional islanding conditions. The main contributions of this paper are as follows:

1) A new scheduling model for microgrids considering the stochastic unintentional islanding conditions is proposed. The microgrid is guaranteed to supply critical demands continuously through quickly adjusting the output of committed DGs and load shedding in case of unintentional islanding.
2) Considering the uncertainties of renewable generation, load, and the occurrence time and duration of unintentional islanding, a two-stage robust optimization model is formulated and solved using the C&CG algorithm.

The reminder of the paper is organized as follows. Section II introduces the proposed two-stage robust microgrid scheduling model considering the stochastic unintentional islanding con-

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ditions. Results of case studies are presented in Section III. Finally, Section IV concludes the paper with major findings.

II. Mathematical Formulation

A. Microgrid Modeling

Generally, a microgrid includes dispatchable and undispatchable generators, ESSs and loads. The dispatchable generators, such as diesel generators, microturbines and fuel cells, could change their power output according to the dispatch order of the microgrid controller, while undispatchable generators, such as wind turbines and PV panels, have uncertain power output depending on the meteorological conditions of wind speed, temperature and solar irradiance. There has been extensive existing literature focused on wind and PV power forecasting. However, the forecast accuracy declines quickly as the lead time increases. Typically, the wind power forecast error is around 10% for hour-ahead forecasting, over 20% for day-ahead forecasting, and even higher for a longer lead time [14]. The forecast error of PV generation is even higher since the PV power output is greatly affected by the cloud coverage with very random pattern. In this paper, the 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 [7]. The focus of this paper is to ensure the microgrid being ready to perform a seamless islanding considering the uncertainties of renewable generation, demand, and occurrence time and duration of the unintentional islanding.

B. Deterministic Microgrid Scheduling

This subsection describes the model of the deterministic microgrid scheduling. The objective is to minimize the total operating cost of the microgrid over the scheduling horizon as shown in (1). Specifically, the first line is the operating cost of DGs (including start-up cost, shut-down cost, and fuel cost); the second line is the energy purchasing cost (or benefit of selling energy to the utility); the third line is the degradation cost of the ESSs; and the fourth line is the cost of load shedding. All terms are in mixed-integer linear form except the start-up cost S_{it}^{U} and shut-down cost S_{it}^{D} , which can be recast into mixed-integer linear form as in [15].

$$
\begin{aligned}
\min \quad & \sum_{t=1}^{N_T}\sum_{i=1}^{N_G}\left[S_{it}^{\mathrm{U}}+S_{it}^{\mathrm{D}}+C_{it}^{\mathrm{ON}}u_{it}+\lambda_{it}P_{it}\right] \\
& +\sum_{t=1}^{N_T}\lambda_t^{\mathrm{PCC}}P_t^{\mathrm{PCC}} \\
& +\sum_{t=1}^{N_T}\sum_{b=1}^{N_B}C_{bt}\left(P_{bt}^{\mathrm{C}}+P_{bt}^{\mathrm{D}}\right) \\
& +\sum_{t=1}^{N_T}\sum_{d=1}^{N_D}C_{dt}^{\mathrm{LS}}P_{dt}^{\mathrm{LS}}
\end{aligned} \tag{1}
$$

The objective function is subject to the following constraints:

$$P_i^{\min}u_{it} \le P_{it} \le P_i^{\max}u_{it} \quad \forall i, \forall t \tag{2}$$

$$0 \le P_{bt}^{\mathrm{C}} \le P_b^{\mathrm{C,max}} \quad \forall b, \forall t \tag{3}$$

$$0 \le P_{bt}^{\mathrm{D}} \le P_b^{\mathrm{D,max}} \quad \forall b, \forall t \tag{4}$$

$$SOC_{bt} = SOC_{b,t-1} + P_{bt}^{\mathrm{C}}\eta_b^{\mathrm{C}}\triangle t - P_{bt}^{\mathrm{D}}\frac{1}{\eta_b^{\mathrm{D}}}\triangle t \quad \forall b, \forall t \tag{5}$$

$$SOC_{bt}^{\min} \le SOC_{bt} \le SOC_{bt}^{\max} \quad \forall b, \forall t \tag{6}$$

$$
\begin{aligned}
& \textstyle\sum_{i=1}^{N_G} P_{it} + \sum_{w=1}^{N_W} P_{wt}^{\mathrm{W}} + \sum_{v=1}^{N_{PV}} P_{vt}^{\mathrm{PV}} + P_t^{\mathrm{PCC}} \\
& + \textstyle\sum_{b=1}^{N_B} P_{bt}^{\mathrm{D}} - \sum_{b=1}^{N_B} P_{bt}^{\mathrm{C}} = \sum_{d=1}^{N_D}\left(P_{dt}^{\mathrm{L}} - P_{dt}^{\mathrm{LS}}\right) \quad \forall t
\end{aligned} \tag{7}
$$

$$-Z_t^{\mathrm{G}}P_t^{\mathrm{PCC,max}} \le P_t^{\mathrm{PCC}} \le Z_t^{\mathrm{G}}P_t^{\mathrm{PCC,max}} \tag{8}$$

$$0 \le P_{dt}^{\mathrm{LS}} \le \alpha_{dt}\% \hat{P}_{dt}^{\mathrm{L}} \quad \forall i, \forall t \tag{9}$$

Constraint (2) is the minimum and maximum power constraint of DGs. It also forces the output of a DG to be zero if it is not committed. For ESSs, the maximum charging/discharging power of an ESS are specified by constraints (3) and (4). The state of charge (SOC) of an ESS in current time interval is defined as the SOC in previous time interval plus the energy charged or minus the energy discharged as in constraint (5). The SOC of an ESS is limited by constraint (6). The generation and demand is balanced in grid-connected mode, which is enforced by (7). The PCC power is limited by constraint (8). It also forces the PCC power to be zero if the microgrid is islanded. The maximum percentage of load shedding of each demand is limited by constraint (9).

C. Robust Microgrid Scheduling

This subsection describes the robust counterpart of the deterministic microgrid scheduling. As mentioned earlier, P_{wt}^{W}, P_{vt}^{PV} and P_{dt}^{L} are modeled as independent, symmetric and bounded random variables which take value in $\left[\hat{P}_{wt}^{\mathrm{W}}-\delta_{wt}^{\mathrm{W}}, \hat{P}_{wt}^{\mathrm{W}}+\delta_{wt}^{\mathrm{W}}\right]$, $\left[\hat{P}_{vt}^{\mathrm{PV}}-\delta_{vt}^{\mathrm{PV}}, \hat{P}_{vt}^{\mathrm{PV}}+\delta_{vt}^{\mathrm{PV}}\right]$ and $\left[\hat{P}_{dt}^{\mathrm{L}}-\delta_{dt}^{\mathrm{L}}, \hat{P}_{dt}^{\mathrm{L}}+\delta_{dt}^{\mathrm{L}}\right]$ with δ_{wt}^{W}, $\delta_{vt}^{\mathrm{PV}}$ and δ_{dt}^{L} nonnegative. The commitment status of DGs are first-stage decisions, which are determined at the beginning of the scheduling horizon to hedge all possible uncertainties of renewable generation and demand as well as unintentional islanding, while the PCC power, output of DGs, charging/discharging power of ESSs and load shedding are second-stage variables, which are determined after the uncertainties are revealed. The robust counterpart is formulated in min-max-min form, which guarantees the solution is feasible for all possible uncertainties and performs well for the worst case.

$$
\begin{aligned}
\min_{\mathbf{u}\in\mathbb{U}} \quad & \sum_{t=1}^{N_T}\sum_{i=1}^{N_G} S_{it}^{\mathrm{U}}+S_{it}^{\mathrm{D}}+C_{it}^{\mathrm{ON}}u_{it} \\
& + \max_{\mathbf{Z^G},\mathbf{P^W},\mathbf{P^{PV}},\mathbf{P^L}\in\mathbb{W}} \quad \min_{\mathbf{P},\mathbf{P^{PCC}},\mathbf{P^C},\mathbf{P^D},\mathbf{P^{LS}}\in\mathbb{X}} \\
& \left\{\sum_{t=1}^{N_T}\sum_{i=1}^{N_G}\lambda_{it}P_{it}+\sum_{t=1}^{N_T}\lambda_t^{\mathrm{PCC}}P_t^{\mathrm{PCC}}\right. \\
& +\sum_{t=1}^{N_T}\sum_{b=1}^{N_B}C_{bt}\left(P_{bt}^{\mathrm{C}}+P_{bt}^{\mathrm{D}}\right) \\
& \left.+\sum_{t=1}^{N_T}\sum_{d=1}^{N_D}C_{dt}^{\mathrm{LS}}P_{dt}^{\mathrm{LS}}\right\}
\end{aligned} \tag{10}
$$

$$s.t. \qquad \mathbb{U} = \{\mathbf{u}: u_{it} \in \{0,1\}, \forall i, t;\} \tag{11}$$

$$\begin{aligned} \mathbb{W} = \Big\{ & \mathbf{P}^{\mathrm{W}}: P_{wt}^{\mathrm{W}} = \hat{P_{wt}^{\mathrm{W}}} - \underline{\mu_{wt}}\delta_{wt}^{\mathrm{W}} + \overline{\mu_{wt}}\delta_{wt}^{\mathrm{W}}, \forall w, t \\ & \mathbf{P}^{\mathrm{PV}}: P_{vt}^{\mathrm{PV}} = \hat{P_{vt}^{\mathrm{PV}}} - \underline{\mu_{vt}}\delta_{vt}^{\mathrm{PV}} + \overline{\mu_{vt}}\delta_{vt}^{\mathrm{PV}}, \forall v, t \\ & \mathbf{P}^{\mathrm{L}}: P_{dt}^{\mathrm{L}} = \hat{P_{dt}^{\mathrm{L}}} - \underline{\mu_{dt}}\delta_{dt}^{\mathrm{L}} + \overline{\mu_{dt}}\delta_{dt}^{\mathrm{L}}, \forall d, t \\ & \underline{\mu_{wt}}, \overline{\mu_{wt}}, \underline{\mu_{vt}}, \overline{\mu_{vt}}, \underline{\mu_{dt}}, \overline{\mu_{dt}} \in [0, 1], \forall w, v, d, t \\ & \sum_{w=1}^{N_W} \left(\underline{\mu_{wt}} + \overline{\mu_{wt}}\right) + \sum_{v=1}^{N_{PV}} \left(\underline{\mu_{vt}} + \overline{\mu_{vt}}\right) \\ & + \sum_{d=1}^{N_D} \left(\underline{\mu_{dt}} + \overline{\mu_{dt}}\right) \le \Gamma_t^{\mathrm{P}}, \forall t \\ & \mathbf{Z^G}: \sum_{t=1}^{N_T} \left(1 - Z_t^{\mathrm{G}}\right) \le \Gamma^{\mathrm{G}}, Z_t^{\mathrm{G}} \in \{0, 1\}, \forall t \\ & \quad Z_t^{\mathrm{G}} \le 1 - (Z_{t-1}^{\mathrm{G}} - Z_t^{\mathrm{G}}), \\ & \quad \forall t \in \left[1, \min\left(N_T, t + \Gamma^{\mathrm{G}} - 1\right)\right] \Big\} \end{aligned} \tag{12}$$

$$\mathbb{X} = \left\{\mathbf{P}, \mathbf{P^{PCC}}, \mathbf{P^{C}}, \mathbf{P^{D}}, \mathbf{P^{LS}} : (2) - (9)\right\} \tag{13}$$

$\mathbb{W}$ represents the uncertainty set. Note that the randomness of wind and PV power as well as demand are modeled as polyhedrons. The aggregated effect over multiple uncertainties are modeled by a budget constraint. Γ_t^{P} is a robust control parameter, which takes values in $[0, N_W + N_{PV} + N_D]$. We are interested in finding an optimal solution that is protected against all scenarios in which up to $\lfloor \Gamma_t^{\mathrm{P}} \rfloor$ of these uncertain coefficients μ are allowed to change, and one coefficient changes by at most $(\Gamma_t - \lfloor \Gamma_t \rfloor)\,\mu$. It is guaranteed that if nature behaves like this then the robust solution will be feasible deterministically. If $\Gamma_t = 0$, the uncertainties are completely ignored, while if $\Gamma_t = N_W + N_{PV} + N_D$, all uncertainties in renewable generation and demands are fully considered, leading to the most conservative solution. By this way, the microgrid controller could adjust the degree of conservatism of the solution based on their risk aversion. Similarly, Γ^{G} is a robust control parameter for the unintentional islanding condition, which takes value in $[0, N_T]$. It guarantees that optimal solution is protected against all scenarios in which up to Γ^{G} time intervals are islanded. If $\Gamma^{\mathrm{G}} = 0$, all Z_t^{G} will be 1, i.e., no unintentional islanding is allowed, while if $\Gamma^{\mathrm{G}} = N_T$, the microgrid is assumed to be islanded for the whole time, leading to the most conservative solution.

$\mathbb{U}$ is the feasible set for the binary commitment status of DGs, and $\mathbb{X}$ is the feasible region for the PCC power, output of DGs, charging/discharging power of ESSs, and load shedding. It should be noted that only the first stage decision are implemented and the second stage decisions would be re-optimized and implemented when the uncertainty is better known base on the forecasts with short lead time.

The proposed two-stage robust microgrid scheduling is actually a tri-level optimization in the form of “min-max-min”. It cannot be solved directly since the three optimization levels impact each other. Generally, there are two solution algorithms for optimization problems with a “min-max-min” structure: Benders decomposition with dual cutting planes [16] and the C&CG algorithm [17]. Comparing with Benders decomposition, the C&CG algorithm generates primal cutting planes to accelerate the convergence. For this reason, the proposed two-stage robust microgrid scheduling is solved using C&CG algorithm.

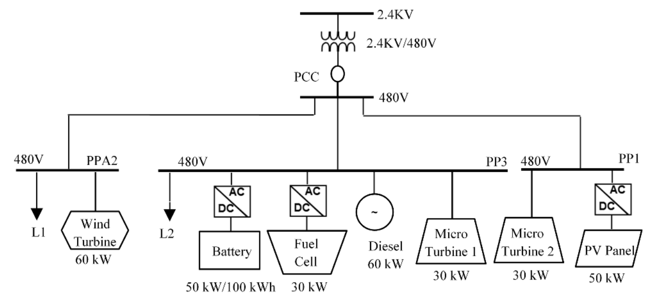


Fig. 1: Modified ORNL DECC microgrid system

III. Case Studies

A. Test System Data

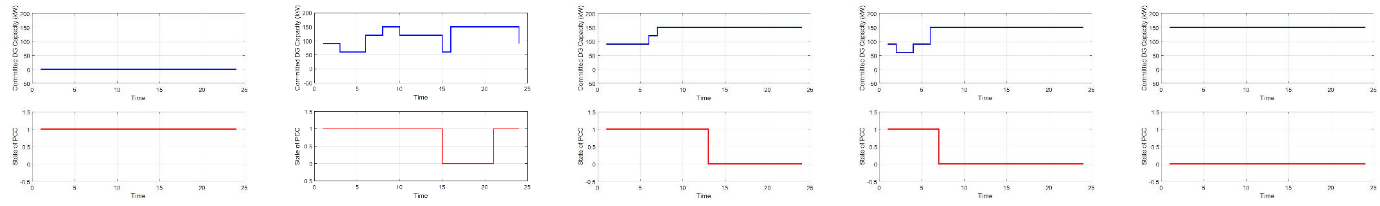
The proposed two-stage adaptive robust scheduling model considering stochastic unintentional islanding conditions was demonstrated on a modified Oak Ridge National Laboratory (ORNL) Distributed Energy Control and Communication (DECC) microgrid test system as shown in Fig. 1. The modified system includes various DGs and ESS. The parameters for the dispatchable generators are taken from [10]. Due to the relatively small capacity of generators, their minimum up and down time are neglected.

The forecast wind and PV power are taken from [10]. A forecast error of ±35% for wind power and ±35% for PV power is considered. The capacity of the battery is 100 kWh with a maximum charging/discharging power of 50 kW. The battery efficiency is assumed to be 0.9. The minimum and maximum SOC of the battery is 25% and 95%, respectively. The initial SOC and final SOC are assumed both 50%. The battery degradation cost is set as 0.02 $/kW. The maximum power at PCC is set as 200 kW. The forecast total demand and day-ahead market prices are the same as in [10]. The total demand is equally divided into 2 loads. A forecast error of ±9% for each load is considered.

The analysis is conducted for a 24-hour scheduling horizon and each time interval is set to be 1 hour. All numerical simulations are coded in MATLAB and solved using the MILP solver CPLEX 12.6 [18]. With a pre-specified optimality gap of 0.1, it takes only a few iterations for the algorithm to converge and the running time of each case is less than 1 minutes on a 2.66 GHz Windows-based PC with 4 GB of RAM.

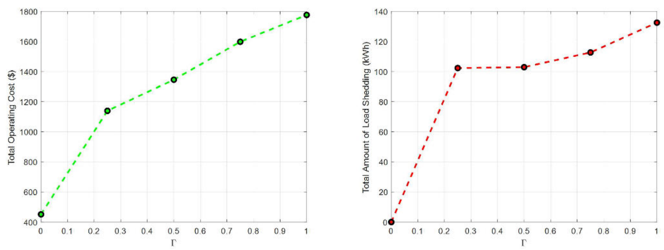
B. Effects of Unintentional Islanding Conditions

For easy illustration, we define a new parameter, i.e., robustness level, as $\Gamma = \Gamma^{\mathrm{G}}/N_T$. Thus, $\Gamma = 0$ means no unintentional islanding is allowed and $\Gamma = 1$ means the microgrid is assumed to be islanded for the whole scheduling



(a) $\Gamma = 0$ (b) $\Gamma = 0.25$ (c) $\Gamma = 0.5$ (d) $\Gamma = 0.75$ (e) $\Gamma = 1$

Fig. 2: Comparison of total capacity of committed DGs and worst unintentional islanding condition under various values of Γ



(a) Total Operating Cost (b) Total Load Shedding

Fig. 3: Comparison of total operating cost and amount of load shedding under various values of Γ

horizon. The results of proposed adaptive robust microgrid scheduling with stochastic unintentional islanding conditions are compared in this subsection. The total capacity of committed DGs and worst realization of unintentional islanding condition under various values of Γ are compared in Fig. 2. As can be seen, no DGs are committed when $\Gamma = 0$, due to the relatively low utility rate comparing with generation cost of DGs. As Γ increase, longer duration of unintentional islanding is considered. As a result, more DGs need to be committed to ensure the microgrid being prepared for all possible islanding events. When $\Gamma = 1$, all DGs are committed.

The total operating cost and total amount of load shedding under various values of Γ are compared in Fig. 3. With Γ increases, the power generated by DGs are increased to mitigate the power at PCC in case of islanding. Thus, the total operating cost increases, i.e., the reliability of microgrids is improved at the cost of increased operating cost. If the DGs and ESSs cannot supply all loads, load shedding will be necessary. As can be seen, the amount of load shedding increase significantly as the unintentional islanding condition is considered at first. However, the growth of load shedding slows down as Γ further increases.

IV. Conclusions

A two-stage adaptive robust optimization model considering stochastic unintentional islanding conditions is proposed and validated in this paper. Future work includes expanding islanding capability from simple power balance constraint to power flow constraint and dynamic stability constraint. In addition, the solution efficiency of C&CG algorithm in large and meshed microgrids will be investigated.

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