Networked Microgrids for Improving Economics and Resiliency

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Abstract—In this paper, we propose networked microgrids to facilitate the integration of variable renewable generation and improve the economics and resiliency of electricity supply in microgrids. A new concept, probability of successful islanding (PSI) is used to quantify the islanding capability of a microgrid considering the uncertainty of renewable energy resources and load as well as exchanged power at PCC. With the goal of minimizing the total operating cost while preserving user specified PSI, a chance-constrained optimization problem is formulated for the optimal scheduling of both individual microgrid and networked microgrids. Numerical simulation results show significant saving in electricity cost can be achieved by proposed networked microgrids without compromising the resiliency. The impact of correlation coefficients among the renewable generation and load as well as exchanged power at PCC. With the goal of minimizing the total operating cost while preserving user specified PSI, a chance-constrained optimization problem is formulated for the optimal scheduling of both individual microgrid and networked microgrids. Numerical simulation results show significant saving in electricity cost can be achieved by proposed networked microgrids without compromising the resiliency. The impact of correlation coefficients among the renewable generation and load as well as exchanged power at PCC.

Index Terms—Networked microgrids, optimal scheduling, probability of successful islanding, economics, resiliency.

NOMENCLATURE

The main symbols used in this paper are defined below. Others will be defined as required in the text. A △ indicates forecast error for the variable while ~ indicates the forecast value.

A. Indices

\( m \) Index of energy blocks offered by generators, running from 1 to \( N_M \).
\( l \) Index of probability intervals, running from 1 to \( N_L \).

B. Variables

1) Binary Variables:
\( u_{it} \) 1 if unit \( i \) is scheduled on during period \( t \) and 0 otherwise.
\( u_{bt}^{C}, u_{bt}^{D} \) 1 if battery \( b \) is scheduled charging/discharging during period \( t \) and 0 otherwise.
\( b_{it}^{U}, b_{it}^{D} \) Binary indicators of probability interval \( l \) during period \( t \).

2) Continuous Variables:
\( p_{it} (m) \) Power output scheduled from the \( m \)-th block of energy offer by dispatchable unit \( i \) during period \( t \). Limited to \( p_{it}^{max} (m) \).
\( p_{it} \) Power output scheduled from dischargeable unit \( i \) during period \( t \).
\( P_{PCC}^{t} \) Exchanged power at PCC during period \( t \).
\( P_{C}^{b}, P_{D}^{b} \) Charging/discharging power of battery \( b \) during period \( t \).
\( P_{bt} \) Output power of battery \( b \) during period \( t \).
\( SOC_{bt} \) State of charge of battery \( b \) during period \( t \).
\( R_{it}^{U}, R_{it}^{D} \) Up- and down-spinning reserve of unit \( i \) during period \( t \).
\( R_{bt}^{U}, R_{bt}^{D} \) Up- and down-spinning reserve of battery \( b \) during period \( t \).
\( PSI_{t} \) Probability of successful islanding during period \( t \).

C. Constants

\( \lambda_{it} (m) \) Marginal cost of the \( m \)-th block of energy offer by dispatchable unit \( i \) during period \( t \).
\( C_{bt} \) Degradation cost of battery \( b \) during period \( t \).
\( \lambda_{t}^{PCC} \) Purchasing/selling price of energy from/to distribution grid during period \( t \).
\( A_{i} \) Operating cost of dispatchable unit \( i \) at the point of \( P_{min}^{i} \).
\( Q_{it}^{U}, Q_{it}^{D} \) Cost of up- and down-spinning reserve of unit \( i \) during period \( t \).
Cost of up- and down-spinning reserve of battery $b$ during period $t$.

Maximum/minimum output of DG $i$.

Wind turbine/PV power output during period $t$.

Power consumption scheduled for demand $j$ during period $t$.

Net demand forecast error of microgrid during period $t$.

Mean and standard deviation of $\Delta N_t^D$.

PSI requirements of microgrid operators.

Maximum charging/discharging power of battery $b$.

Maximum/minimum state of charge of battery $b$ during period $t$.

Battery charging/discharging efficiency factor.

Amount of time available of DGs and batteries to ramp up/down their output to deliver the reserve.

I. INTRODUCTION

While the utilization of a microgrid for local power reliability during grid outage and emergencies is a well-known benefit, networked microgrids, defined as the aggregation of interconnected adjacent microgrids, on the other hand, offer a new, more efficient and resilient alternative to traditional individual microgrids. Due to such benefits, networked microgrids has attracted growing attention in recent years [1]-[5]. Normally, a two-layer energy management strategy for networked microgrids scheduling in distribution system has been used. In the inner layer, each microgrid schedules its own the generation resources and loads, while the outer layer optimization coordinates the power sharing among all microgrids. From control perspective, P-Q based primary control with droop characteristics in facilitating energy transaction of the microgrids and maintaining voltage and frequency stabilities under disturbances is presented in [6].

In the existing literature, research studies on networked microgrids have been mostly focused on the optimal energy transaction strategies to meet economic objectives. However, the resiliency of microgrid and networked microgrid is rarely considered in the optimization. In fact, the most important feature of a microgrid is its ability to separate itself from the distribution utility during outage and continue supplying all or selected critical loads in its own islanded portion. Therefore, the economic benefits of networked microgrids cannot be validated without considering the system resiliency.

In view of the shortcomings of the existing networked microgrids scheduling strategies, a new scheduling strategy for both networked microgrids and independent microgrids operation considering probabilistic constraints of successful islanding is developed in this paper. Considering the uncertainty of renewable generation and power at the PCC, a new concept, probability of successful islanding (PSI), has been proposed to indicate the probability that a microgrid is maintaining adequate up- and down-spinning reserve to meet local demand and accommodate local renewable generation after instantaneously islanding from the main grid in [7].

The networked microgrids and independent microgrids are scheduled with specified PSI. The main contributions of this paper are as follows:

1) Validated the benefit of economics and resiliency of networked microgrids comparing with independent microgrids, and

2) Performed sensitivity analysis to demonstrate the impacts of correlation coefficients among the renewable generation and load of adjacent microgrids.

The rest of this paper is organized as follows. In Section II, the microgrid scheduling strategy with chance-constrained islanding capability is presented. The model is expended to networked microgrids in Section III. Case study and conclusions are given in Section IV and V.

II. MICROGRID SCHEDULING WITH CHANCE-CONSTRAINED ISLANDING CAPABILITY

A. Component Models

The microgrid considered in this paper consists of distributed generators (e.g., diesel generators, microturbines and fuel cells), renewable generation (e.g., wind turbines and PV panels), energy storage (e.g., battery systems) and local demands. The distributed generators are considered dispatchable units, which can be controlled by a microgrid master controller to provide both power and reserve. Depending on unit type, dispatchable units are subject to various constraints, such as, capacity limits, minimum power output limits, ramping rates, minimum on/off time, and so on. In contrast, renewable generation, such as, wind turbines and PV panels, are taken as non-dispatchable units, which depend on the meteorological conditions of wind speed, temperature and solar irradiance. Thus, renewable generation is subject to variability. Extensive research has been done on wind and PV power forecasting [8], [9]. For simplicity, we assume both wind and PV power forecast error can be modeled as independent normally distributed random variables [10]. The load forecast error is assumed to follow a normal distribution and be independent of renewable generation forecast [11]. Due to the limited size of microgrid, relatively large standard deviations are used for both renewable generation and load forecast errors.

B. Problem Formulation

This subsection describes the model of a microgrid scheduling strategy with chance-constrained islanding capability. In the context of microgrids with dispatchable and undispatchable generation as well as electrical energy storage (e.g., batteries) integration, the objective aims at minimizing the total operation cost, including generation cost and spinning reserve cost of local resources as well as purchasing cost of energy form main grid. The objective function is shown in (1). Specifically, the first and second line is the fuel cost of DGs (including DGs start-up cost); the third line is the energy purchasing/selling cost/benefit from distribution grid; the fourth line is the battery degradation cost, the fifth and sixth lines are cost of up- and down-spinning reserve from both DGs and batteries. All terms
are in mixed-integer linear form except the startup cost of
generators (line 2), which can be recast into mixed-integer
linear form as in [12].

$$
\min \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} \left[ \sum_{m=1}^{N_t} \lambda_{it}(m) p_{it}(m) + A_i u_{it} \right] \\
+ \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} S_{it}(u_{it}, u_{i,t-1}) \\
+ \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} P_{it}^{PCC} p_{it}^{PCC} \\
+ \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} U_{it}^{PCC} u_{it}^{PCC} \\
+ \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} (Q_{it}^{U} R_{it}^{PCC} + Q_{it}^{D} R_{it}^{PCC}) \\
+ \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} (Q_{it}^{U} R_{it}^{PCC} + Q_{it}^{D} R_{it}^{PCC})
$$  \hspace{1cm} (1)

The objective function is subject to the following constraints:

$$
P_{it} = \sum_{m=1}^{N_t} p_{it}(m) + u_{it} P_{it}^{min} \forall i, \forall t
$$  \hspace{1cm} (2)

$$
0 \leq p_{it}(m) \leq p_{it}^{max}(m) \forall i, \forall t, \forall m
$$  \hspace{1cm} (3)

$$
P_{it}^{min} u_{it} \leq P_{it} \leq P_{it}^{max} u_{it} \forall i, \forall t
$$  \hspace{1cm} (4)

$$
R_{it}^{U} \leq P_{it}^{max} u_{it} - P_{it} \forall i, \forall t
$$  \hspace{1cm} (5)

$$
P_{it}^{U} / U_{it}^{max} \forall i, \forall t
$$  \hspace{1cm} (6)

$$
R_{it}^{D} \leq P_{it} - P_{it}^{min} \forall i, \forall t
$$  \hspace{1cm} (7)

$$
P_{it}^{D} / u_{it}^{min} \forall i, \forall t
$$  \hspace{1cm} (8)

$$
0 \leq P_{bt}^{C} \leq P_{bt}^{C, max} \forall b, \forall t
$$  \hspace{1cm} (9)

$$
0 \leq P_{bt}^{D} \leq P_{bt}^{D, max} \forall b, \forall t
$$  \hspace{1cm} (10)

$$
SOC_{bt} = SOC_{bt-1} + \sum_{t=1}^{N_t} P_{bt}^{C} / \Delta t - \sum_{t=1}^{N_t} P_{bt}^{D} / \Delta t \forall b, \forall t
$$  \hspace{1cm} (12)

$$
SOC_{bt}^{min} \leq SOC_{bt} \leq SOC_{bt}^{max} \forall b, \forall t
$$  \hspace{1cm} (13)

$$
P_{bt} = P_{bt}^{D} - P_{bt}^{C} \forall b, \forall t
$$  \hspace{1cm} (14)

$$
R_{bt}^{U} \leq P_{bt}^{D, max} - P_{bt} \forall b, \forall t
$$  \hspace{1cm} (15)

$$
R_{bt}^{D} \leq \eta_{bt}^{D} (SOC_{bt} - SOC_{bt}^{min}) / \tau \forall b, \forall t
$$  \hspace{1cm} (16)

$$
SOC_{bt}^{max} \leq SOC_{bt} \leq SOC_{bt}^{min} \forall b, \forall t
$$  \hspace{1cm} (17)

$$
\sum_{t=1}^{N_t} P_{it} + P_{it}^{W} + P_{it}^{PV} + P_{it}^{PCC} + \sum_{b=1}^{N_b} P_{bt}^{U} - \sum_{b=1}^{N_b} P_{bt}^{D} \leq \sum_{t=1}^{N_t} u_{it}^{PCC} \sum_{j=1}^{N_j} P_{jt} \forall i, \forall t
$$  \hspace{1cm} (19)

$$
- \sum_{i=1}^{N_G} P_{it}^{D} - \sum_{b=1}^{N_b} R_{bt}^{D} \leq P_{t}^{PCC} + \Delta N_{D}^{D} \leq \sum_{i=1}^{N_G} R_{it}^{U} + \sum_{b=1}^{N_b} U_{bt} \forall t
$$  \hspace{1cm} (20)

$$
\Delta N_{D}^{D} = \sum_{j=1}^{N_D} P_{jt} - \Delta P_{jt}^{W} - \Delta P_{jt}^{PV} \forall t
$$  \hspace{1cm} (21)

For DGs, constraints (2) and (3) approximate the production
cost of dispatchable generators by blocks [13]. Constraint (4)
forces the output of DG to be zero if it is not committed. The
up-spinning reserve of DG is limited by the difference between
its maximum capacity and current output in (5) and its ramping
rate in (6). Similarly, the down-spinning reserve constraints
are included in (7) and (8). For batteries, constraints (9) and
(10) are the maximum charging/discharging power of a battery.

These two states are mutually exclusive, which is ensured by
(11). The battery state of charge (SOC) is defined by (12) and
the limit of SOC is enforced by (13). The output power of a
battery is represented in (14). Similar to DGs, the up-spinning
reserve of a battery is constrained by the difference between
its current SOC and minimum SOC in (15) and the difference
between its maximum discharging power and current output in
(16). In the same way, the down-spinning reserve constraints
of a battery are included as in (17) and (18). The energy
balance is enforced by (19). The spinning reserve requirement
is as (20), which guarantees adequate spinning reserve for
successful islanding of the microgrid considering the forecast
errors of demand, wind power and PV power. The net demand
forecast error $\Delta N_{D}^{D}$ is formulated in (21). Additionally, each
unit or demand is subject to its own operating constraints, such
as, minimum up/down time, initial condition, etc. See [14] for
details about formulations of these constraints.

As mentioned in subsection II-A, we assume both wind
and PV power forecast error as well as demand forecast error
can be modeled as independent normally distributed random
variables. Thus, the net demand forecast error $\Delta N_{D}^{D}$ also
follows normal distribution, i.e., $\Delta N_{D}^{D} \sim N(\mu_{t}, \sigma_{t}^{2})$.
The PSI can be expressed as (22). The microgrid is considered as
successfully islanded if the net demand forecast error $\Delta N_{D}^{D}$

$$
\left[ -\sum_{i=1}^{N_G} R_{it}^{D} - \sum_{b=1}^{N_b} R_{bt}^{D} - P_{t}^{PCC} - \sum_{i=1}^{N_G} R_{it}^{U} + \sum_{b=1}^{N_b} U_{bt} \right]^T
$$  \hspace{1cm} (22)

The formulation of PSI considers probability distributions
of forecast errors of wind, PV and loads. A multi-interval
approximation of PSI is proposed in [7], which reformulates
PSI into a mixed integer format. Thus, the chance-constrained
programming model for microgrid scheduling could be solved
by mixed integer linear programming. Finally, the microgrid
optimal scheduling with chance-constrained islanding capabil-

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Fig. 1: Example of networked microgrids

As demand forecast error in a microgrid can be modeled as independent normally distributed random variables with zero mean. Due to the geographic proximity of networked microgrids, the wind power forecast errors of any two microgrids are correlated. Taking a networked microgrids consisting of 3 microgrids for example, the mean of total wind power forecast error is zero, while the deviation of total wind power forecast error can be calculated according to equation (24), where $\sigma_n^w$ is the standard deviation of wind power forecast error in microgrid $n$ and $\rho_{nn'}^w$ is the correlation coefficient between wind power forecast errors of microgrid $n$ and $n'$. 

$$(\sigma^w)^2 = \begin{bmatrix} \sigma_1^w & \rho_{12}^w & \rho_{13}^w \\ \rho_{21}^w & \sigma_2^w & \rho_{23}^w \\ \rho_{31}^w & \rho_{32}^w & \sigma_3^w \end{bmatrix} \begin{bmatrix} 1 \\ \rho_{12}^w \\ \rho_{13}^w \\ \rho_{21}^w \\ \rho_{23}^w \\ \rho_{31}^w \\ \rho_{32}^w \\ 1 \end{bmatrix}$$

(24)

The standard deviation of total PV power forecast error and total demand forecast error can be calculated similarly. Since the wind and PV power forecast as well as demand forecast are independent, the total net demand forecast error of networked microgrids $\Delta N_D^T$ follows normal distribution, i.e., $\Delta N_D^T \sim N (\mu, \sigma^2)$, where $\sigma^2$ can be easily calculated based on the result of (24). With these two modifications, the resiliency-constrained scheduling model of single microgrid has been adapted to handle the resiliency-constrained scheduling of networked microgrids.

IV. CASE STUDIES

In order to test the proposed networked microgrids scheduling strategy with chance-constrained islanding capability, we build a test system by connecting 3 modified ORNL Distributed Energy Control and Communication (DECC) lab microgrid on the same bus like Fig. 1. The 3 microgrids are identical. All parameters for generators, forecast wind power, PV power and demand as well as the day-ahead market prices can be found in [7]. The forecast errors of wind power and PV power are assumed to be Gaussian distribution with zero mean and 15% of standard deviation. The demand forecast error is assumed to be Gaussian distribution with zero mean and 3% of standard deviation. The analysis is conducted for a 24-hour scheduling horizon and each time interval is set to be one hour. All numerical simulations are coded in MATLAB and solved using the MILP solver CPLEX 12.2. With a pre-specified duality gap of 0.1%, the running time of each case is less than 10 seconds on a 2.66 GHz Windows-based PC with 4 G bytes of RAM.

A. Comparing Cost of Networked Microgrids and Independent Microgrids under the Same PSI

In order to show the benefit of networked microgrids, the total operating cost of networked microgrids and independent microgrids under the same resiliency requirements, PSI$_{req}$, are compared in Fig. 2. As can be seen, the operating costs of networked microgrids are always lower than that of independent microgrids under the same resiliency requirements. As the resiliency requirement PSI$_{req}$ increases, the economic benefit of networked microgrids becomes more significant.
The economic benefit of networked microgrids gets smaller as the microgrids are more correlated, i.e., the correlation coefficients between different microgrids increase. Nevertheless, the economic benefit of networked microgrid is validated.

B. Comparing PSI of Networked Microgrids and Independent Microgrids under the Same Cost

In order to show the benefit of networked microgrids in improving system resiliency, the cost by networked and independent microgrids with different levels of PSI requirements are compared in Fig. 3. As can be seen, under the same operating cost, the networked microgrids always have higher resiliency. This effect is much more obvious when the microgrids are less correlated. This clearly validates the resiliency benefit of networked microgrids.

V. CONCLUSIONS

In this paper, we modified the resiliency-constrained scheduling model of single microgrid to handle the case of networked microgrids. The model explicitly defines the resiliency of a microgrid and networked microgrids considering islanding situations and forecast uncertainties. Numerical simulations validated the benefit of networked microgrids in the aspect of economics and resiliency comparing with independent microgrids. In addition, the impact of correlation coefficients among the renewable generation and load of adjacent microgrids has been studied as well.

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