Microgrid Planning Under Uncertainty

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***Abstract*—This paper presents a model for the microgrid planning problem with uncertain physical and financial information. The microgrid planning problem investigates the economic viability of microgrid deployment and determines the optimal generation mix of distributed energy resources (DERs) for installation. Net metering is considered for exchanging power with the main grid and lowering the cost of unserved energy and DER investments. A robust optimization approach is adopted for considering forecast errors in load, variable renewable generation, and market prices. The microgrid islanding is further treated as a source of uncertainty. The microgrid planning problem is decomposed into an investment master problem and an operation subproblem. The optimal planning decisions determined in the master problem are employed in the subproblem to examine the optimality of the master solution by calculating the worst-case optimal operation under uncertain conditions. Optimality cuts sent to the master problem will govern subsequent iterations. Numerical simulations exhibit the effectiveness of the proposed model and further analyze the sensitivity of microgrid planning results on variety levels of uncertainty.**

***Index Terms*—Microgrid planning, real-time market price, distributed energy resource, robust optimization, uncertainty.**

I. NOMENCLATURE

Indices

b	Index for hour
ch	Superscript for energy storage charging mode
dch	Superscript for energy storage discharging mode
g	Superscript for uncertain renewable generation
h	Index for day
i	Index for DERs
l	Superscript for uncertain load
p	Superscript for uncertain market price
t	Index for year
$\wedge$	Index for calculated/given variables
$\sim$	Index for forecasted parameters

Sets

D	Set of dual variables
G	Set of dispatchable units
P	Set of primal variables
S	Set of energy storage systems
U	Set of uncertain parameters
W	Set of nondispatchable units

Parameters

c	Generation price for dispatchable units
CC	Annualized investment cost of generating units
CE	Annualized investment cost of storage – energy
CP	Annualized investment cost of storage – power
$C^{\max}$	Rated capacity of energy storage systems
d	Discount rate
D	Load demand
K	Large positive constant
$P^{\max}$	Rated power of DERs
$P_M^{\max}$	Flow limit between microgrid and the main grid
κ	Coefficient of present-worth value
ρ	Market price
v	Value of lost load (VOLL)
η	Energy storage efficiency
Γ	Limit on uncertainty option

Variables

LS	Load curtailment
P	DER output power
P_M	Main grid power
Q	Total operation cost
u	Auxiliary binary variables for uncertain parameters
x	DER investment state
z	Microgrid deployment state
Λ	Projected operation cost in the investment problem
$\lambda, \pi, \vartheta, \mu, \psi, \xi, \theta$	Dual Variables

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I. INTRODUCTION

THE high investment cost of the microgrid is a major obstacle in widespread and rapid deployment of this viable technology. Microgrids, which were initially introduced to streamline the operation and control of a large number of distributed energy resources (DERs) in distribution networks, offer unprecedented economic and reliability benefits to electricity consumers [1]-[10]. These benefits, however, must be scrutinized and compared with the microgrid investment cost for ensuring a complete return on investment and further justify microgrid deployments [11]. An accurate assessment of microgrid economic benefits is a challenging task due to significant uncertain data involved in the assessment. Moreover, some of the assessment results such as reliability improvements are difficult to comprehend for consumers when represented in supply availability terms. Thus, efficient planning models are required for ensuring the economic viability of microgrid deployments and further justifying investments based on cost-worth analyses in uncertain conditions.

Although the microgrid optimal operation and control has been extensively studied in the literature, the research on microgrid roadmaps for investment planning is limited. The study in [12] proposes a model to determine optimal combinations of renewable and conventional energy resources in microgrids and further analyzes the effect of emission tax on distributed system planning results. The errors in forecasting diesel fuel prices and average wind speed are considered by specifying sensitivity variables. The study in [13] investigates the application of DERs in microgrids in lieu of conventional generation and transmission planning. It is shown in the study that a coordinated and market-based approach to the deployment of microgrids would make the most out of emerging microgrid planning alternatives. The study in [14] investigates the optimal design and the planning of hybrid microgrids by taking into account emission caps and lifecycle costs of renewable energy resources. The study concludes that a mix of diesel and renewable sources in microgrids offers the lowest net present cost and a small carbon footprint, when compared to stand-alone diesel-based microgrids. The study further suggests that additional analyses are required to address mixed options based on renewable generation, because of high initial capital costs. The study in [15] proposes a two-stage multi-objective microgrid planning model for identifying the optimal region for microgrid installations and determining locations and sizes of a specified number of distributed generation units within the microgrids. The study in [16] presents a method for optimally siting and sizing distributed generation units in microgrids which is based on stipulated reliability criteria. The study develops a technique based on simulated annealing for determining the optimal locations and sizes of distributed generation units in a microgrid, given the network configuration and the heat and power requirements at various load points. The study in [17] offers an optimal microgrid deployment approach with respect to locations, capacity sizes, and types of DERs. Optimal DER locations are obtained based on the loss sensitivity index at each bus. The optimal size and combination is obtained for maximizing the benefit-to-cost ratio, using the particle swarm optimization technique, and satisfying the load point reliability index. The study in [18] investigates the microgrid generation expansion planning considering the low carbon economy. A matrix real-coded genetic algorithm is applied for expansion planning, and the study concluded that the proper utilization of wind and solar energy in microgrids could limit carbon emissions. The study in [19] presents a two-stage optimal planning and design method for microgrids with a combined utilization of cooling, heat, and power. The optimal objective in that study is to simultaneously minimize the total net present cost and carbon dioxide emission in microgrids. The study in [20] presents an overall review of the modeling, planning, and energy management of combined cooling, heating, and power in microgrids. The study in [21] explores new applications of agent-based simulations for exploiting renewable energy resources in microgrids. A bi-layer multi-agent microgrid planning model is proposed to maximize microgrid payoffs and to alleviate environmental obligations in energy markets. A co-optimized microgrid-based power system expansion planning is proposed in [22]. The proposed problem in [22] is solved from a system operator's point of view.

It is evident that the prior work on microgrid planning is rather limited and the existing studies often overlook some important factors in the planning process, such as data uncertainty. This paper aims at addressing the need for efficient and viable microgrid planning models. The applications of accurate forecasting techniques in microgrid planning models would supply sufficient local resources for microgrid islanding and the economic utilization of available resources in grid-connected modes. The accurate data forecasting, however, is a formidable task as the planning data are subject to a variety of uncertainties. The uncertain data include forecast errors for loads, variable renewable generation, market prices, and islanding incidents [23]-[27].

The rest of the paper is organized as follows. Section II introduces uncertain variables in microgrid planning. Sections III and IV respectively present the model outline and formulation of the proposed microgrid planning problem. Section V provides numerical simulations for a test microgrid. The discussion on the proposed model and conclusions are provided in Sections VI and VII, respectively.

II. Uncertain Variables in Microgrid Planning

The long-term microgrid load forecast is a major source of uncertainty. The fixed load could be forecasted with an acceptable accuracy. The flexible load, on the other hand, cannot be easily forecasted as it depends on variations in hourly prices, weather conditions, and consumers' decisions.

Variable renewable generation is another source of uncertainty. A high degree of renewable energy resources, commonly wind and solar energy, are utilized in microgrids that would produce a variable power. The availability of variable renewable generation typically does not follow a repetitive pattern in the daily operation of microgrids. The accurate forecasting of variable generation is challenging as it highly depends on site and weather conditions.

The market price forecast also implicates a high degree of error as several uncertain factors are involved in the forecasting process, including offers by generation companies, transmission network congestion and losses, and consumer participation with ability to respond to market prices. The market price (i.e., the real-time electricity price at the microgrid point of common coupling) is the most significant source of uncertainty in the microgrid planning problem as it considerably impacts the commitment and dispatch of DERs.

The last major type of uncertainty is the microgrid islanding. A microgrid would switch to an islanded mode when there is a disturbance at the main grid distribution network. The microgrid would be resynchronized with the utility system when the disturbance is removed. The time and duration of such disturbances, however, are not known to microgrids. Although microgrids are infrequently switched to the islanded mode, there could be significant social cost savings and load point reliability enhancements offered by microgrids during major outages (such as hurricanes) which would justify the islanding design as part of microgrid planning decisions.

In this paper, a microgrid planning model considering prevailing forecast errors in load, variable renewable generation, and market prices, as well as islanding uncertainty is proposed. The planning problem objective aims at ensuring the economic viability of microgrid deployment and determining the optimal mix of DERs in the microgrid. The microgrid economic deployment is examined in this study by analyzing whether microgrid payoff would recover investment cost. The proposed robust optimization model analyzes the worst-case solution, considering the potential uncertainties, for the optimal microgrid operation. The proposed model utilizes uncertainty intervals as opposed to distribution functions employed in stochastic optimization methods. The size of the microgrid planning model, with uncertainties, is modestly larger than that of the deterministic model, which can be solved efficiently by available computing tools.

III. Microgrid Planning Problem Model Outline

Microgrid DERs require a higher investment cost compared to conventional energy resources. However, DERs could provide a less expensive energy compared to the energy purchased from the main grid, in particular in peak hours when the market price is high. Thus, the microgrid could significantly benefit from generating power at peak hours to supply local loads and selling the excess power to the main grid. The energy storage system would also assist in promoting this objective as it could be charged at low-price hours and discharged at high price hours. The microgrid would increase the supply reliability of local loads in case of main grid disturbances. If there is an outage in the main grid, the load supply might be interrupted for maintaining the system operational feasibility (i.e., the load would be curtailed). However, islanding capability of the microgrid ensures that local loads would be supplied even if the main grid power is not available. The economic benefits from selling back the excess power to the main grid plus monetized reliability improvements represent the microgrid revenue. The microgrid economic viability is ensured when the microgrid total revenue during the planning horizon surpasses the investment cost.

A multiple time-scale analysis is performed, comprising the microgrid long-term investment and short-term operation, for ensuring economic viability of the microgrid deployment. Fig. 1 depicts the flowchart of the proposed microgrid planning model where the original planning problem is decomposed to an investment master problem and an operation subproblem. The investment decisions, i.e., the least cost DER generation mix that ensure a seamless islanding, are determined in the investment master problem. The investment plan is employed in the operation subproblem for finding the optimal schedule of installed DERs while considering energy transfer with the main grid. A robust optimization approach is employed for integrating uncertainties of load, variable renewable generation, and market price forecasts, as well as the microgrid islanding, to the operation subproblem [28]. The robust optimization finds out the worst-case optimal operation of the microgrid under prevailing uncertainties.

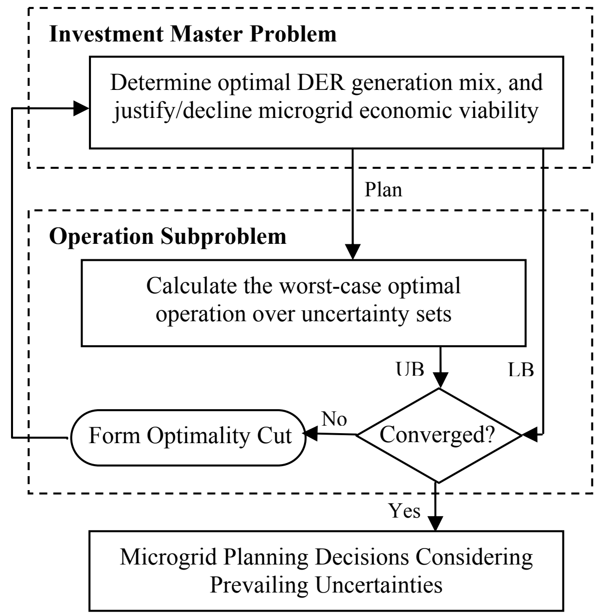

Fig. 1 Flowchart of the microgrid planning model with uncertain parameters

The solution convergence is examined based on the proximity of a lower bound (calculated in the investment master problem) and an upper bound (calculated in the operation subproblem) of the original planning problem. If not converged, the optimality cut generated in the operation subproblem will be sent back to the investment master problem for revising the current plan. The iterative process continues until the convergence criterion is met and the solution is proven optimal. If the microgrid deployment is not economical, i.e., the microgrid revenue does not exceed the investment cost, the microgrid would not be deployed in the investment master problem. In this case all DER investment decisions would be zero, hence the operation subproblem would find the cost of supplying local loads from the main grid for the entire planning horizon. The investment master problem is solved annually while the operation subproblem is solved hourly for each day of the planning horizon. The hourly analysis of the operation subproblem permits an accurate modeling and scheduling of microgrid components.

Data uncertainty is addressed by assuming that uncertain data belong to bounded and convex uncertainty sets. Each uncertain parameter has a known nominal value, which is obtained from the forecast, and expands around an associated range of uncertainty. The range of uncertainty defines an interval within which the uncertain parameter is expected to lie within a specified level of confidence. The robust optimization will find the worst-case optimal operation solution as uncertain parameters vary within their associated uncertainty intervals. The worst-case solution is obtained by maximizing the minimum value of the operation subproblem objective over uncertainty sets. The obtained complex problem is further converted to a tractable problem using the duality theory. Uncertainties will impact the investment master problem solution via optimality cuts formed in the operation subproblem. A limit on uncertainty option is added to the model for limiting the number of uncertain data that can take their worst-case values and further allowing the microgrid planner to control the solution degree of conservatism.

Although several components of the distribution network must be upgraded to install the microgrid, only the investment cost related to DERs is considered in this paper as it represents the largest portion of the microgrid investment cost. Costs associated with distribution network upgrades, installation of smart switches, sensors and measurement devices, and deployment of master and local controllers are overlooked, since these costs could be added as a constant to the objective of the microgrid planning problem.

IV. Microgrid Planning Problem Formulation

The objective of the microgrid planning problem (1) includes the DER investment cost, microgrid operation cost, and the cost of unserved energy.

$$\begin{aligned}\mathit{Planning\,Cost} = &\sum_t \sum_{i\in\{\mathrm{G,W}\}} \kappa_t CC_{it} P_i^{\max} x_i \\ &+\sum_t \sum_{i\in \mathrm{S}} \kappa_t (CP_{it} P_i^{\max} + CE_{it} C_i^{\max}) x_i \\ &+\sum_t \sum_h \sum_b \sum_{i\in \mathrm{G}} \kappa_t c_i P_{ibht} \\ &+\sum_t \sum_h \sum_b \kappa_t \rho_{bht} P_{M,bht} \\ &+\sum_t \sum_h \sum_b \kappa_t v_{bht} LS_{bht}\end{aligned} \tag{1}$$

The investment cost of generating units (dispatchable and nondispatchable) is a function of their generating capacity. The investment cost of energy storage systems is a function of the rated power and rated energy storage capacity. The microgrid operation cost includes that of DERs in the microgrid plus the cost of energy purchase from the main grid. The generation cost of nondispatchable units and energy storage systems are assumed to be zero. A single-step price curve is considered for dispatchable units. The cost of energy purchase is defined as the amount of purchased energy times the market price at the point of common coupling. The main grid power P_M would be negative if the microgrid is exporting its excess power to the main grid (paid at market price). The cost of unserved energy, which represents the microgrid reliability, is defined as the load curtailment quantity times the value of lost load (VOLL). VOLL is the energy price for compensating curtailed consumers, which depends on several factors including the types of consumers, quantities and durations of curtailments, and the time of outages. A higher VOLL corresponds to more critical loads [29]-[30]. The objective is evaluated in terms of discounted costs, where discount rates are incorporated in the present-worth cost components, i.e., $\kappa_t = 1/(1+d)^{t-1}$.

In (1), investment costs are defined annually while operation costs are calculated hourly in the planning horizon. The microgrid planning problem is decomposed to an investment master problem and an operation subproblem as discussed in the following:

A. Investment Master Problem

The investment master problem determines the optimal DER generation mix for installation by minimizing the investment cost (2). The first two terms in the objective represent DER investment costs. The last term in the objective is the projected operation cost that will be determined via the optimality cuts formed in the operation subproblem.

$$\begin{aligned}\min &\sum_t \sum_{i\in\{\mathrm{G,W}\}} \kappa_t CC_{it} P_i^{\max} x_i \\ &+\sum_t \sum_{i\in \mathrm{S}} \kappa_t (CP_{it} P_i^{\max} + CE_{it} C_i^{\max}) x_i + \sum_t \kappa_t \Lambda_t\end{aligned} \tag{2}$$

The salient feature of the microgrid is its capability to be islanded from the main distribution network in the case of main grid disturbances. Therefore, the installed dispatchable generation capacity at microgrid must be larger than its annual peak load (3). A microgrid deployment binary variable *z* is employed in (4) to determine whether or not the microgrid is installed (the binary variable is set to one for installation, otherwise zero). A zero value for *z* relaxes (3), otherwise, (3) is added which would require an installed generating capacity larger than the annual peak load. The annual peak load is determined considering the available load adjustment options, including load curtailment and shifting, which would not result in consumer inconvenience.

$$D_t^{\max} - \sum_{i\in\{\mathrm{G,W,S}\}} P_i^{\max} x_i \le K(1-z) \tag{3}$$

$$x_i \le z \le \sum_i x_i \tag{4}$$

If the microgrid deployment is deemed to be uneconomical, the binary variables will be zero and the investment master problem will only consider the cost of supplying local loads entirely from the main grid.

B. Operation Subproblem

The operation subproblem for each planning year *t* is defined in (5)-(12).

$$\begin{aligned}\max_{\mathrm{U}} \min_{\mathrm{P}} &\sum_h \sum_b \sum_{i\in \mathrm{G}} c_i P_{ibht} + \sum_h \sum_b \rho_{bht} P_{M,bht} \\ &+\sum_h \sum_b v_{bht} LS_{bht}\end{aligned} \tag{5}$$

$$\sum_{i\in\{\mathrm{G,W}\}} P_{ibht} + \sum_{i\in \mathrm{S}} (P_{ibht}^{dch} - P_{ibht}^{ch}) + P_{M,bht} + LS_{bht} = D_{bht} \quad \forall b, \forall h \tag{6}$$

$$-P_M^{\max} u_{M,bht} \le P_{M,bht} \le P_M^{\max} u_{M,bht} \qquad \forall b, \forall h \tag{7}$$

$$0 \le P_{ibht} \le P_i^{\max} \hat{x}_i \qquad \forall i \in \mathrm{G}, \forall b, \forall h \tag{8}$$

$$P_{ibht} = \hat{P}_{ibht} \hat{x}_i \qquad \forall i \in \mathrm{W}, \forall b, \forall h \tag{9}$$

$$0 \le P_{ibht}^{dch} \le P_i^{dch,\max} \hat{x}_i \qquad \forall i \in \mathrm{S}, \forall b, \forall h \tag{10}$$

$$0 \le P_{ibht}^{ch} \le P_i^{ch,\max} \hat{x}_i \qquad \forall i \in \mathrm{S}, \forall b, \forall h \tag{11}$$

$$0 \le \sum_{k\le b} (P_{ikht}^{ch} - P_{ikht}^{dch} / \eta_i) \le C_i^{\max} \hat{x}_i \qquad \forall i \in \mathrm{S}, \forall b, \forall h \tag{12}$$

$$0 \le LS_{bht} \le D_{bht} \qquad \forall b, \forall h \tag{13}$$

The objective of the operation subproblem is to minimize the microgrid operation cost, i.e., cost of local generation, cost of energy purchases from the main grid, and the cost of unserved energy. The objective is maximized over uncertainty sets to achieve the worst-case microgrid optimal operation solution.

The power balance equation (6) ensures that the sum of power generated by DERs (i.e., dispatchable and nondispatchable units, and energy storage systems) and power from the main grid matches the hourly load. The net output power of the energy storage can be positive (discharging), negative (charging) or zero (idle). The main grid power can be positive (import), negative (export) or zero. The power transfer with the main grid is limited by flow limits of the line connecting the microgrid to the main grid (7). This constraint also considers a binary parameter for the outage of this line which represents the microgrid islanding. The dispatchable unit generation is subject to generation capacity limits (8). The nondispatchable unit generation is obtained based on the forecast (9). The energy storage output power is subject to charging and discharging limits depending on its mode (10)-(11). The energy storage state of charge (SOC) is calculated based on the amount of charged/discharged power and the energy storage efficiency, and is further restricted with capacity limits (12). Finally, the hourly load curtailment is restricted to participating loads (13). The distribution network congestion is neglected as line flows are relatively small.

The complex objective function makes it challenging to solve the problem. So, the dual problem of the inner minimization problem is combined with the outer maximization problem. The proposed problem with dual variables and uncertain parameters is given as follows:

$$\begin{aligned}\max_{\mathrm{U,D}} & \sum_h \sum_b \lambda_{bht} D_{bht} + \sum_h \sum_b (\mu_{bht}^- + \mu_{bht}^+) P_M^{\max} u_{bht} \\ & + \sum_h \sum_b \sum_{i\in \mathrm{W}} \vartheta_{ibht} \hat{P}_{ibht} \hat{x}_i + \sum_h \sum_b \sum_{i\in \mathrm{G}} \pi_{ibht} P_i^{\max} \hat{x}_i \\ & + \sum_h \sum_b \sum_{i\in \mathrm{S}} \psi_{ibht}^{dch} P_i^{dch,\max} \hat{x}_i + \sum_h \sum_b \sum_{i\in \mathrm{S}} \psi_{ibht}^{ch} P_i^{ch,\max} \hat{x}_i \\ & + \sum_h \sum_b \sum_{i\in \mathrm{S}} \xi_{ibht}^{+} C_i^{\max} \hat{x}_i \\ & + \sum_h \sum_b \theta_{bht} D_{bht}\end{aligned} \tag{14}$$

$$\lambda_{bht} + \pi_{ibht} \le c_i \qquad \forall i \in \mathrm{G}, \forall b, \forall h \tag{15}$$

$$\lambda_{bht} + \vartheta_{ibht} = 0 \qquad \forall i \in \mathrm{W}, \forall b, \forall h \tag{16}$$

$$\lambda_{bht} + \psi_{ibht}^{dch} - \sum_{k\ge b} (\xi_{ikht}^{+} - \xi_{ikht}^{-}) / \eta_i \le 0 \qquad \forall i \in \mathrm{S}, \forall b, \forall h \tag{17}$$

$$-\lambda_{bht} + \psi_{ibht}^{ch} + \sum_{k\ge b} (\xi_{ikht}^{+} - \xi_{ikht}^{-}) \le 0 \qquad \forall i \in \mathrm{S}, \forall b, \forall h \tag{18}$$

$$\lambda_{bht} + (\mu_{bht}^{+} - \mu_{bht}^{-}) = \rho_{bht} \qquad \forall b, \forall h \tag{19}$$

$$\lambda_{bht} + \theta_{bht} \le v_{bht} \qquad \forall b, \forall h \tag{20}$$

where λ, μ, π, υ, ψ^{dch}, ψ^{ch}, ξ and θ are dual variables of constraints (6)-(13), respectively. Considering polyhedral uncertainty sets, and assuming that worst-case solution occurs at extreme points of uncertain parameters, loads and variable renewable generation are represented in (21) and (22), respectively [31]. The market price uncertainty is considered in (23).

$$D_{bht} = \tilde{D}_{bht} - \underline{D}_{bht} \underline{u}_{bht}^{l} + \overline{D}_{bht} \overline{u}_{bht}^{l} \quad \forall b, \forall h \tag{21}$$

$$P_{ibht} = \tilde{P}_{ibht} - \underline{P}_{ibht} \underline{u}_{ibht}^{g} + \overline{P}_{ibht} \overline{u}_{ibht}^{g} \quad \forall i \in \mathrm{W}, \forall b, \forall h \tag{22}$$

$$\tilde{\rho}_{bht} - \underline{\rho}_{bht} \underline{u}_{bht}^{p} \le \rho_{bht} \le \tilde{\rho}_{bht} + \overline{\rho}_{bht} \overline{u}_{bht}^{p} \qquad \forall b, \forall h \tag{23}$$

where inserted bars in each row represent upper/lower bounds of parameters. To prevent simultaneous occurrence of extreme points, one binary variable can be set at one at any hour, i.e., $\underline{u}_{ibht}^{g} + \overline{u}_{ibht}^{g} \le 1$, $\underline{u}_{bht}^{l} + \overline{u}_{bht}^{l} \le 1$, $\underline{u}_{bht}^{p} + \overline{u}_{bht}^{p} \le 1$.

The limit on uncertainty option is imposed to limit the freedom on binary variables associated with a specific type of uncertainty. The limit on uncertainty option adjusts the solution robustness against uncertainties by limiting the maximum number of uncertain parameters which can reach their bounds. For example, a limit on uncertainty option of 1000 allows a maximum of 1000 binary variables associated with that type of uncertainty to obtain a value of 1, hence the uncertain parameter will be at its bounds (either upper or lower) in the corresponding hours. In the remaining hours the binary variables will be zero, therefore forecasted values will be used. Using this limit, the solution degree of conservatism would be controlled which further enables application to a variety of microgrid developers based on their risk-aversion. Three levels of risk-aversion could be considered: conservative, moderate, and aggressive. A larger limit on uncertainty option translates into a more robust solution against uncertainties, and accordingly a larger investment cost (i.e., a conservative solution). A smaller limit on uncertainty option, however, results in a less robust solution, as it considers fewer uncertainties in the planning process, and thus represents an aggressive developer. A moderate developer considers some level of uncertainty in between. A conservative solution will result in a larger investment cost, however, the cost of unserved energy will be reduced. The investment cost of an aggressive solution will be lower, while the cost of unserved energy will be increased as the possibility of losing supply of power in islanding incidents is increased. The uncertainty options for variable renewable generation, load, market prices, and islanding are given in (24)-(27), respectively.

$$\sum_h \sum_b (\underline{u}_{ibht}^{g} + \overline{u}_{ibht}^{g}) \le \Gamma_{it}^{g} \qquad \forall i \in \mathrm{W} \tag{24}$$

$$\sum_h \sum_b (\underline{u}_{bht}^{l} + \overline{u}_{bht}^{l}) \le \Gamma_{t}^{l} \tag{25}$$

$$\sum_h \sum_b (\underline{u}_{bht}^{p} + \overline{u}_{bht}^{p}) \le \Gamma_{t}^{p} \tag{26}$$

$$\sum_h \sum_b u_{M,bht} \le \Gamma_{t}^{M} \tag{27}$$

The addition of binary variables to the planning problem would create a nonlinear optimization problem. However, bilinear terms are converted to linear terms [32]. The solution would provide an upper bound of the original problem as in (28):

$$UB = \sum_{t} \sum_{i \in \{G,W\}} \kappa_t CC_{it} P_i^{\max} \hat{x}_i + \sum_{t} \sum_{i \in S} \kappa_t (CP_{it} P_i^{\max} + CE_{it} C_i^{\max}) \hat{x}_i + \sum_{t} \sum_{h} \sum_{b} \sum_{i \in G} \kappa_t c_{it} \hat{P}_{ibht} + \sum_{t} \sum_{h} \sum_{b} \kappa_t \rho_{bht} \hat{P}_{M,bht} + \sum_{t} \sum_{h} \sum_{b} \kappa_t v_{bht} \hat{L}S_{bht} \quad (28)$$

The solution of the master problem offers a lower bound. The final solution of the original problem is found when the difference between two bounds is less than a threshold. If the convergence criterion is not met, the optimality cut (29) is formed and added to the investment master problem in the next iteration.

$$\Lambda_t \geq \hat{Q}_t + \sum_{h} \sum_{b} \sum_{i \in G} \pi_{ibht} P_i^{\max} (x_i - \hat{x}_i) + \sum_{h} \sum_{b} \sum_{i \in W} \vartheta_{ibht} \hat{P}_{ibht} (x_i - \hat{x}_i) + \sum_{h} \sum_{b} \sum_{i \in S} (\psi_{ibht}^{dch} P_i^{dch,\max} + \psi_{ibht}^{ch} P_i^{ch,\max} + \xi_{ibht}^{+} C_i^{\max})(x_i - \hat{x}_i) \quad (29)$$

where $\hat{Q}$ is the calculated objective value of the operation subproblem, i.e., (14). The optimality cut (29) includes three terms associated with the installation of dispatchable units, nondispatchable units, and energy storage systems. This cut indicates that the solution of the revised investment plan could lead to a more economical solution of the operation subproblem.

V. Numerical Examples

A microgrid is to be installed for a group of electricity consumers with a peak annual load demand of 8.5 MW. The set of candidates includes eleven DERs (i.e., six dispatchable units, two nondispatchable units, and three energy storage systems) as represented in Tables I-III. Nondispatchable units 1 and 2 represent wind and solar generators, respectively [33]-[35]. Energy storage efficiency is considered to be 90% for all candidates. The load, variable renewable generation, and market price, are forecasted based on historical data obtained from the IIT Campus Microgrid [34]. Load, market price, and renewable generation forecast errors are ±10, ±20, and ±20, respectively. Nine hours of islanding per year is considered. The impact of islanding hours on planning results is further investigated in the following case studies. The planning horizon is 20 years. Following cases are studied:
Case 1: Microgrid planning with forecasted average values
Case 2: Microgrid planning with uncertainty in load and renewable generation forecasts
Case 3: Microgrid planning with uncertainty in market price
Case 4: Impact of islanding on microgrid planning
Case 5: Impact of forecast errors on microgrid planning

Table I
Dispatchable Units Characteristics

Unit No.	Rated Power (MW)	Cost Coefficient ($/MWh)	Annualized Investment Cost ($/MW)
1	5	90	50000
2	5	90	50000
3	3	70	70000
4	3	70	70000
5	2	60	100000
6	2	60	100000

Table II
Nondispatchable Units Characteristics

Unit No.	Rated Power (MW)	Cost Coefficient ($/MWh)	Annualized Investment Cost ($/MW)
1	2	0	120000
2	2	0	180000

Table III
Energy Storage Systems Characteristics

Storage No.	Rated Power (MW)	Rated Energy (MWh)	Annualized Investment Cost – Power ($/MW)	Annualized Investment Cost – Energy ($/MWh)
1	1	6	60000	30000
2	2	6	30000	30000
3	3	6	20000	30000

Case 1: The microgrid planning problem is solved using forecasted average values for hourly load, renewable generation, and market price. The islanding is considered within nine hours in a planning year. The microgrid planning solution would install dispatchable units 3-6, nondispatchable unit 2, (i.e., the solar unit), and energy storage 3. The total planning cost is $38,774,994. The cost of purchasing energy from the main grid in case the microgrid was unavailable would be $39,105,693 which is larger than the total planning cost. The difference in cost indicates that the microgrid deployment is economical and the DER investments will be recompensed from revenues.

The DER planning results show the installation of dispatchable units 5 and 6 with large capital investments is more economical than that of units 1 and 2 with considerably lower capital investments. The reason is that the planned units offer a less expensive power generation, and when compared with hourly market prices, are better options than purchasing power from the main grid. In addition, the excess power generated by dispatchable units 5 and 6 could be sold back to the main grid. Dispatchable units 3 and 4 offer lower benefits than those of units 5 and 6; however, these two units are installed for guaranteeing a reliable and seamless islanding. The selection of nondispatchable unit 2 with a high investment cost, as compared to nondispatchable unit 1, suggests that the selection between renewable units depends mostly on the generation capacity factor rather than investment costs. The two renewable units produce energy similarly on an annual basis; however, the generation pattern of the solar unit coincides with load and market price variations. During the day, when the hourly market price is higher, the solar energy is available to reduce the net load supplied by the expensive thermal energy. However, the wind energy is available mostly at early morning hours when the market price is relatively low.

The energy storage 3 has a higher rated power than the other two candidates; therefore it can shift a larger sum of load to low price hours. In addition, a higher rated storage is helpful for islanding since it reduces the need for utilizing local generation. The energy storage is mostly charged and discharged once in each day, mainly due to the monotonically increasing market prices from early morning off-peak hours to late evening peak hours.

This study suggests that a) when selecting microgrid DERs, the operation cost plays a more important role than investment cost; b) solar energy is more favorable than wind energy for supplying the microgrid load as the solar unit operation cycle coincides with that of load and price variations; and c) energy storage systems with a higher rated power are more effective in satisfying economic goals.

Case 2: Considering load and renewable generation with forecast errors of ±10 and ±20, respectively, and a limit on uncertainty option of 1000 hours/year, the microgrid total planning cost will be increased by 1.75% from Case 1 to $39,454,447. This increase represents the cost of robustness that is paid to strengthen the microgrid against load and renewable generation uncertain variations. The solution suggests that an economic deployment of microgrid is achievable at higher costs when the data are not totally reliable. The DER investment is similar to that in Case 1. To analyze the sensitivity of uncertain variations on the optimal DER selection, this study is repeated for a variety of limits on uncertainty option for renewable generation. The result shows that with a limit on uncertainty option that is larger than 4000 hours/year none of the renewable units will be installed. The higher uncertainty in the utilization of renewable generation would make these units less attractive economically. This study exhibits that the installation of renewable energy resources greatly depends on the accuracy of forecasts.

At extreme points of uncertainty, the load is at its upper bound and the renewable generation is at its lower bound which offers the worst-case economic solution. This result is intuitively conceivable which can be perceived from the primal problem solution as well. Considering the primal problem, a higher load and a lower renewable generation would require a higher thermal generation for supplying the net load which will increase the microgrid operation cost. This conclusion points out that binary variables associated with lower bounds of uncertain loads and upper bounds of uncertain renewable generation could be set to zero and thus remove a significant number of binary variables at the solution stage. Accordingly, the computation burden could be less, running time could be smaller, and number of iterations could be lower.

Case 3: The market price forecast error with a limit on uncertainty option of 2000 hours/year, is considered in the microgrid planning problem in addition to load and renewable generation uncertainties. Despite uncertain load and renewable generation, market prices would choose either its upper bound or lower bound at different hours and would not set at one of the bounds for the entire planning horizon. A more robust solution is obtained compared to previous cases with an increased total planning cost of $42,451,534. The 9.48% increase in the planning cost from Case 1 is the cost of robustness against load, renewable generation, and market price uncertainties, while it ensures that the microgrid deployment is still economic and the initial investment will be paid back. In this case, more iterations are required to converge to an optimal solution (i.e., 10 iterations compared to 6 iterations in previous cases). Moreover, a different DER plan is obtained in which none of energy storage systems is selected and dispatchable unit 1 is installed instead of dispatchable units 4 and 6.

As the price forecast uncertainty increases, by increasing the limit on uncertainty option, the microgrid revenues become larger. When the main grid offers energy at a high price, the microgrid master controller has the option of utilizing local resources rather than purchasing power from the main grid. Thus, by increasing uncertainties in price forecasts, microgrid would be considered as a more economic and viable solution to supply local loads. In other words, the microgrid provides a hedging mechanism for local loads against high market prices.

Table IV compares the results in Cases 1-3. In all cases, the difference between the non-microgrid operation cost and the microgrid operation cost is larger than the DER investment cost. Thus, savings in the operation cost would ensure the return on investment.

TABLE IV
COMPARISON OF RESULTS IN CASES 1-3

Cases	Non-Microgrid Operation Cost ($)	Microgrid Costs ($)		
		Investment	Operation	Total
Case 1	39,105,693	23,683,416	15,091,578	38,774,994
Case 2	39,785,147	23,683,416	15,771,031	39,454,447
Case 3	43,124,191	17,012,031	25,439,503	42,451,534

Case 4: The impact of number of islanding hours is studied in this case by solving the microgrid planning problem for a variety of islanding hours. As the worst-case operation solution demonstrates, the islanding always occurs at times that results in the lowest cost of unserved energy, i.e., when the load is at its lowest. For islanding less than 7 hours/year, microgrid deployment is not economical, i.e., the microgrid revenue would not compensate the DER investment cost. However, as the number of islanding hours increases the microgrid deployment would be justified. The microgrid economic viability is justified for islanding of greater than or equal to 8 hours/year. Increasing the number of islanding hours significantly lowers the payback time. For 8 islanding hours/year the investment will be paid back in 20 years, while for 12 islanding hours/year this time would be reduced to 19. This is mainly due to the high cost of unserved energy which will not occur when the microgrid is deployed. This study shows that the microgrid, besides providing economic benefits by utilizing local resources, is a viable solution to consumers' reliability problems and would significantly reduce consumers' load curtailments. Moreover, it can be concluded that when the reliability of the system is high, i.e., the microgrid islanding hours are limited, the microgrid installation cost may outweigh its merits, hence the microgrid deployment would not be economical. Load criticality, which is represented by VOLL, also plays a critical role in the

studies and could potentially change the microgrid planning results.

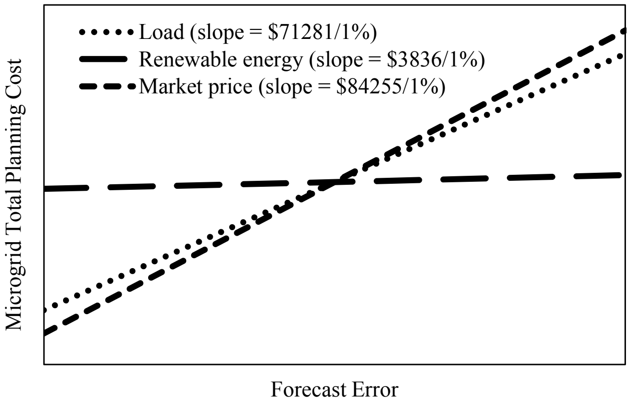

Fig. 2 Sensitivity of microgrid planning solutions to forecast errors; intersection is the initial forecast error (load forecast error = ±10%, renewable generation forecast error = ±20%, market price forecast error = ±20%)

Case 5: The sensitivity of microgrid planning solutions with respect to load, renewable generation, and market price forecast errors is further analyzed. Three cases are considered; in the first case the initially assumed forecast errors of renewable generation and market price, i.e., ±20%, are used while the load forecast error is changed with a step of ±1% to obtain load forecast error scenarios. The planning problem is accordingly solved for each scenario for obtaining sensitivity to load forecast errors. Similar studies are performed for the renewable generation and market price in the second and the third cases, respectively, to find respective sensitivities. Once calculated, the changes in the total planning cost are approximated with a constant-slope line in each case. The slope of each line represents the sensitivity of the total planning cost with respect to the changing parameter. The slopes of changes are calculated as $71,281, $3,836, and $84,255 per 1% change of load, renewable generation, and market price forecast errors, respectively. These lines are depicted in Fig. 2 in which the intersection represents the initially assumed forecast errors. The result advocates that the planning solution is more sensitive to market price forecast errors than the other two errors, mainly due to the impact of market prices on DER scheduling. The planning solution is considerably less sensitive to renewable generation forecast errors compared to the other two. The low impact of renewable generation forecasts errors on the microgrid planning solution is due to the fact that renewable generation represents a small portion of the generation mix in the microgrid, which is less than 14% of the total installed capacity in the studied test system. Therefore, even a large change in generation of these resources would not significantly change the results. Furthermore, renewable generation is variable, i.e., the power output is not always available and may reach zero for several hours during the scheduling horizon. Thus, the renewable generation could be much lower than the generation of a dispatchable unit with the same size. The investment plan is the same in all scenarios, however, as the renewable generation forecast error exceeds ±50% none of the nondispatchable units will be installed, since the investment cost of these units may outweigh the economic benefits stemmed from produced energy during the planning horizon.

VI. Discussions

Microgrids provide significant benefits for electricity consumers in terms of reliability and economy. However, the economic benefits of microgrids should be assessed to justify the large investment on DERs while considering various prevailing uncertainties in the planning process. Specific features of the proposed microgrid planning under uncertainty model are listed as follows:

- Decision on microgrid investment: The proposed model would determine whether the microgrid revenues would enable a return on the DER investment cost, and would further justify or decline the economic viability of the microgrid deployment.
- Optimal DER selection: The optimal DER generation mix to minimize the total planning cost is determined in the proposed model based on economic and reliability considerations, and for further enabling a seamless islanding.
- Inclusion of uncertainties: A robust optimization approach is adopted to incorporate the forecast errors in load, renewable generation, and market prices, as well as uncertainty in islanding incidents. Data uncertainty is addressed in the operation subproblem by assuming that uncertain parameters belong to bounded convex uncertainty sets and maximizing the minimum value of the objective over uncertainty sets.
- Time-scale considerations: The short-term operation and long-term investment problems are decoupled using a decomposition method. The short-term operation includes hourly operation of DERs and microgrid-main grid interactions, while the long-term problem incorporates decisions on DER investments. The two problems are linked via optimality cuts generated in the operation subproblem. The decomposition method further separates the uncertain physical and financial information with deterministic investment variables.
- Microgrid islanding consideration: A significant benefit of the microgrid deployment comes from its islanding capability, thus this feature is efficiently incorporated into the model. The improved reliability offered by microgrid islanding is translated into economic terms using VOLL. The obtained cost of unserved energy is included in the objective of the microgrid planning problem for reliability considerations.

VII. Conclusions

The high investment cost of DERs within the microgrid introduces a barrier in deployment of this technology by consumers/developers who are skeptical about return of their investment. In addition, the microgrid long-term revenues cannot be accurately determined as there exist forecast errors in load, renewable generation, and market prices. In this paper, a model for microgrid planning under uncertainty was proposed. The proposed model examined the economic deployment of the microgrid, by investigating if the microgrid revenue would pay off the investment, and accordingly determined the optimal DER generation mix to be deployed in the microgrid. The planning problem was decomposed into an investment master problem and an operation subproblem. Two problems were linked and coordinated via the Benders decomposition method. A robust optimization model was adopted to account for uncertain data. The robust model provided a solution that performs reasonably well even when the distribution of the uncertain data is not known. Numerical simulations on a practical microgrid demonstrated that by adjusting the limit on uncertainty option and tuning the solution robustness, a variety of solutions could be obtained.

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