Integrated Microgrid Expansion Planning in Electricity Market With Uncertainty

Aida Khayatian, *Student Member, IEEE,* Masoud Barati, *Member, IEEE,* and Gino J. Lim *Member, IEEE*

***Abstract*—This paper addresses the microgrid expansion planning (MEP) problem. In such a competitive electricity market, it will assist Community Microgrid (COMG) companies in deciding whether or not they should invest in microgrid installation. A two-stage stochastic optimization approach is proposed to eliminate the traditional centralized planning which has led to competition among COMGs, Generation Companies (GENCOs), and Transmission Companies (TRANSCOs) for power delivery. The objective of the two-stage stochastic programming model is to maximize the expected revenue from these three power companies while ensuring the cost-effectiveness and reliability of the power system under uncertain factors such as load growth and component outages. The proposed model is solved by decomposing the planning problem into two stages. The goal of the first stage is to maximize the profits of COMGs, GENCOs, and TRANSCOs; the second stage is to minimize short-term operation cost considering uncertainty to enhance the reliability of the system. Computational results from two IEEE test systems are presented to analyze the effectiveness of the proposed approach.**

***Index Terms*—Benders decomposition, component outages uncertainty, electricity market, microgrid expansion planning, rural electrification, two-stage stochastic mixed-integer programming.**

NOMENCLATURE

Indices:

$\wedge$	A symbol to indicate pre-determined variables.
b	Load block subscript index, $b = \{1, ..., NLB\}$, *NLB*: Number of seasons at each year.
C	Candidate unit or line superscript index.
E	Existing unit or line superscript index.
$(.)$	Power output/outage subscript indices: Generator (G), Line (L), Microgrid (M), and Imaginary unit (R), Bus (B).
i	Generation unit subscript index, $i = \{1, ..., NG\}$, *NG*: Number of units.
j	Transmission line subscript index, $j = \{1, ..., NL\}$, *NL*: Number of lines.
k	MG subscript index, $k = \{1, ..., NM\}$, *NM*: Number of MGs.
n	Bus or substation subscript index, $n = \{1, ..., NB\}$, *NB*: Number of substations.
s	Scenario subscript index, $s = \{1, ..., S\}$, *S*: Number of Scenarios.
t	Time subscript index, $t = \{1, ..., T\}$, *T*: Number of planning horizon years.
r	Iteration index.

Parameters:

ΔT_b	Time block duration.
c	Operational cost for imaginary unit (\$/MWh).
D	Total demand (MW).
$d(t)$	The present worth coefficient based on discount rate δ, $d(t) = (1+\delta)^{t-1}$.
$in_{(.)}$	Investment cost (\$/MW/year).
$ip_{(.)}$	Incentive payment (\$/MW/year).
$K_{(.)}$	Incidence matrix.
$mc_{(.)}$	Marginal operating cost (\$/MWh).
P_{DM}	Local demand in COMG (MW).
$P_{(.)}^{max}$	Maximum capacity (MW).
$re_{(.)}$	Obtained revenue from LMP and SMP (\$/MWh).
$SF(\hat{Y})$	Shift factor matrix based on power gird topology.
$U_{(.)}$	Availability status of components (G), (L), and (B).

Variables:

$\mathbf{P_G}$	Dispatched capacity of generation (MW).
$\mathbf{P_L}$	Transmission line flow (MW).
$\mathbf{P_M}$	Aggregated dispatched capacity of COMG (MW).
$\mathbf{P_R}$	Dispatched capacity of imaginary generation (MW).
$\mathbf{P_{EX}}$	Power exchange between MG and main grid (MW).
$\mathbf{S}$	Slack variables.
$\mathbf{X}, \mathbf{Y}, \mathbf{Z}$	Installation status of units, lines, and MGs.
$\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\pi}$	Dual variables.
$\boldsymbol{\lambda}, \boldsymbol{\mu}$	System lambda and shadow price.
φ	Total operational cost.

A. Khayatian and G. J. Lim are with the Department of Industrial Engineering, University of Houston, TX 77204 USA (e-mail: akhayatian@uh.edu; ginolim@uh.edu). M. Barati is with the Department of Electrical and Computer Engineering, Louisiana State University, LA, 70803 (e-mail: mbarati@lsu.edu).

I. INTRODUCTION

Grid modernization has increased attention in recent years, by revamping the traditional way of supplying and delivering electricity [1]. Many critical lifeline systems are dependent on electricity infrastructure, which is subject to an increase in extreme natural disasters and other major unexpected disruptions. Therefore, developing a new electric power system with the ability to provide reliable, economical, and environmentally friendly levels of power is essential. The traditional power system can be modernized by utilizing Microgrids (MG). An MG is an advanced technology that can improve power system reliability, resiliency, and sustainability. Deploying MGs with the ability to supply local loads is a desirable alternative to promote rural electrification, energy efficiency, and total cost saving of the system, as well as congestion reduction on transmission lines and distribution main feeders [2]. In the past, however, these realized abilities were rarely obvious in terms of quantifiable for power investors [3]. It motivates us to design a more practical and cost-effective power grid by utilizing MGs based on a capacity market mechanism. This mechanism provides real market price signals and incentive payment as a guide and encouragement for power investors. A community microgrid (COMG) integrates Distributed Energy Resources (DERs) into advanced power distribution grids. DERs are the smaller power resources include nondispatchable renewable generation such as the wind and solar units; and small scale dispatchable resources such as diesel generators, microturbines, and energy storage [4].

Although a significant amount of research has been reported in literature quantifying and optimizing the benefits of using an MG [5]–[9], only a few studies have been dedicated to developing an optimization model of the grid-connected MG investment in the power market. Some studies in microgrid planning have considered microgrids in islanded mode [7]–[9]. These studies have considered microgrid expansion planning (MEP) separately from generation expansion planning (GEP) and transmission expansion planning (TEP) in the power system [10]–[14]; However, power sectors are not separable in a vertically integrated utility system [15]–[19] and a modern power market includes generation units, transmission lines, and microgrids. Khodaei *et al.* [19] suggests a model that plans the deployment of MGs in the grid and considers the impact of integrated MEP with GEP and TEP under uncertainties while minimizing the total investment and operational costs. This paper has primarily focused on power expansion planning to minimize the total operation, investment, and load shedding costs of the system for MG investment as an alternative to traditional GEP and TEP problem in electric power grid. However, in reality, the owners of GENCOs, TRANSCOs, and COMGs make decisions on the new component deployment that can maximize their own profits in such a competitive electricity market [20], [21]. The location and capacity of each new MG depend on the financial sustainability of the individual investor's decision. The cost associated with implementing the investment of MG is a great concern to investors. The main motivation of this paper is to develop a new model for COMG investors to find optimal installation location, size, and time for MGs in the electricity market while maximizing their profits. Therefore, this paper enhances the long-term microgrid planning method presented in [5], [6], [19], [22] by explicitly addressing competitive capacity and operation of electricity market, and microgrid for rural electrification.

In this paper, a market-based planning framework is proposed to integrate MEP with coordinated GEP and TEP in a competitive environment. In the proposed coordinated framework, planner (ISO) maintains the system reliability in predefined acceptable level by reliability evaluation to determine if and when additional capacity is needed. The power grid including (static) network flows and grid injections is modeled with DC power flow. The DC power flow is computationally light within the scope of coordinated problems.

Due to the uncertainty of forecasted electrical loads and power system outages of substations, generation units, and transmission lines [23], [24], optimization of electric power over a planning time horizon is inherently a stochastic decision problem. In this regard, we provide a two-stage stochastic mixed-integer programming model to address both uncertainties. The resulting model, however, is not easily scalable to more realistic problem instances due to the binary variables in the optimization model. To overcome this issue, a three-phase algorithm is developed using Benders decomposition to account for long-term planning while maximizing the total profits and considering uncertainty impacts [25]–[27]. The proposed algorithm features a tradeoff between the gained profits and the level of reliability in the system.

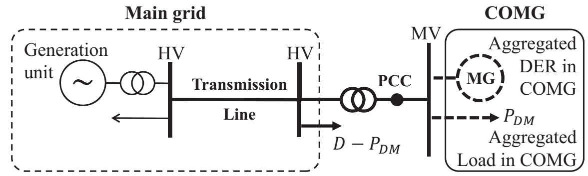

Fig. 1. Aggregated Community Microgrid architecture.

Major contributions of this paper include: 1) to present optimal market-based planning and operation of gird-connected microgrids; 2) to utilize correct and effective market-orinted price signals to plan power components in power grid based on the competitive electricity market; and 3) to quantify and optimize positive effects of deploying grid-connected microgrid on operating condition and rural electrification.

The rest of this paper is organized as follows. In section II, Community Microgrid model is explained. The mathematical formulations and the proposed solution method are discussed in section III. Section IV provides numerical studies to examine the efficiency of the proposed method. Section V concludes this paper with future research.

II. Community Microgrid Model

As shown a typical COMG structure in Fig. 1, the Department Of Energy (DOE) defines the COMG as a group of the aggregated load and aggregated DERs that act as a single controllable entity with respect to the grid at the Point of Common Coupling (PCC) [28], [29]. The DOE considers MG as an integrated energy system with the ability to operate in a grid connected mode or in an islanded mode. Our approach offers MGs interconnection at the Medium-Voltage level with the main grid at the High-Voltage level by taken into consideration the design without considering details of DERs in COMG. Another benefit of considering the interconnected MG is increasing revenue of the COMG by selling surplus electricity to the main grid. Therefore, a cetraint portion of the load demand at any bus with the connected MG can be supplied by the local MG, and the rest of the load demand will be supplied by conventional generation units through the main grid. P_{EX} in (1) shows the power exchange between MG k and the main grid. P_{EX} is positive, if MG k supplies its local demand and sends its excess power output to the main grid. Otherwise, it is negative.

$$P_{Mbks}(t) = P_{DMbks}(t) + P_{EXbks}(t) \qquad ,\forall k, b, s, t \tag{1}$$

III. Problem Formulation and Solution Methodology

Regarding Benders decomposition approach [25]–[27], we propose a practical optimization approach in which three optimization phases are solved in sequence to address "Investment Planning", "Feasibility Check on Reliability", and "Optimality Check on Operation Cost" as illustrated in Fig. 2.

A. Master Problem for Investment Planning

Investment planning aims to maximize the profits of each GENCO, TRANSCO, and COMG according to the installation location and capacity size. The investment status of generation units, transmission lines, and COMG units are determined in the master problem (MP) in Phase A. The incentive payment and revenue parameters on the objective function encourage all market investors to share more capacity in the system. How to determine and update these two parameters based on the reliability evaluation and the operation cost assessment for the system by the ISO in the first and second subproblem, respectively is explained. The corresponding optimization model is:

$$
\begin{aligned}
&\max I_G(P_G, X, re_G, ip_G) + I_L(P_L, Y, re_L, ip_L)\\
&+ I_M(P_M, Z, re_M, ip_M) - \varphi \qquad (2)\\
&S.t.\\
&0 \leq P^{E}_{Gbi}(t) \leq P^{E,max}_{Gi} \qquad ,\forall b, i, t\\
&0 \leq P^{C}_{Gbi}(t) \leq P^{C,max}_{Gi} X(t) \qquad ,\forall b, i, t\\
&0 \leq P_{Mbk}(t) \leq P^{max}_{Mk} Z(t) \qquad ,\forall b, k, t\\
&\left|P^{C}_{Lbj}(t)\right| \leq P^{C,max}_{Lj} Y(t) \qquad ,\forall b, j, t \qquad (3)\\
&X_i(t) \leq X_i(t+1) \qquad ,\forall i, t\\
&Y_j(t) \leq Y_j(t+1) \qquad ,\forall j, t\\
&Z_k(t) \leq Z_k(t+1) \qquad ,\forall k, t \qquad (4)
\end{aligned}
$$

The MP is formulated as a mixed-integer programming model. The objective function (2) maximizes the investors' profits by taking the total obtained income and subtracting the operational cost of the system (φ) in a short term system operation. Constraint set (3) enforces the production capacity limits of all components. Constraint set (4) preserves the status of installed components for the following years.

$$
\begin{aligned}
I_G(\boldsymbol{P_G}, \boldsymbol{X}, \boldsymbol{re_G}, \boldsymbol{ip_G}) &= \sum_{t,b,i} \frac{\Delta T_b(t)}{d(t)} [re^{E}_{Gbi}(t) P^{E}_{Gbi}(t)\\
&+ re^{C}_{Gbi}(t) P^{C}_{Gbi}(t) + ip_{Gbi}(t) X_i(t)] - \sum_{t,i} \frac{in_i(t) X_i(t)}{d(t)} \qquad (5)
\end{aligned}
$$

$$
\begin{aligned}
I_L(\boldsymbol{P_L}, \boldsymbol{Y}, \boldsymbol{re_L}, \boldsymbol{ip_L}) &= \sum_{t,b,j} \frac{\Delta T_b(t)}{d(t)} [re^{C}_{Lbj}(t) P^{C}_{Lbj}(t)\\
&+ ip_{Lbj}(t) Y_j(t)] - \sum_{t,j} \frac{in_j(t) Y_j(t)}{d(t)} \qquad (6)
\end{aligned}
$$

$$
\begin{aligned}
I_M(\boldsymbol{P_M}, \boldsymbol{Z}, \boldsymbol{re_M}, \boldsymbol{ip_M}) &= \sum_{t,b,k} \frac{\Delta T_b(t)}{d(t)} [re_{Mbk}(t) P_{Mbk}(t)\\
&+ ip_{Mbk}(t) Z_k(t)] - \sum_{t,k} \frac{in_k(t) Z_k(t)}{d(t)} \qquad (7)
\end{aligned}
$$

Functions (5)-(7) represent the obtained income of the strategic investors including the GENCOs, TRANSCOs and COMGs, respectively. The first and second terms in I_G represent the income of using existing and candidate units. The first term in I_L represents the income of using candidate lines. The third term in I_G and second term in I_L represent the rising income owed to obtained revenue from incentive payments for enhancing the system reliability at each iteration. The first term in I_M is the COMG's revenue of generating power by its DERs. The second term represents the generated incentive payment by the ISO to promote the COMGs for installing the new MG in grid buses. The last term in I_G, I_L, and I_M is the installation cost of the units, lines, and MGs.

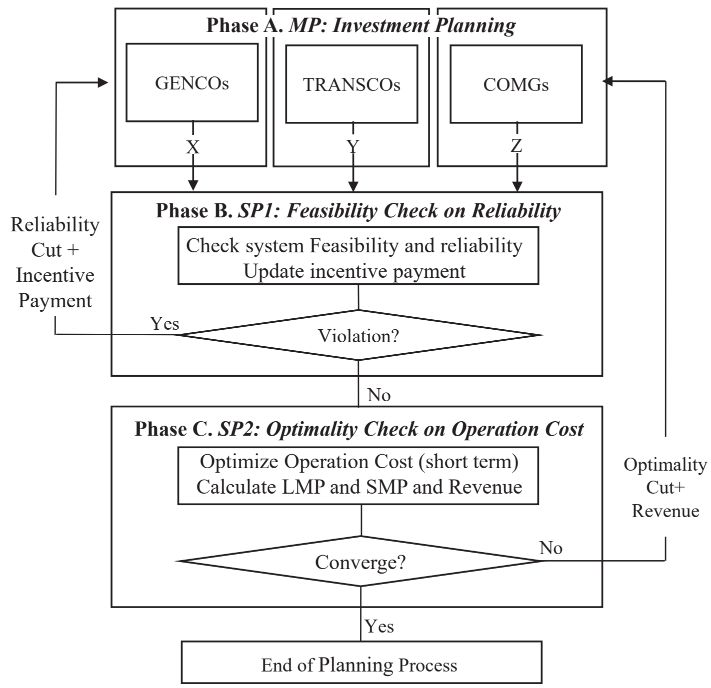

Fig. 2. Three-phase algorithm for the proposed MG-based planning model.

B. Subproblem 1: Feasibility Check on Reliability

In Phase B, the reliability criterion is checked to ensure the reliability index of the system planning, which is satisfied based on the given arrangement of the generation units, MGs, and transmission topology. Subproblem 1, $SP1_{bst}$ is given for each scenario s, time t, and load block b according to the determined $\hat{X}^r$, $\hat{Y}^r$, and $\hat{Z}^r$, as follow:

$$
\begin{aligned}
&v_{bs}(\hat{X}^r(t), \hat{Y}^r(t), \hat{Z}^r(t)) = min \mathbf{1^T} \boldsymbol{S^+_s} + \mathbf{1^T} \boldsymbol{S^-_s} \qquad (8)\\
&S.t.\\
&\mathbf{1^T}\left(\boldsymbol{K_G P_{Gs}} + \boldsymbol{K_M P_{Ms}} - \boldsymbol{D_s}\right) = 0 \qquad (9)\\
&\boldsymbol{SF(\hat{Y})}\left(\boldsymbol{K_G P_{Gs}} + \boldsymbol{K_M P_{Ms}} - \boldsymbol{D_s}\right) - \boldsymbol{S^+_s} \leq \boldsymbol{P^{max}_L} \qquad (10)\\
&\boldsymbol{SF(\hat{Y})}\left(\boldsymbol{K_G P_{Gs}} + \boldsymbol{K_M P_{Ms}} - \boldsymbol{D_s}\right) + \boldsymbol{S^-_s} \geq \boldsymbol{P^{max}_L} \qquad (11)\\
&P^{E}_{Gbis}(t) \leq P^{E,max}_{Gi} U^{E}_{Gbis}(t) \qquad ,\forall i \qquad (12)\\
&P^{C}_{Gbis}(t) \leq P^{C,max}_{Gi} \hat{X}^r_i(t) U^{C}_{Gbis}(t) \qquad ,\forall i; \alpha^r_{1bis}(t) \qquad (13)\\
&\left|P^{E}_{Lbjs}(t)\right| \leq P^{E,max}_{Lj} U^{E}_{Lbjs}(t) \qquad ,\forall j \qquad (14)\\
&\left|P^{C}_{Lbjs}(t)\right| \leq P^{C,max}_{Lj} \hat{Y}^r_j(t) U^{C}_{Lbjs}(t) \quad ,\forall j; \underline{\beta}^r_{1bjs}(t), \overline{\beta}^r_{1bjs}(t) \qquad (15)\\
&P_{Mbks}(t) \leq P^{max}_{Mk} \hat{Z}^r_k(t) \sum_n K_{Mkn} U_{Bbns}(t) \quad ,\forall k; \gamma^r_{1kbs}(t) \qquad (16)\\
&P^{E}_{Gbis}(t), P^{C}_{Gbis}(t), P_{Mbks}(t), S^+_s, S^-_s \in \mathbb{R}^+ \qquad ,\forall i, j, k \qquad (17)
\end{aligned}
$$

The proposed reliability index is based on the unserved load at each bus of the system. But, the objective function

(8) minimizes transmission flow congestion. Constraint (9) is system energy balance. Constraints (10)-(11) show that the total optimal transmission flow congestion is equal to the total nodal real power imbalance of the grid. Constraints (14)-(16) enforce the capacity limits regarding availability of components. Generation units, transmission lines, and substations can be damaged due to an extreme event. Relevant to this issue, uncertain binary parameters U_{Gbis}, U_{Lbjs}, and U_{Bbns} are determined using simulation to formulate the impact of electrical failures due to a unexpected distribution system interruption. Moreover, failure of a substation (U_{Bbjs}) causes failure of the generation unit and transmission lines connected to this substation. This effect of a failure of a substation on the related components can be calculated using Algorithm 1.

Algorithm 1 Substation failure

```
for b, i, j, s, t do
    if Σ_n K_{Gin} U_{Bbns}(t) < 1 then
        U_{Gbis} ← 0
    end if
    if Σ_n K_{Ljn} U_{Bbns}(t) < 2 then
        U_{Lbjs} ← 0
    end if
end for
```

The power system reliability assessment is to evaluate the total expected unserved energy of the system load. The Loss Of Energy Probability (LOEP) index is often used as a performance metric to calculate the expected unserved energy. LOEP is the ratio of the Expected Unserved Energy (EUE) to the total energy demand of the system. The LOEP index determines reliability violation based on the total unserved load at each load block b for each year t, and each scenario s, which is associated with transmission congestion, and contingencies on generation units, lines and MGs. The total unserved load is automatically calculated by (8). When the expected ratio of total unserved energy over the total required energy is greater than the threshold value of LOEP, $\mathbb{E}_s\left[\hat{v}_{bs}(t)\Delta T_b(t)/L_{bs}(t)\Delta T_b(t)\right] \geq LOEP$, the reliability cut (18) will be generated and added to the MP. This will force the investors to revisit and modify the values of X, Y, and Z to reduce the expected unserved energy. The cut (18) is calculated based on Benders decomposition approach. The cut is a function of the dual variables α_1, β_1, and γ_1 of constraints (13), (15) and (16) contain pre-determined variables X, Y, and Z, respectively. These pre-determined variables are sent by the MP (2).

$$\begin{aligned}
&\mathbb{E}_s[\sum_i \alpha^r_{1bis}(t) P^{C,max}_{Gi} U^C_{Gbis}(t)\left(X_i(t)-\hat{X}^r_i(t)\right)\\
&+\sum_j (\underline{\beta}^r_{1bjs}(t)+\overline{\beta}^r_{1bjs}(t)) P^{C,max}_{Lj} U^C_{Lbjs}(t)\left(Y_j(t)-\hat{Y}^r_j(t)\right)\\
&+\sum_k \gamma^r_{1bks}(t) P^{max}_{Mk} U_{Bbn_ks}(t)\left(Z_k(t)-\hat{Z}^r_k(t)\right)\\
&+\hat{v}_{bs}(\hat{X}^r(t),\hat{Y}^r(t),\hat{Z}^r(t))] \leq LOEP\times\mathbb{E}[L_{bs}(t)], \forall b, \forall t. \quad (18)
\end{aligned}$$

The MP (2) with this added reliability cut (18) may result in different optimal solutions. Note that the main objective of the MP is a profit maximization for each investor. In order to take the impact of the reliability cut into account in the investor's decision making problem, the reliability cut must be projected into the profit function of each investor in MP (2). This can be viewed as an incentive payment, which is called *an incentive reliability signal*. Particularly, the ISO is authorized to establish a power system planning incentive program to support the installation of additional generation resources and an adaption of certain advanced power generation technologies to improve the global reliability of the power grid. This incentive reliability signal encourages power investors to expand more capacity to the locations with weak power. The resulting MIP investment problem with this signal requires adding an additional pair of linear constraints $0 \leq X, Y, Z \leq 1$ to formulation (2). This revised model is solved and the corresponding dual variable (π) of constraint (18) is calculated to update the incentive reliability income for each investor, at each block b, and per year t in (19).

$$\begin{aligned}
&ip^r_{Gbi}(t) = \pi^r_{bt}\mathbb{E}_s\left[\alpha^r_{1bis}(t)P^{C,max}_{Gi}U^C_{Gbis}(t)\right]\\
&ip^r_{Lbi}(t) = \pi^r_{bt}\mathbb{E}_s\left[\left(\overline{\beta}^r_{1bjs}(t)+\underline{\beta}^r_{1bjs}(t)\right)P^{C,max}_{Lj}U^C_{Lbjs}(t)\right]\\
&ip^r_{Mbi}(t) = \pi^r_{bt}\mathbb{E}_s\left[\gamma^r_{1bks}(t)P^{max}_{Mk}U_{Bbn_ks}(t)\right] \quad (19)
\end{aligned}$$

The incentive payment functions (19) updates at each iteration r by multiplying the dual variable π^r, which can be interpreted as the price of one unsatisfied load (MW) to the expected value of extra added capacity of candidates. The incentive payment for a new capacity investment is updated in the objective function of MP as an incentive reliability signal for all participants by the ISO.

C. Subproblem 2: Operation Cost Checking

The system operation cost including the total short run marginal cost of all existing and installed candidate capacities of is minimized in Phase C. Subproblem 2, $SP2_{bst}$ at each load block b in year t for each scenario s is formulated as:

$$\begin{aligned}
&w_{bs}(\hat{X}^r(t),\hat{Y}^r(t),\hat{Z}^r(t)) = \min\sum_i \Big(mc^E_{Gbi}(t)P^E_{Gbis}(t)+\\
&mc^C_{Gbi}(t)P^C_{Gbis}(t)\Big)+\sum_j mc^C_{Lbj}(t)P^C_{Lbjs}(t)\\
&+\sum_k mc_{Mbk}(t)P_{Mbks}(t)+\sum_n c_R P_{Rbns}(t) \quad (20)
\end{aligned}$$

$S.t.$

$$\mathbf{1^T}\left(\boldsymbol{K_G P_{Gs}}+\boldsymbol{K_M P_{Ms}}+\boldsymbol{K_R P_{Rs}}-\boldsymbol{D_s}\right)=0, \boldsymbol{\lambda^r_s} \quad (21)$$

$$\left|\boldsymbol{SF^E}(\boldsymbol{\hat{Y}})\left(\boldsymbol{P_{Rs}}+\boldsymbol{K_G P_{Gs}}+\boldsymbol{K_M P_{Ms}}-\boldsymbol{D_s}\right)\right| \leq \boldsymbol{P^{E,max}_{Ls}} \quad ;\left(\underline{\boldsymbol{\mu}}^{\boldsymbol{E}^r}_{\boldsymbol{s}}, \overline{\boldsymbol{\mu}}^{\boldsymbol{E}^r}_{\boldsymbol{s}}\right) \quad (22)$$

$$\left|\boldsymbol{SF^C}(\boldsymbol{\hat{Y}})\left(\boldsymbol{P_{Rs}}+\boldsymbol{K_G P_{Gs}}+\boldsymbol{K_M P_{Ms}}-\boldsymbol{D_s}\right)\right| \leq \boldsymbol{P^{C}_{Ls}} \quad ;\left(\underline{\boldsymbol{\mu}}^{\boldsymbol{C}^r}_{\boldsymbol{s}}, \overline{\boldsymbol{\mu}}^{\boldsymbol{C}^r}_{\boldsymbol{s}}\right) \quad (23)$$

$$0 \leq P^E_{Gbis}(t) \leq P^{E,max}_{Gi}U^E_{Gbis}(t) \qquad ,\forall i \quad (24)$$

$$0 \leq P^C_{Gbis}(t) \leq P^{C,max}_{Gi}\hat{X}^r_i(t)U^C_{Gbis}(t) \qquad ,\forall i; \alpha^r_{2bis}(t) \quad (25)$$

$$0 \leq P^C_{Lbjs}(t) \leq P^{C,max}_{Lj}\hat{Y}^r_j(t)U^C_{Lbjs}(t) \qquad ,\forall j; \beta^r_{2bjs}(t) \quad (26)$$

$$0 \le P_{Mbks}(t) \le P_{Mk}^{max}\hat{Z}_k^r(t)U_{Bbn_ks}(t) \qquad ,\forall k;\gamma_{2bks}^r(t) \tag{27}$$
$$0 \le P_{Rbns}(t) \qquad ,\forall n \tag{28}$$

The objective function (20) is the total operation cost of the system. It should be noted that the considered uncertainties may cause the unexpected unserved load in some scenarios. To provide feasibility of the operational cost problem, an amount of imaginary generation units are considered as reserve to serve the residual unserved energy of the system at each buses. Constraint (21) represents energy balance of the system and constraints (22)-(28) indicate components' capacity limits.

The ISO simulates energy payment for all participants based on the nodal Locational Marginal Prices (LMP) and line Shadow Marginal Prices (i.e., SMP) as a revenue signal [30]. LMP reflects the marginal cost of supplying one unit of increased energy at a specific bus and SMP is the marginal cost of supplying the next increment of maximum line capacity. The $\boldsymbol{\lambda_s^r}$, $\boldsymbol{\mu_s^{E^r}}$, and $\boldsymbol{\mu_s^{C^r}}$ are dual variables of constraints (21)-(23), represent system lambda, shadow price of existing and candidate lines, respectively. The expected **LMP** and **SMP** are calculated from $\boldsymbol{\lambda_s^r}$, $\boldsymbol{\mu_s^{E^r}}$, and $\boldsymbol{\mu_s^{C^r}}$ (29)-(31).

$$\boldsymbol{LMP^r} = \mathbb{E}_s\left[\boldsymbol{\lambda_s^r} + \boldsymbol{\lambda_{cong,s}^r}\right] \tag{29}$$
$$\boldsymbol{\lambda_{cong,s}^r} = \boldsymbol{SF_s^T(\hat{Y})}\left(\boldsymbol{\underline{\mu}_s^r} - \boldsymbol{\overline{\mu}_s^r}\right) \tag{30}$$
$$\boldsymbol{SMP^r} = \mathbb{E}_s\left[\boldsymbol{\underline{\mu}_s^{C^r}} - \boldsymbol{\overline{\mu}_s^{C^r}}\right] \tag{31}$$

Furthermore, the generated optimality cut (32) for all scenarios sends to MP at each iteration based on Benders decomposition, where φ calculates the system operational cost in the objective function (2).

$$\begin{aligned}&\mathbb{E}_s[\sum_i \alpha_{2bis}^r(t)P_{Gi}^{C,max}U_{Gbis}^C(t)\left(X_i(t)-\hat{X}_i^r(t)\right)\\&+\sum_j \beta_{2bjs}^r(t)P_{Lj}^{C,max}U_{Lbjs}^C(t)\left(Y_j(t)-\hat{Y}_j^r(t)\right)\\&+\sum_k \gamma_{2bks}^r(t)P_{Mk}^{max}U_{Bbn_zs}(t)\left(Z_k(t)-\hat{Z}_k^r(t)\right)\\&+\hat{w}_{bs}(\hat{X}^r(t),\hat{Y}^r(t),\hat{Z}^r(t))] \le \varphi \qquad ,\forall b,\forall t\end{aligned} \tag{32}$$

By the Duality theorem [27], our proposed algorithm provides upper and lower bounds to the solution in each iteration. Once the operation cost problem is solved, the lower and upper bounds to the solution should be calculated. The upper bound (33) and lower bound (34) solutions at the r^{th} iteration update with total obtained income of all market participants and total system operation cost.

$$\begin{aligned}\rho_{upper}^r =&I_G(\boldsymbol{P_G^{*}}^{\boldsymbol{r-1}},\boldsymbol{\hat{X}}^{r-1},\boldsymbol{re_G}^{r-1},\boldsymbol{ip_G}^{r-1})\\&+I_L(\boldsymbol{P_L^{*}}^{\boldsymbol{r-1}},\boldsymbol{\hat{Y}}^{r-1},\boldsymbol{re_L}^{r-1},\boldsymbol{ip_L}^{r-1})\\&+I_M(\boldsymbol{P_M^{*}}^{\boldsymbol{r-1}},\boldsymbol{\hat{Z}}^{r-1},\boldsymbol{re_M}^{r-1},\boldsymbol{ip_M}^{r-1})-\varphi^*\end{aligned} \tag{33}$$

$$\begin{aligned}\rho_{lower}^r =&I_G(\boldsymbol{P_G^{*}}^{\boldsymbol{r}},\boldsymbol{\hat{X}}^{r},\boldsymbol{re_G}^{r},\boldsymbol{ip_G}^{r})+I_L(\boldsymbol{P_L^{*}}^{\boldsymbol{r}},\boldsymbol{\hat{Y}}^{r},\boldsymbol{re_L}^{r},\boldsymbol{ip_L}^{r})\\&+I_M(\boldsymbol{P_M^{*}}^{\boldsymbol{r}},\boldsymbol{\hat{Z}}^{r},\boldsymbol{re_M}^{r},\boldsymbol{ip_M}^{r})\\&-\sum_{b,t}\mathbb{E}_s\left[w_{bs}(\hat{X}^r(t),\hat{Y}^r(t),\hat{Z}^r(t))\right]\end{aligned} \tag{34}$$

The algorithm continues until the stopping criterion (35) is met, where ε is a small tolerance value between 5×10^{-6} and 3×10^{-3} [26], [31]. We set ε at 0.003.

$$\left|\left(\rho_{upper}^r-\rho_{lower}^r\right)/\rho_{upper}^r\right| \le \varepsilon \tag{35}$$

Algorithm 2 depicts all calculation steps described above in our proposed algorithm and it is self-explanatory.

Algorithm 2 The proposed algorithm

```
Initialize ε, r, X̂^r, Ŷ^r, Ẑ^r, ρ^r_lower, ρ^r_upper, v̂_bs,
while |(ρ^r_upper − ρ^r_lower)/ρ^r_upper| > ε do
    while v̂_bs > ε do
        Solve (8) for all b, t, and s to obtain optimal v̂_bs(t) and
            dual variables α^r_1bis(t), β̲^r_1bjs(t), β̄^r_1bjs(t), γ^r_1kbs(t).
        Generate reliability Benders cut (18).
        Add the generated cut to MP (2).
        Solve relaxed MP (2) to obtain the dual value π^r_bt
            of reliability cut (18).
        Update incentive payments ip_G, ip_L, ip_M at (2)
            by (19).
        r ← r + 1.
        Solve (2) to obtain optimal X̂^r(t), Ŷ^r(t), Ẑ^r(t).
    end while
    Solve (20) for all b, t, and s to obtain optimal ŵ_bs(t) and
        dual variables λ^r_s, μ̲^{E^r}_s, μ̄^{E^r}_s, μ̲^{C^r}_s, μ̄^{C^r}_s, α^r_2bis(t)
        , β̲^r_2bjs(t), β̄^r_2bjs(t), γ^r_2bks(t).
    Generate optimality cut (32).
    Add the generated cut to MP (2).
    Calculate LMP and SMP by (29) and (31), respectively.
    Update re_G, re_L, re_M based on calculated LMP and
        SMP.
    r ← r + 1.
    Solve (2) to obtain optimal X̂^r(t), Ŷ^r(t), Ẑ^r(t).
    Calculate ρ^r_upper and ρ^r_lower by (33) and (34).
end while
```

IV. Case Studies

This section presents numerical results from two case studies based on the IEEE six-bus and modified 118-bus test systems described in [32]. Model (2)-(35) has been solved using CPLEX 12.6.1.0 [33] under GAMS [34] on a Linux server with 24 processors at 2.53 GHz and 128 GB of RAM.

A. Six-Bus System

A six-bus test system is considered [21], where it has seven existing and seven candidate lines, three existing and eleven candidate units and one candidate COMG. One candidate COMG is connected to bus 3. The loads are located at buses 3, 5, and 6. More details of the test system and the figure can be found in [32]. The following model parameters are given as inputs: the planning horizon is ten years, there are four load blocks, the base year peak load is 25 MW, and the base year energy demand is 107.8 GWh, the LOEP is at 5% for all load blocks at every planning year, and the discount rate δ is assumed at 5%, which is used for net present value calculation. A normal probability distribution function with 0 mean and 0.01 standard deviation values are used to generate random values for peak load and load growth rate at each load block. A uniform probability distribution function in the range

TABLE I
INSTALLATION YEAR OF CANDIDATE GENERATION UNITS AND COMOG

	G1	G3	G4	G5	G6	G7	G8	MG
Case 0	1	8	-	10	5	2	-	1
Case 1	1	8	8	1	1	4	5	1

TABLE II
INSTALLATION YEAR OF CANDIDATE TRANSMISSION LINES

	L1	L2	L3	L4	L5	L6	L7
Case 0	-	1	1	1	1	1	1
Case 1	1	1	1	1	1	1	1

TABLE III
TOTAL OPERATION COSTS AND UNSERVED ENERGY

	Case 0	Case 1	Case 2	Case 3
Total Opr. cost($ $\times 10^3$)	28.834	38.531	35.966	43.692
Unserved energy(MWh)	0	18.463	0	20.663

of 0 and 1 is used to randomize the component outages. One thousand scenarios are generated using the Latin Hypercube Sampling program to represent the uncertainties in demand and component outages [35]. Recall that the scenario reduction is applied to reduce the computation efforts while maintaining the solution accuracy using the SCENRED tool [36]. Thus, the initially generated 1000 scenarios were reduced to 10 scenarios using SCENRED and more details can be found in [32].

Five case studies are designed to study model performance based on two factors: load growth and component outages uncertainty and COMG planning conditions. Under the assumption that COMG planning is considered in the model, the first two cases compare the difference between two modeling approaches: a deterministic model and a stochastic model (2)-(35). The second two cases are to show the model performance when COMG planning is not considered. The last case is studied to observe the effect of COMG planning on different locations.

- **Case 0)** Deterministic model with COMG planning.
- **Case 1)** Stochastic model with COMG planning.
- **Case 2)** Deterministic model without COMG planning.
- **Case 3)** Stochastic model without COMG planning.
- **Case 4)** Stochastic model with mutliple COMG planning.

The experiment results are presented in Tables I and II which summarize the installation year of candidate generation units, COMGs and transmission lines results for Case 0 and Case 1.

Case 0) Deterministic model with COMG planning: The goal of this model is to determine the coordinated investment planning of three power company investors by maximizing their profits. This model is solved by our proposed algorithm without considering uncertainties. In the original six-bus test system, the existing lines are congested because the existing line capacities are not enough to supply the demand at load buses. Hence, a new component investment is needed to satisfy load demand and relieve the transmission line congestion. The solution results show the deterministic reliability criterion (18) is violated in the first iteration of the algorithm. This fact forces ISO to activate incentive payment as an incentive reliability signal to encourage the investors of candidate lines 2-7. As it is shown in Table II, the obtained solution proposes the installation of L2-L7 in Year 1. According to tables I-II, our investment plan prefers to construct the lines more than generators. This is because the operation and investment costs are cheaper compared to the candidate generators and microgrid. The plan suggests the installation of generation units G1, G3, and G5-G7. For example, there are two candidate generators G1 and G2 connected to bus 1, where G1 is considered to be installed at year 1. G1 offers a less expensive operation cost and higher generation capacity compared to G2. Summing up all these, from the investors viewpoint, we can claim that our model selects the more profitable offers based on market prospective while considering the system reliability.

From the COMG point of view, MG is installed at year 1, at the earliest year. MG investment is more profitable; however, there are two other candidate generation units G2 and G4 with a higher capacity and smaller investment cost. These results verify that the installation of MG with the ability to supply the local load and lower operational cost reduces the transmission line investment cost as well as the system operational cost by $\$7132.62$. This is a consequence of local supplying.

Case 1) Stochastic model with COMG planning: The coordinated planning of three power companies is applied under uncertainties. The solution of the stochastic model (in Tables I and II) suggests installing the additional candidate generation units G4 and G8 and hastening the installation of G5 and G6. Even though G4 and G8 are the most expensive candidate units, the reliability constraint (18) forces the investors to install them. Because they are associated with lower Forced Outage Rate (FOR). Adding more reliable generators with less FOR to the network will reduce the total power mismatch considering power outages. As compared with Case 0, generators are installed earlier in Case 1 due to an anticipated higher amount of unserved energy under uncertainties. As a result, there is an increase in power supply by 18.50MWh to satisfy the system reliability level.

In Case 0, the solution process required fourteen price signal loop iterations to check operational cost in Phase C which is taken 16.409 seconds to solve. Compared to the results of Case 0, Case 1 required six price signal loop iterations and took 63.486 seconds to converge. Consequently, the solution time is higher in Case 1, even though the scenario reduction is applied. Figure 3 shows that the stochastic model's CPU solution time increases exponentially as the number of scenarios. It indicates the importance of scenario reduction on CPU calculation time.

Case 2) Deterministic model without COMG planning: The result of this case is given in Table III, it shows 24.74% total operation costs addition compared with Case 0.

Case 3) Stochastic model without COMG planning: The generation and transmission expansion planning problem is solved without considering the MG installation. The solution result shows that applying COMG reduced the expected amount of unserved energy by 11.92%, because the COMG supplies the local load without using transmission lines that inherently have the possibility of outage.

Another factor affecting the investment decision of MG is the impact of the electricity market LMP in a short term operation. at the local COMG. Figure 4 illustrates the expected LMP at bus 3 for block 1 for Case 1 and 3. The expected LMP

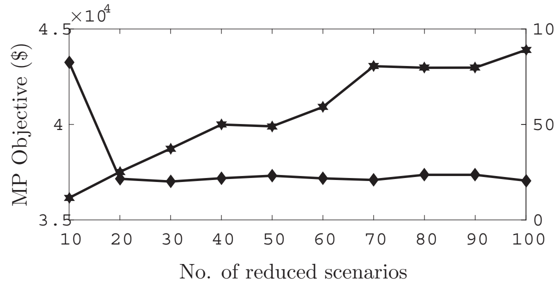

Fig. 3. The required CPU time to solve the proposed model based on number of scenarios.

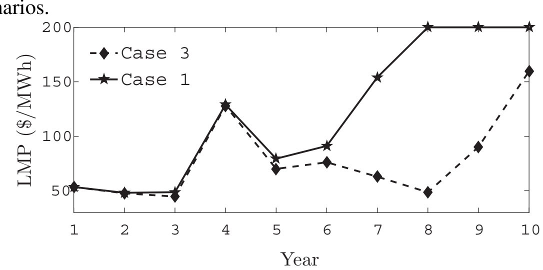

Fig. 4. LMP over planning years at bus 3 for the first load block.

TABLE IV
INSTALLATION YEAR OF CANDIDATE GENERATION UNITS AND COMGS

	G1	G3	G4	G5	G6	G7	G8	M1	M2
Case 1	1	8	-	10	5	2	-	1	-
Case 4-1	1	8	8	3	1	4	5	1	1
Case 4-2	1	8	-	3	1	1	5	1	1

TABLE V
TOTAL OPERATION COSTS AND UNSERVED ENERGY

	Case 1	Case 4-1	Case 4-2
Total Opr. cost($ $\times 10^3$)	38.531	36.011	35.038
Unserved energy(MWh)	18.463	14.414	17.583

profiles for other blocks are the same as block 1. This figure verifies that in Case 1 the MG installation at year 2 creates lower LMP at bus 3 ($47.677/MWh) in comparison to Case 3, without MG ($48.127/MWh). Therefore, MG investment improves the LMP profile fluctuation at lower level values over the planning horizon.

Case 4) Stochastic model with mutliple COMG planning.: In this case as well as the initial MG candidate at bus 3, one more MG is added into the system in two different locations: 1) bus 5 and 2) bus 3. Table IV-V shows the result of our investment plan for Cases 1 and 4. In Case 4-1, the plan prefers to install second MG at year 1 in bus 5. As a result, second MG helps to reduce the expected unserved energy and total operation costs by 28.091% and 6.998%, respectively. However, from Case 4-2, it can be concluded that increasing the penetration of MG not necessarily causes a significant reduction in the unserved energy because both MGs are connected at bus 3. Accumulation MG in bus 3, due to the congestion of the network cannot significantly improve the system load satisfaction. Therefore, the penetration and spread of MGs over the power grid may have a significant impact on less transmission congestion and more total load serving in whole system.

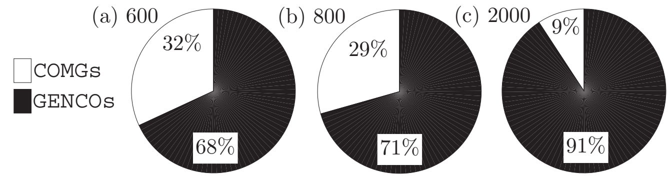

Fig. 5. Ratio of used capacity of COMGs and GENCOs in the system to served energy with different MGs investment cost: (a) $600, (b) $800, (c) $2,000/MWh/year

It should be emphasized that the operation cost of existing transmission line is not considered in the objective function of SP2. The existing literature has been verified that more than 80% of the total expansion planning cost belongs to generation units [37]. The optimization results also show less congestion and generation costs with marginally greater total operation cost in comparing to another case when the operation cost of existing transmission line is considered on the objective function SP2. In this case, the value of feedback price signals to candidate transmission line investors in MP will be decreased in the wake of lower congestion prices. Therefore, deployment of new candidate transmission line will be also diminished. Consequently, the SP2 utilizes the full capacity of the existing transmission line to satisfy the total demand in the system instead of the new candidate transmission lines. In addition to above consequences, the computational effort is pretty much less and the CPU calculation time becomes faster. Note that considering the exising lines operation cost in (20) results in 1.7% total cost saving, however, it raises the computational time by 184.35%.

B. 118-Bus System

A modified IEEE 118-bus system is analyzed to study the performance of the proposed solution approach. The system includes 118 buses, 53 existing generation and 10 candidate generation units, and 180 existing and 5 candidate lines [32]. The MGs can be deployed at a selected subset of the buses and the MG's marginal cost is assumed to be $1/MWh. Four load blocks are assumed for a 10-year planning horizon. FORs of generation units and transmission lines are 4% and 1%, respectively. The initial system peak load is $3,000$ MW and the initial energy demand is $21,576$ GWh with an annual load and energy growth rate of 5%. One thousand scenarios on demand and component outages are generated and were reduced to ten scenarios using SCENRED. The probability of each reduced scenario is presented in Table VI.

We analyzed the model sensitivity of changing investment cost for MG in three different cases as shown in Fig. 5 and Table VII. The sensitivity analysis is done for low, medium, and high MG investment costs: $(600, 800, and 2000)/MWh/year. The last three columns of Table VII show the installation year of MGs for each case. In the case of $600/MWh/year, five MGs are to be installed in years 1, 4, 5, and 7, while only one MG (MG2) is suggested for installation in year 1 when the investment cost is $\$2,000$/MWh/year. This makes economic sense because it is less profitable to have MGs installed when the investment cost of MG is higher. Figure 5 illustrates

TABLE VI
PROBABILITY OF EACH SCENARIO AFTER SCENARIO REDUCTION

Scenario	1	2	3	4	5
Probability	0.077	0.078	0.119	0.109	0.095
Scenario	6	7	8	9	10
Probability	0.083	0.085	0.086	0.137	0.131

TABLE VII
COMG INSTALLATION YEAR

	Bus	Capacity. (MW)	Inv. Cost ($/MWh/year) 600	800	2000
MG2	12	200	1	1	1
MG3	25	200	4	7	-
MG5	80	200	7	5	-
MG10	54	200	5	-	-
MG12	56	200	5	8	-

the influence of MG investment cost on the penetration of GENCOs and COMGs in the system. Under the scenario of \$600/MWh/year (Fig. 5 (a)), GENCOs supplied 68% of the total amount of served energy and COMGs supplied 32%. However, the share of supplied energy by these two resources changed to 91% (GENCOs) and 9% (COMGs) when the MG installation cost was increased to $\$2,000$/MWh/year.

Rural electrification provides few incentives for business development such as GENCOs and TRANSCOs due to the high investment cost associated with transmission lines and low density customer basis per square mile [2]. Nevertheless, COMGs offer renewable generation with the capability of installing MGs at a remote region. To examine the impact of our proposed framework on rural electrification, bus 12 is elected at a remote location in the network, with 1.3364% of load factor. Even though the $\$2,000$/MW/year investment cost on a MG is much more expensive than a candidate generation unit [32], the installation of MG at bus 12 (MG2) is still profitable in year 1, because there are multiple benefits to have MG2 for the power system operator and its investor. Benefits include 1) unserved energy reduction by 11.23% in remote areas, 2) $\$2.611 \times 10^{15}$ cost savings corresponding to rejection of additional generation units and additional transmission lines in remote areas, and 3) the highest incentive payment paid by ISO to MG2 investor is 50.92% greater than the next highest incentive payment to another market participant. This high payment is because MG2 enhanced the system reliability LOEP by 6.77×10^{-4} at remote bus 12. Hence, rural electrification can be enhanced by investing on COMGs if it is profitable. These results show that our proposed model not only reduces investment cost as well as unserved energy, but also enhances the system reliability in remote location of power grid.

As the network size gets larger, the computational burden to solve the corresponding optimization model can become more challenging. For the 118-bus system, the original model without considering parameter uncertainty took 16 minutes to solve, while our proposed stochastic approach with reduced scenarios found the optimal solution in 6 minutes. Furthermore, Fig. 6 shows progression of the proposed solution approach until it converges. It displays the stopping criterion (35) and the operation cost over iteration. The algorithm converged with a negligible gap at 2.60×10^{-7} at iteration 6. The cost made a big jump to $\$3.7,242 \times 10^{14}$ at iteration 3 and finally converged to $\$3.7,336 \times 10^{14}$ at the final iteration.

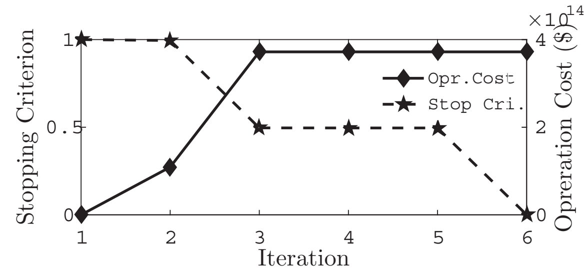

Fig. 6. Convergence for the 118-bus system.

From the results presented in Table I to VII, the following observations can be made regarding competitive markets.

(a) Even at a higher investment cost, a COMG is an excellent alternative to traditional power resources under extreme events because those events can cause a power outage. Since MGs do not rely on the transmission system, having COMGs can decrease the unserved energy and enhance the system reliability.
(b) Having correct and effective price signals is a key factor for a successful electricity market. LMP is the basis for market-based congestion management and achieving market efficiency. COMGs can help transmission congestion reduction and minimize the consequence of transmission outages in the network. Due to the fact that a higher transmission line congestion leads to a higher LMP value, the LMP value is a good indicator to identify potential locations for COMGs installation. Hence, COMG is installed at highly congested locations based on the LMP signal and reduces the LMP.
(c) Having COMGs in the power network can enhance rural electrification. In many cases, COMGs can be sufficient enough to supply electricity to rural areas where the load is relatively low. As a result, it will eliminate the need for extending traditional power resources, which are often expensive to install and maintain.

Although similar observations have been made in previous studies, they focused primarily on a system-wide perspective, not on competitive electricity markets.

V. CONCLUSION

In this paper, a new two-stage stochastic programming model for integrating COMG with GENCO and TRANSCO as power investors was introduced based on electricity market under uncertainty. This model provides appropriate market price signals for all investors to determine their investment status based on maximizing profits as well as keeping the reliability and operational cost of the power system at acceptable levels. The proposed model was applied to two modified IEEE test systems. The results illustrate that integrating energy initiative resources with traditional resources enhances the reliability and reduces high operational cost of the system. Moreover, adding COMGs can enhance rural electrification.

The extension of this work may consider environmental impact of power plants on the power system and risk associated with fuel price fluctuations.

References

[1] M. Shahidehpour and S. Pullins, "Is the Microgrid Buzz Real?," *IEEE Electr. Mag.*, vol. 2, no. 1, pp. 2-5, Mar. 2014.

[2] M. Shahidehpour and S. Pullins, "Microgrids, Modernization, and Rural Electrification [About This Issue]," *IEEE Electr. Mag.*, vol. 3, no. 1, pp. 2-6, Mar. 2015.

[3] M. Shahidehpour and J. F. Clair, "A functional microgrid for enhancing reliability, sustainability, and energy efficiency," *Electr. J.,* vol. 25, no. 8, pp. 21-28, Oct. 2012.

[4] Community Microgrids [Online]. Available: http://www.clean-coalition.org/our-work/community-microgrids/.

[5] S. Wang, Z. Li, L. Wu, M. Shahidehpour, and Z. Li, "New metrics for assessing the reliability and economics of microgrids in distribution system," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2852-2861, Aug. 2013.

[6] A. Kargarian, B. Falahati, Y. Fu, and M. Baradar, "Multiobjective optimal power flow algorithm to enhance multi-microgrids performance incorporating IPFC," in *IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, pp. 16, Jul. 2012.

[7] L. Che, X. Zhang, M. Shahidehpour, A. Alabdulwahab, and Y. Al-Turki, "Optimal planning of loop-based microgrid topology," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1771-1781, May 2017.

[8] L, Che, X. Zhang, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, "Optimal interconnection planning of community microgrids with renewable energy sources," *IEEE Trans. Smart Grid*, vol. 8, no. 3, pp. 1054-1063, Aug. 2015.

[9] H, Lotfi and A. Khodaei, "AC versus DC microgrid planning," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 296-304, Jan. 2017.

[10] L. Wu, M. Shahidehpour, and Z. Li, "GENCO's risk-constrained hydrothermal scheduling," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1847-1858, Nov. 2008.

[11] S. Kamalinia, M. Shahidehpour, and L. Wu, "Sustainable resource planning in energy markets," *Appl. Energy*, vol. 113, pp. 112-120, Nov. 2014.

[12] J. H. Roh, M. Shahidehpour, and Y. Fu, "Security-constrained resource planning in electricity markets," *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 812-820, May 2007.

[13] M. O. Buygi, G. Balzer, H. M. Shanechi, and M. Shahidehpour, "Market-based transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2060-2067, Nov. 2004.

[14] S. Kamalinia and M. Shahidehpour, "Generation expansion planning in wind-thermal power systems," *IET Gener. Transm. Distrib.*, vol. 4, no. 8, pp. 940-951, Aug. 2010.

[15] R. Hemmati, R.-A. Hooshmand, and A. Khodabakhshian, "Comprehensive review of generation and transmission expansion planning," *IET Gener. Transm. Distrib.*, vol. 7, no. 9, pp. 955964, Sep. 2013.

[16] A. Liu, B. F. Hobbs, J. Ho, J. McCalley, V. Krishnan, M. Shahidehpour, and Q. Zheng, "Co-optimization of transmission and other supply resources," *Prepared for the Eastern Interconnection States Planning Council, NARUC.*, Dec. 2013.

[17] L. Wu, M. Shahidehpour, and Y. Fu, "Security-constrained generation and transmission outage scheduling with uncertainties," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1674-1685, Aug. 2010.

[18] Y. Fu, M. Shahidehpour, and Z. Li, "Security-constrained optimal coordination of generation and transmission maintenance outage scheduling," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1302-1313, Aug. 2007.

[19] A. Khodaei and M. Shahidehpour. "Microgrid-based co-optimization of generation and transmission planning in power systems," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1582-1590, May 2012.

[20] J. H. Roh, M. Shahidehpour, and Y. Fu, "Market-based coordination of transmission and generation capacity planning," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1406-1419, Nov. 2007.

[21] J. H. Roh, M. Shahidehpour, and W. Lei, "Market-based generation and transmission planning with uncertainties," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1587-1598, Aug. 2009.

[22] A. khayatian, M. Barati, and G. J. Lim, "Market-based and resilient coordinated Microgrid planning under uncertainty," *T&D conf. and Expo., IEEE/PES*, pp. 1-5, May 2016.

[23] S. Kamalinia, L. Wu, and M. Shahidehpour, "Stochastic midterm coordination of hydro and natural gas flexibilities for wind energy integration," *IEEE Trans. Sustain. Energy*, vol. 5 no. 4 pp. 1070-1079, Oct. 2014.

[24] L. Wu, M. Shahidehpour, and T. Li, "Stochastic security-constrained unit commitment," *IEEE Power Energy Mag.*, vol. 22, no. 2, pp. 800-811. May 2007.

[25] Y. Fu, Z. Li, and L. Wu, "Modeling and solution of the large-scale security-constrained unit commitment," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3524-3533, Nov. 2013.

[26] M. Shahidehopour and Y. Fu, "Benders decomposition: applying Benders decomposition to power systems," *IEEE Power & Energy Mag.*, vol. 3, no. 2, pp. 2021, Mar. 2005.

[27] G. Infanger, "Monte Carlo (importance) sampling within a Benders decomposition algorithm for stochastic linear programs," *Annals of Operations Research* vol. 39, no. 1, pp. 69-95, Dec. 1992.

[28] N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay, "Microgrids," *IEEE Power Energy Mag.*, vol. 5, no. 4, pp. 78-94 Aug. 2007.

[29] P. Agrawal, "Overview of DOE microgrid activities," *Symposium on Microgrid, Montreal,* Vol. 23. Jun. 2006.

[30] Y. Fu and Li Z, "Different models and properties on LMP calculations," in *Proc. IEEE 2006 Power Eng. Soc. General Meeting,* pp. 1122, Jun. 2006.

[31] M. Shahidehpour and Y. Fu, "Benders decomposition in restructured power systems," *IEEE Techtorial,* Apr. 2005.

[32] Data set for Manuscript "Integrated Microgrid Planning in Electricity Market with Uncertainty" [Online]. Available: https://goo.gl/ozi80Q.

[33] *The ILOG CPLEX*, 2008. [Online]. Available: http://www.ilog.com/products/cplex/.

[34] R. E. Rosenthal, "GAMS: A Users Guide," GAMS Development Corporation, Washington, Sep. 2016.

[35] G. D. Wyss and K. H. Jorgensen, "A users guide to LHS: Sandias Latin hypercube sampling software." SAND98-0210, Sandia National Laboratories, Albuquerque, NM, 1998.

[36] GAMS/SCENRED Documentation [Online]. Available: http://www.gams.com/docs/document.htm.

[37] B. Alizadeh and S. Jadid. "Reliability constrained coordination of generation and transmission expansion planning in power systems using mixed integer programming," *IET Gen. Trans. Distr.*, vol. 5.no. 9, pp. 948-960, Sep. 2011.

Aida Khayatian is a Ph.D. student in the Industrial Engineering Department at the University of Houston, Houston. Her research interests include Microgrid and integrated resource planning.

Masoud Barati received the Ph.D. degree in electrical engineering from Illinois Institute of Technology, Chicago, in 2013. Presently, he is a research and instructional assistant professor in the Electrical and Computer Engineering Department at University of Houston, Houston. His research interests include microgrid operation and planning, microeconomics, mathematical modeling and multiple infrastructure assesment.

Gino J. Lim is a professor and chair of industrial engineering, and Hari and Anjali Faculty Fellow at the University of Houston. He holds a Ph.D. in Industrial Engineering from University of Wisconsin-Madison. His research interest lies in developing optimization techniques for solving large scale decision making problems in areas such as network resiliency, supply chain under disruption and transportation networks. His current research projects include robust optimization in transportation problems, smart ports, and scheduling. His e-mail address is ginolim@uh.edu.