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Exploring the Potentials of Demand Side Flexibilities on the Investment Decisions of Renewable-Powered Microgrids

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In distribution networks with substantial penetrations of variable generation (VG), demand side management (DSM) schemes might be seen as an ideal replacement for delivering spatiotemporal energy arbitrage. From a system viewpoint, it would be advantageous to include DSM into the microgrid (µG) planning issue, but it may lead to profit scarcity for µG operators or end-users. To that purpose, the equilibrium issue in this work examines interactions between DSM and µG planning within a competitive electricity market. Reliability requirements place restrictions on the issue in order to ensure that there is adequate supply of µGs in the islanding mode. The scenarios are reduced to make the model more obedient while taking into account the uncertainty brought on by VG. Finally, the suggested issue is resolved on a test-bed with VG portfolio and various techno-economic characteristics of potential DSM and µG cutting-edge technologies using the diagonalization approach. The case study demonstrates that the availability of DSM schemes has a substantial impact on the optimum µG investment choices. As a result, implementing DSM not only allows for a large delay in the investments but also improves the system's flexibility and dependability in times of crisis. Overall, the DSM programs have the potential to positively impact on investment decisions in µG planning by reducing capital expenditure, optimizing resource utilization, improving grid reliability, providing cost savings, and facilitating the integration of renewable energy sources.

keywords: *Microgrid Planning, Demand Side Management, Renewables Harvesting, Energy Flexibility.*

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1. INTRODUCTION

Today, designers of distribution networks are faced with multiple challenges such as exponential increasing demand for electrical energy, limited fossil fuel resources, environmental considerations about global warming and low reliability of distribution systems due to their radius structures and geographical expansion of customers. These issues have attracted the attention of power systems planners towards microgrids (µG) as a reliable and sustainable resource [1]. The µG, which consists of merging several dispersed energy resources (DER) at low and medium voltage levels, is one of the most compatible options for power generating in the future energy systems, so that this cutting-edge technology would be provided the ability to generate the electricity and heat simultaneously for clients [2]. By integrating miscellaneous DERs and demand side management (DSM) facilities in the form of µG, the sustainability and security of distribution grids will be increased due to its ability to locally supply the customers at the different operation conditions. In all over the world, several projects are concluded to promote green energy technologies, for example, the electricity plan of Great Britain comprises supplying 35% of its consumption from renewable generations by 2020 [3], or energy system design for 100% renewables in Germany in 2050 [4].

The clustering of power distribution grid as a set of linked µGs is one of the most pivotal steps in moving towards increasing energy efficiency. Under this context, it is anticipated that future distribution systems will be clusters of multiple µGs which can exchange energy with each other with the aim of maximizing the profit of whole system. On the other hand, with an impressive growth of smart metering instruments, the consumers play an influential role in the optimal planning of µGs which will ultimately lead to reduce and postpone the investment volumes. So, the investigating the impact of DSM schemes on the operational planning of µGs will be essential and beneficial for both operators and customers. It should be mentioned that the evolution of µGs has strongly become more dependent on renewable resources and energy storage systems (ESS) due to climate change and environmental issues caused by utilizing the fossil fuels. For example, the ESS units can efficiently provide a set of grid-scale services such as: power quality and transient stability services, regulation and load following, spinning reserves (for both event-based and nonevent-based), voltage control, energy arbitrage, congestion alleviation, and upgrade postpone [5].

The operators and mangers of networked µGs are confronted with new difficulties in maintaining the dependability and security of systems at an acceptable and sufficient level, despite the promise and exceptional benefits of grid-connected renewable resources. The µGs may be seen as one of the best ways to handle these crucial issues because of their practical and sophisticated control architecture. Under addition to being able to sell their excess energy to the main grid while operating normally, the µGs may also operate autonomously, or independently of the rest of the network, in emergency conditions such the occurrence of contingencies [6]. These crucial µGs characteristics may significantly strengthen and increase the dependability of contemporary distribution networks, improving the sustainability and quality of power systems for both operators and customers. Figure 1 graphically displays the interactions between the operators of the networked µGs and the distribution network operator (DNO) under competitive energy market.

Demand management programs are initiatives designed to reduce the overall demand for energy during peak periods. These programs aim to incentivize consumers to reduce their energy consumption during peak times in exchange for lower rates or other benefits. By reducing demand during peak periods, utilities can avoid having to build additional generation capacity, which is often expensive and can take years to construct. One of the impacts of demand management programs on investment decisions in µGs is that they can increase the attractiveness of investing in these systems. µGs are often used to provide reliable power during peak periods, which is when demand management programs are most effective. By investing in a µG, a community can reduce its reliance on the larger power grid during peak times, which can lead to lower energy costs and greater reliability.

Demand management programs can also impact investment decisions by creating new revenue streams for µG operators. Many demand management programs offer financial incentives to consumers who reduce their energy consumption during peak periods. µG operators can take advantage of these incentives by offering demand response services to their customers. By reducing their energy consumption during peak periods, customers can earn financial incentives, and the µG operator can earn revenue for providing the demand response service.

Furthermore, demand management programs can also influence the design and operation of µGs. By incentivizing energy reduction during peak periods, demand management programs can encourage µG operators to design and operate their systems in a way that maximizes energy efficiency and minimizes energy

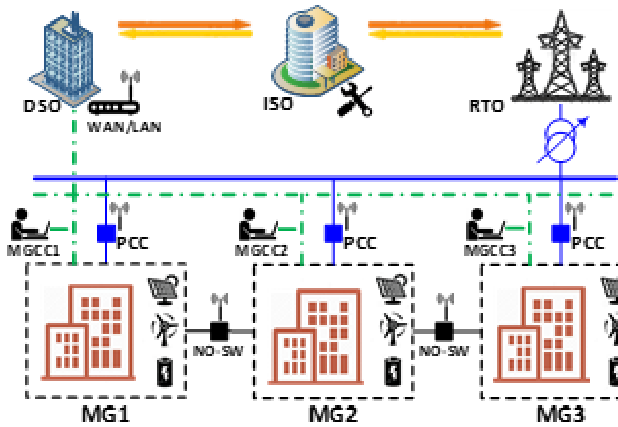

Fig. 1. The structure for µG considering the interactions between system operator and private agents.

waste. This can lead to more sustainable and environmentally friendly µGs. Generally, the design of the µGs is carried out in two main phases, including DERs allocation and boundaries determining. The main aim of first phase is to convert the passive power distribution grid into the active one and the second phase tries to cluster the grid as a set of interconnected µGs [7]. Different works have explored various approaches to design µGs from diverse points of view [8]. In particular, reference [9] proposed an optimal model for the design of linked µGs concerning the reliability and security of end-users. To construct a compromise between cost and security, reference [10] has proposed a multi-objective approach for the design of a standalone µG considering the probabilistic nature of renewable resources. The design of the µGs has been investigated in reference [11] on the basis of self-healing property against potential high impact events. In this work, the partitioning of the distribution grid as a group of linked µGs was evaluated with the aim of minimizing system downtime under islanding conditions and optimizing operating costs at the normal operation mode. The purpose of [12] was to zoning distribution networks in the form of small scale zones in order to improve the security and robustness of the whole system against natural and rare events. In this paper, an optimal operational strategies has been presented relies on networked µGs when high-amplitude and low-probability events are occurred. It is worth noting that the µGs design problem can be done in both static and dynamic programming. In the static design, all of the planning decisions will be determined in the first year of design, while in the dynamic model, the investments can be exploited in different years during the planning horizon [13]. For example, the design of multiple µGs has been reported in [13]-[16] based on different risk-oriented strategies. The design of multiple interconnected µGs has been carried out in [14] using the minimal cut-set method. An ideal model for the design of µGs was put out in reference [15], taking into consideration the uncertainty caused by wind turbines and solar devices. The installation and operating costs of generating units and energy storage resources, as well as dependability and environmental considerations, are all part of this paper's objective function. The design of µGs is suggested in reference [16] using the graph theory. In this work, the design of µGs structure is determined using circular partitioning theory of graphs with regard to system reliability. On the other hand, the design of the µGs can be modeled and solved in different ways.

For example, in references [7],[17], the multi-objective modeling approaches based on intelligent algorithms are proposed for the design of multiple µGs. Besides, bi-level optimization [13], single-objective modeling based on robust optimization [18], and two-step programming [19] have been widely used to design the µGs. In this work, the design of µGs is reported considering the development of transmission lines and the delay of upstream network upgrading. References [20] and [21] have performed the optimal integration of DERs on the middle-voltage side of the power distribution grid with the aim of improving the reliability and adequacy of the network using the harmonic search algorithm. Furthermore, the clustering of multiple µGs has been done in [22] to improve the controllability and observability considering preventive maintenance scheduling. The selection of AC and DC µGs has been optimally investigated in [23] considering uncertainties. It should be pointed out that each uncertainty modelling method has its own advantages and disadvantages. Scenario-based programming, for example, regardless of its simplicity and applicability is very time-consuming and needs the probability density function (PDF) of uncertain parameters. The stochastic scenario-based optimization method introduces substantial risk into the model since the goal function's value fluctuates from one situation to another. For the Monte Carlo simulation (MCS) to provide a decision maker any degree of confidence, several iterations are necessary. Due to its repetitive nature and need for many function evaluations, MCS often imposes a heavy computational cost. Additionally, as the degree of freedom of the solution space rises, more simulations are required. The fuzzy modeling technique necessitates the execution of several simulations for various membership degrees. Furthermore, other approaches like info-gap or robust optimization models are too conservative and inflict considerable non-linearity into the proposed problem at hand. Although the design of µGs has been reported in previous references, they have not assessed the impact of DSM schemes on the investment volumes. To this end, this paper attempts to present an optimal procedure to split the distribution networks into the supply-sufficient µGs considering the demand flexibility. The proposed model offers multiple options to enhance system reliability and reduce load shedding. The problem is executed under the probabilistic environment through generating scenarios to cover the uncertainties. In general, the paper innovations include:

- Optimal splitting of distribution networks into supply-sufficient µGs
- Allocating various DERs considering spatial-temporal constraints
- Assessing the impact of DSM on the investment decisions of µGs
- Handling the uncertainties of the problem by scenario generation

The structure of this paper is organized as below: The mathematical formulation is given in the Section 2. The uncertainty modelling is done in Section 3 and Section 4 depicts the results achieved from simulations to prove the applicability of the developed model. Eventually, Section 5 concludes the major findings of the proposed model compared to state-of-the-art.

2. PROBLEM FORMULATION

This paper tries to develop an optimized procedure to incorporate the DSM schemes into the operational planning of µGs to postpone the investments decisions and lessen the capital costs.

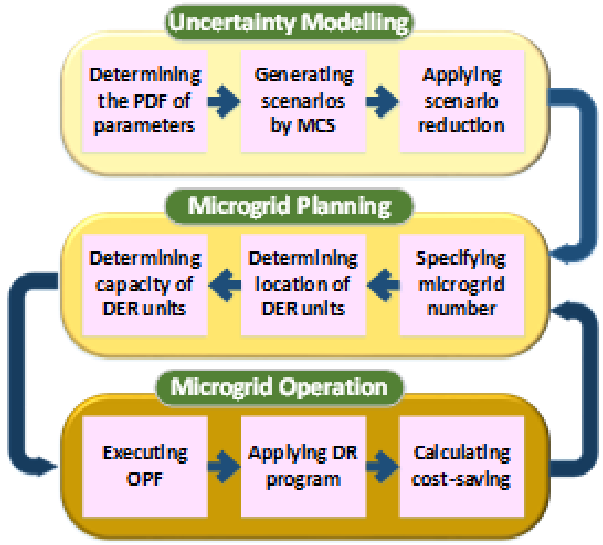

Fig. 2. The overall algorithm proposed for operational-planning of µGs.

Fig. 2 visually illustrates the procedure of the proposed model to incorporate DSM schemes into the µGs planning problem. Mathematical modeling of the problem at hand with various constraints and functions will be represented in this section with detailed explanations.

A. Mathematical Programming

A.1. Objective Function

The main objective function consists of three sections as exhibited in (1). The first two parts in (1), respectively, are the costs of distributed generation (DG) planning and remotely controlled switch (RCS) placement and also the third part expresses the implementation cost of DSM schemes during planning horizon time (10 years). In this equation, $\varsigma_{s,i,b}$ and $\psi_{s,i,b}$ are binary and integer variables to determine the installation and type of ith DG at bth busbar and sth scenario, respectively. $P^{\mathrm{DG}}_{s,i,b}$ illustrates the capacity of ith DG installed at bth busbar and sth scenario as well as C^{DG}_{i} denotes to its capital cost [$/kW]. In addition, $\tau_{s,j,l}$ is a binary variable to allocate jth RCS in l_{th} line and s_{th} scenario and C^{RCS}_{j} shows its installation cost. Finally, $P^{\mathrm{int}}_{s,b,t}$ denotes the initial power consumed at b_{th} busbar before applying the DSM; $P^{\mathrm{sec}}_{s,b,t}$ is the power demanded at b_{th} busbar after implementing DSM program and $\Pi^{E}_{s,t}$ is also the energy price in the day-ahead market at t_{th} hour.

$$\begin{aligned} Min\ F = &\sum_{s}\sum_{i\in \mathrm{DG}}\sum_{b}\varsigma_{s,i,b}\ \psi_{s,i,b}\ P^{\mathrm{DG}}_{s,i,b}\,C^{\mathrm{DG}}_{i} \\ &+\sum_{s}\sum_{j\in \mathrm{RCS}}\sum_{l}\tau_{s,j,l}\ C^{\mathrm{RCS}}_{j} \\ &+10\times 365\sum_{s}\sum_{t\in T}\sum_{b}\left[P^{\mathrm{int}}_{s,t,b}-P^{\mathrm{sec}}_{s,t,b}\right]\times \Pi^{E}_{s,t} \end{aligned} \tag{1}$$

A.2. DG Resources

In the proposed model, various DGs including WT, PV and MT along with ESS units have been taken into account within the µGs to locally supply a part of µGs demand. There are several constraints regarding to these resources in order to be safely operated during operation horizon time. Note that the prohibited operation zones of generation units are shown in equations

(2) to (4). In these equation, κ_w^{WT}, κ_c^{PV}, and κ_m^{MT}, respectively, represent binary variables for on/off status of WT, PV and MT throughout the day. Furthermore, the variables P_{wt}^{WT} , P_{ct}^{PV} and P_{mt}^{MT} express their productions at each time interval.

$$\kappa_w^{WT}\underline{P_w^{WT}} \le P_{w,t}^{WT} \le \overline{P_w^{WT}}\kappa_w^{WT}, \quad \forall t \tag{2}$$

$$\kappa_c^{PV}\underline{P_c^{PV}} \le P_{c,t}^{PV} \le \overline{P_c^{PV}}\kappa_c^{PV}, \quad \forall t \tag{3}$$

$$\kappa_m^{MT}\underline{P_m^{MT}} \le P_{m,t}^{MT} \le \overline{P_m^{MT}}\kappa_m^{MT}, \quad \forall t \tag{4}$$

A.3. Battery Energy Storage Systems

The technical operating constraints related to ESS units which should be satisfied $\forall e \in$ ESS & $\forall t \in T$ are as (5) to (10). The electrical energy stored in e_th batteries at hour t, (i.e.,$ES_{e,t}$) directly depends on the energy stored in the previous time slot and its charging/discharging powers ($P_{e,t}^{CH}$,$P_{e,t}^{DIS}$) as mentioned in equation (5). In this equation, parameters η^{CH} and η^{DIS} respectively depict the efficiency of batteries in the charge/discharge modes, and also $\zeta_{e,t}^{CH}$ and $\zeta_{e,t}^{DIS}$ are binary variables to display the charge and discharge modes of ESS at each time slot. Not that the stored energy in batteries should be kept between specific limits ($\underline{ES_e}$,$\overline{ES_e}$) as enforced by (6). The charge/discharge ranges of batteries have been restricted in (7) and (8), respectively. Moreover, equation (9) shows the storage internal losses at t_{th} hour and constraint (10) dedicates that ESS units at each time can be operated only at one mode (i.e., charging or discharging).

$$ES_{e,t} = ES_{e,t-1} + \left(\zeta_{e,t}^{CH}P_{e,t}^{CH}\eta^{CH} - \zeta_{e,t}^{DIS}P_{e,t}^{DIS}/\eta^{DIS}\right)\Delta t \tag{5}$$

$$\underline{ES_e} \le ES_{e,t} \le \overline{ES_e}, \quad \forall e, \forall t \tag{6}$$

$$\zeta_{e,t}^{CH}\underline{P_e^{CH}} \le P_{e,t}^{CH} \le \overline{P_e^{CH}}\zeta_{e,t}^{CH}, \quad \forall e, \forall t \tag{7}$$

$$\zeta_{e,t}^{DIS}\underline{P_e^{DIS}} \le P_{e,t}^{DIS} \le \overline{P_e^{DIS}}\zeta_{e,t}^{DIS}, \quad \forall e, \forall t \tag{8}$$

$$L_t^{ESS} = \left(1-\eta^{CH}\right)P_{e,t}^{CH}\zeta_{e,t}^{CH} + \zeta_{e,t}^{DIS}P_{e,t}^{DIS}\left(1/\eta^{DIS}-1\right) \tag{9}$$

$$\zeta_{e,t}^{CH} + \zeta_{e,t}^{DIS} \le 1, \quad \forall e, \forall t \tag{10}$$

A.4. Power Flow Equations

The power flow equations that should be satisfied $\forall n \in N$ & $\forall t \in T$ are as below (11) to (16). In equations (11) and (12), $P_{n,t}^{net}$ and $Q_{n,t}^{net}$, respectively, represent the net active and reactive powers injected to node n at hour t. Constraint (13) confirms that the voltage magnitude at each node should be kept within the allowed bound ($\underline{V_n}$,$\overline{V_n}$). In equations (14) and (15), Y_{nm} and θ_{nm} are the magnitude and angle of the nmth element of admittance matrix, respectively. Furthermore, $I_{l,t}$ in equation (16) is the current passing through l_{th} line and I_l^{max} is its maximum allowable current.

$$P_{n,t}^{net} = P_{n,t}^{G} - P_{n,t}^{D} - P_{e,t}^{CH} + P_{e,t}^{DIS} \tag{11}$$

$$Q_{n,t}^{net} = Q_{n,t}^{G} - Q_{n,t}^{D} \tag{12}$$

$$\underline{V_n} \le V_{n,t} \le \overline{V_n} \tag{13}$$

$$P_{n,t}^{net} = V_{n,t}\sum_m Y_{nm}V_{m,t}\cos\left(\delta_{n,t}-\delta_{m,t}-\theta_{nm}\right) \tag{14}$$

$$Q_{n,t}^{net} = V_{n,t}\sum_m Y_{nm}V_{m,t}\sin\left(\delta_{n,t}-\delta_{m,t}-\theta_{nm}\right) \tag{15}$$

$$I_{l,t} = Y_{nm}\left(\left|V_{n,t}\prec\delta_{n,t} - V_{m,t}\prec\delta_{m,t}\right|\right) \le I_l^{\max} \tag{16}$$

B. Demand flexibility modelling

By creating smart control and telecommunication infrastructures in the distribution networks, the customers can participate in the DSM such as demand response (DR) programs to achieve an affordable and sustainable energy system by changing its daily consumption pattern [24]. Smoothing the daily load profile of system by exercising DR programs could be recognized as a profitmaking pattern for both customers (to decrease their billing costs) and distribution companies (to reduce their peak demand and costs). In doing so, the objective of this paper is concentrated on proposing an e strategic program for integrating demand flexibility into the operational planning of µGs in order to deferral the investment decisions. To do so, time of use (TOU) program is taken into account to alter the load profile of system by proposing different electricity price tariffs [25]. Equations (17) to (23) mathematically express the proposed DR program. In the TOU scheme, the shiftable load is taken into account as a variable which may be defined by DNO as shown in (17) and (18). In this equation, DRt is the participation level of customers in the TOU program; P_t^{inc} and P_t^{dec} are increased and decreased demand and also $P_t^{D,int}$ shows the initial demand of system before applying TOU program. Constraint (19) implies that some of increased and decreased demand throughout the day should be equal with participation level of customers. The ramping up and -down restrictions to raise and lower the demand at each time interval are indicated by constraints (20) and (21). Additionally, limitations (22) and (23) imply that the maximum penetration rate ($\overline{DR}$) is limited and that the flexible demand cannot concurrently rise and decrease at each time slot, respectively.

$$P_t^D = (1-DR_t)\,P_t^{D,int} + \left(\beta_t^{inc}P_t^{inc} - P_t^{dec}\beta_t^{dec}\right) \tag{17}$$

$$P_t^{D,int} - P_t^D = DR_t \times P_t^{D,int} - \left(\beta_t^{inc}P_t^{inc} - P_t^{dec}\beta_t^{dec}\right) \tag{18}$$

$$\sum_t\left(\beta_t^{inc}P_t^{inc} - P_t^{dec}\beta_t^{dec}\right) = \sum_t DR_t \times P_t^{D,int} \tag{19}$$

$$P_t^{inc} - P_{t-1}^{inc} \le \beta_t^{inc}\overline{P^{inc}} \tag{20}$$

$$P_{t-1}^{dec} - P_t^{dec} \le \beta_t^{dec}\overline{P^{dec}} \tag{21}$$

$$DR_t \le \overline{DR} \tag{22}$$

$$\beta_t^{inc} + \beta_t^{dec} \le 1 \tag{23}$$

C. Reliability Assessment

Increasing the reliability of end-users is the one of most beneficial reasons behind the dividing distribution grids into the networked µGs [26]. Keeping this in mind, in this paper we use a reliability criteria to design the µGs in terms of loss of load probability (LOLP). The times and scenarios of load curtailment is determined via (24). In this equation, when the value of $\omega_{s,t,n}^{LC}$ would be one, it means that there is load curtailment at the system and the LOLP can be calculated in (25). In equation (26), $P_{s,t,n}^{LC}$ expresses the load curtailment; FOR_n represents the acceptable demand that could be curtailed; is the forced outage rate, and $T_{s,t,n}^{LC}$ is the time of unserved load. Finally, it is necessary to mention that the LOLP must be less than its predefined target value ($LOLP^{\text{Target}}$) as shown in (26).

$$0 \le P_{s,t,n}^{LC} \le \Lambda \times \omega_{s,t,n}^{LC} \tag{24}$$

$$LOLP = \sum_s\sum_t\sum_n FOR_n \times T_{s,t,n}^{LC} \times \omega_{s,t,n}^{LC} \times P_{s,t,n}^{LC} \tag{25}$$

$$LOLP \le LOLP^{\text{Target}} \tag{26}$$

3. UNCERTAINTY MODELLING

The prediction errors in electricity price, hourly load demand, and the production profile of the renewables are only a few of the important uncertainties that the DNO must deal with while operating the μGs in the proposed situation [27]. A stochastic scenario-based model to manage the uncertainties in combination with input parameters has been suggested in this study. The generation of a collection of scenarios for realizations of the random parameters while expressing their probabilistic properties is the initial stage in scenario-based models. The original set of scenarios was created for this purpose using the Monte Carlo simulation (MCS), which was run using the probability distribution functions of the prediction errors. In the stochastic programming, an additional term is added to the forecasted parameters to include the forecast error as (27). It should be mentioned that the error term ($\phi_{s,t}^{error}$) for each uncertain parameter is a zero-mean noise with a standard deviation that determines via its probability distribution function. Scenarios are represented with $\Phi_{s,t}$. The notion of a scenario tree may clearly demonstrate how a bigger set of scenarios can be created by combining the discrete outcomes for each stochastic input. A scenario tree is made up of nodes that reflect the random variable's states at certain time points (as given in equations (28) to (33)), branches that indicate the variable's various realizations (34), and a root that represents the starting point when the first stage choices are made. Keep in mind that, according to equation, the chance for each scenario should be equal to 1 as presented in (35).

$$\Phi_{s,t} = \phi_t^{forecast} + \phi_{s,t}^{error}, \quad \forall s, \forall t \tag{27}$$

$$\phi_{s,t}^{D} = \left\{ \left(v_d^1, \gamma_d^1\right), \left(v_d^2, \gamma_d^2\right), ..., \left(v_d^s, \gamma_d^s\right) \right\} \tag{28}$$

$$\gamma_d^1 + \gamma_d^2 + ... + \gamma_d^{s-1} + \gamma_d^s = 1 \tag{29}$$

$$\phi_{s,t}^{WT} = \left\{ \left(v_{wt}^1, \gamma_{wt}^1\right), \left(v_{wt}^2, \gamma_{wt}^2\right), ..., \left(v_{wt}^s, \gamma_{wt}^s\right) \right\} \tag{30}$$

$$\gamma_{wt}^1 + \gamma_{wt}^2 + ... + \gamma_{wt}^{s-1} + \gamma_{wt}^s = 1 \tag{31}$$

$$\phi_{s,t}^{PV} = \left\{ \left(v_{pv}^1, \gamma_{pv}^1\right), \left(v_{pv}^2, \gamma_{pv}^2\right), ..., \left(v_{pv}^s, \gamma_{pv}^s\right) \right\} \tag{32}$$

$$\gamma_{pv}^1 + \gamma_{pv}^2 + ... + \gamma_{pv}^{s-1} + \gamma_{pv}^s = 1 \tag{33}$$

$$S = \Phi_{s,t}^{D} \times \Phi_{s,t}^{WT} \times \Phi_{s,t}^{PV} \tag{34}$$

$$\sum_{s \in S} \gamma_d^s + \gamma_{wt}^s + \gamma_{pv}^s = 1 \tag{35}$$

It is important to note that the optimization issue becomes more complex when all possible circumstances are taken into account. Therefore, it is necessary to strike a balance between model correctness and calculation speed without sacrificing the primary statistical properties of the original dataset [28]. In order to do this, an effective scenario reduction approach has been used here to scale down the issue and make it computationally manageable. These scenario reduction methods combine situations with similar statistic metrics and eliminate scenarios with low likelihood (36). In actuality, the primary goal of the scenario reduction strategy is to identify a scenario subset of the given cardinality and probability that, according to a probability metric, is closest to the original distribution (37). Fig. 3 displays the scenarios produced by MCS for unknown factors (such as wind speed, solar irradiance, and power pricing).

$$S_1 = \arg\left\{ \min_{s' \in S} \sum_s \gamma_s \times C\left(s, s'\right) \right\} S = \{S_1\} \tag{36}$$

$$S_1 = \arg\left\{ \min_{s' \in S} \sum_s \gamma_s \times C\left(s, s'\right) \right\} S = \{S_1\} \tag{37}$$

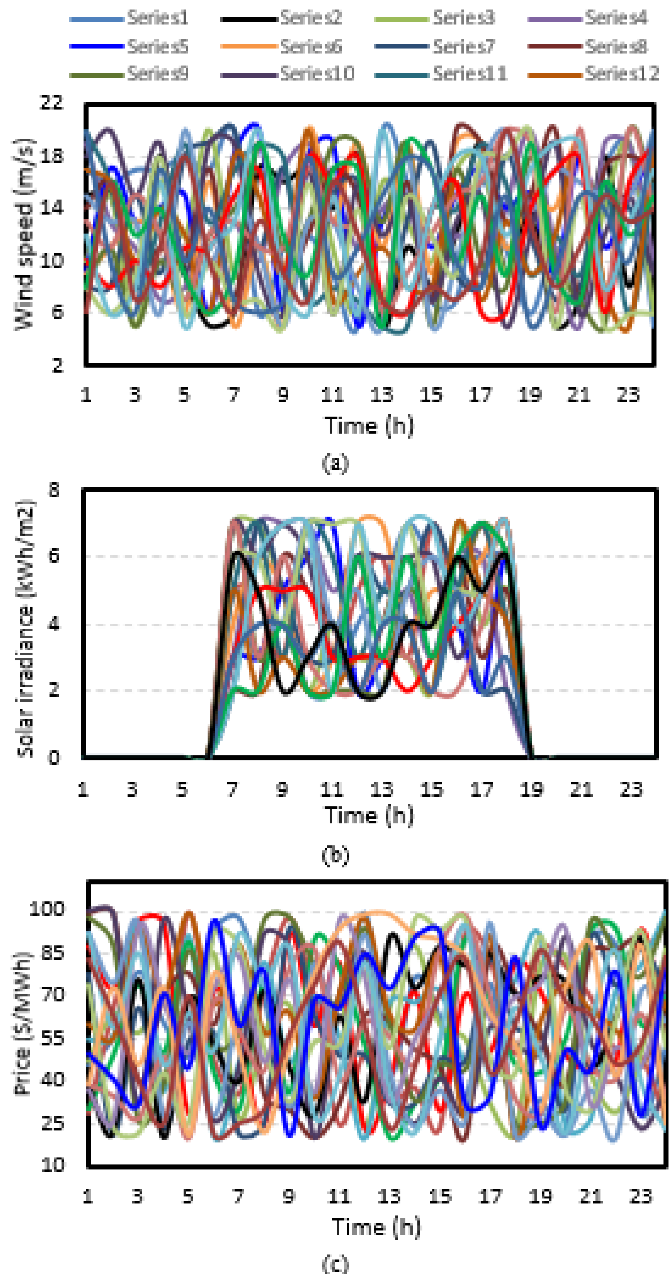

Fig. 3. The scenarios generated for uncertain parameters

4. NUMERICAL RESULTS

The case study was carried out on the modified IEEE 33-bus distribution test-bed to justify the applicability of the proposed framework [29]. The number of planning years in the proposed problem is considered to be 10 years. The proposed model is an MINLP that has been implemented in GAMS environment [30] and solved by BARON [31]. In the proposed problem, it is assumed that a commercial DR collector is available that concludes bilateral contracts between DNO and customers to run DSM schemes when needed. The proposed approach attempts to divide the distribution grid into a set of µGs and to assess the impact of DSM programs on the µG planning problem. In other words, the proposed model determines the volume of investments in the planning stage considering the demand flexibility at the operation stage. The data required to solve the problem has been extracted from [6], [18], [20] and [32]. The final

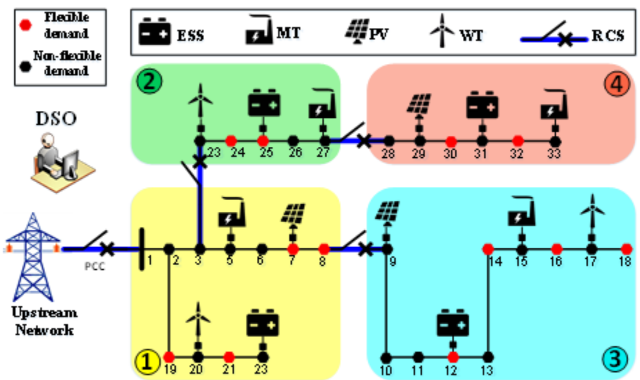

Fig. 4. IEEE 33-bus test-bed with four supply-sufficient µGs.

structure of the system is visually illustrated in Fig. 4. It can be seen that the power distribution network is divided into four µGs with heterogeneous DERs. The important point in forming the boundaries of µGs is to create power balance, as much as possible, inside them so that the level of network security is at its maximum value in island mode. Some of the loads within the µGs is provided by local sources and the rest is purchased from the upstream network or other µGs. Note that the load profiles and demand patterns of the connected loads within the µGs are significant factors. The electrical boundaries of µGs are determined based on the distribution network's ability to meet the load requirements of these specific customers efficiently. On the other hand, voltage and power quality requirements are essential factors in determining the electrical boundaries of µGs. The electrical boundaries are defined to ensure that these requirements are met for the connected loads, considering factors such as voltage drop, and reactive power control. By connecting the µGs to each other, they can exchange the power between themselves through RCSs installed in the interregional lines. The active and reactive powers at all nodes of system are given in Fig. 5 and their consumption patterns are shown in Fig. 6. In this work, three different users including residential, commercial and industrial load have been taken into account. Furthermore, the electricity price at spot market is depicted in Fig. 7. In the proposed TOU program, in order to modify the load profile we consider energy prices as 6.824, 1.269 and 0.175 US$ per kWh, respectively, during on-peak, off-peak and low-load periods. However, the DR programs can also pose challenges to investment decisions of µGs. For example, if a demand management program is too successful in reducing energy demand during peak periods, it may reduce the need for a µG altogether. In this case, the financial benefits of investing in a µG may not outweigh the costs.

To clarify the impact of DSM schemes on the investment decisions as well as operational planning of µGs at both interconnected and islanded modes, the simulations have been performed in two different case studies:

- Case I: In this case, loads are assumed to be fixed and the importance and prioritization of loads are not considered.

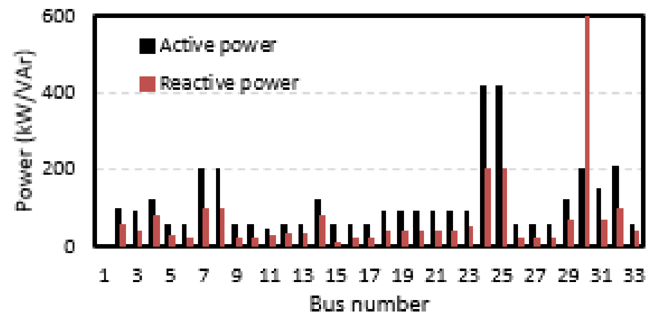

Fig. 5. Active and reactive powers of demand at the nodes of network.

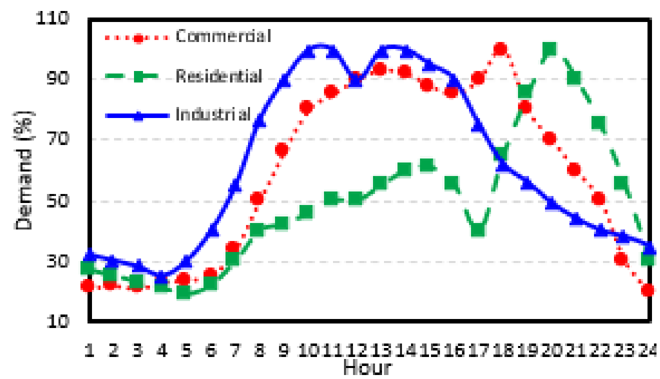

Fig. 6. Daily load profiles of different end-users

- Case II: In this case, it is assumed that the consumption management aggregator is available and can control part of the network loads.

First of all, it should be pointed out that the participation level of consumers in the proposed DR scheme is set to be 25%. It is worth noting that the DR participation level depends on many factors such as level of automation and system intelligence, geographic position of the network, type of users and their risk attitude. To compare the impact of DSM schemes on the DER planning problem, the results have been presented for two cases in Table 2. We should mention that the step size of DER units is considered as 25 kW because of their limitations at the production process. Regarding to this table, it can be concluded that executing DR program will reduce the installed capacities of WT, PV and MT by about 23.52%, 20.83% and 16.12%, respectively. This is because that by implementation of TOU program, the customers lessen their energy usage at the peak hours in order to decrease the billing costs and therefore, this issue causes to smooth the peak load of system along with valley filling (i.e., flattening the load profile). As a result, the proposed time-based

Table 1. Self and cross elasticities of demand

	Low	Off-peak	Peak
Low-load	-0.125	0.064	0.138
Off-peak	0.064	-0.125	0.172
On-peak	0.138	0.172	-0.125

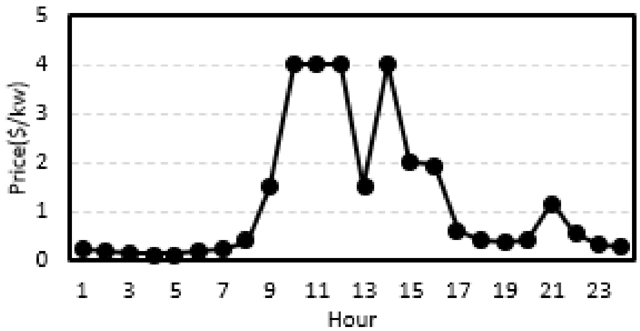

Fig. 7. Expected electricity price in the pool market

Table 2. DER planning with/without DR program

DER	Number	Location (bus)		Capacity (kW)	
		Without DR	With DR	Without DR	With DR
WT	WT1	20	20	300	250
	WT2	24	23	300	200
	WT3	18	17	250	200
PV	PV1	6	7	200	150
	PV2	9	9	200	175
	PV3	29	29	200	150
MT	MT1	4	5	450	300
	MT2	26	27	400	300
	MT3	15	15	350	350
	MT4	32	33	350	350
ESS	ESS1	23	23	200	175
	ESS2	25	25	200	150
	ESS3	11	12	250	150
	ESS4	30	31	250	125

DSM scheme reduces the installed capacity of ESS units from 900 kWh to 600 kWh (i.e., 33.33%).

The results of different objective functions have been given in Table 3, in which both case studies are considered. It should be stated out that this table has been shown for three distinct scenarios, i.e., low-cost, mid-cost and high-cost. As is clear from the results, the utilization of demand flexibility has positive impact on reducing investment and operation costs of whole system. This is due to the fact that smoothing the load profile not only reduces the volume of investments, but also minimizes the operating costs of system. In other words, flexible loads increase the generation adequacy of network during peak hours and prevent the need to build new production sources. Actually, the DSM schemes can help reduce the need for additional capacity investments in µGs. By actively managing and shifting electricity demand during peak periods, these programs can alleviate strain on the existing infrastructure, thereby minimizing the need for costly upgrades or expansions. For example, in the low-cost scenario, the planning costs in Case II has been

Table 3. System planning costs with/without DR program

Metric	Case	µG planning cost scenario		
		Low	Med	High
Planning costs ($)	Without DR	68311.74	73550.08	82760.12
	With DR	56991.25	62874.66	70119.84
Operating costs ($)	Without DR	27594.10	35447.23	42115.66
	With DR	15489.34	20874.66	24798.11
DR profit ($)	Without DR	-	-	-
	With DR	11667.01	14700.35	17898.22
LOLP (MWh)	Without DR	314.260	386.071	412.753
	With DR	248.551	282.687	304.702

reduced by about 16. 57% compared to Case I. In addition, the operation costs in Case II show 43.86% decrease in comparison with Case I. The energy not supplied during operation horizon time has also been decrease from 314.26 MWh to 248.551 MWh (20.98%). Fig. 8 graphically illustrates the load profiles of

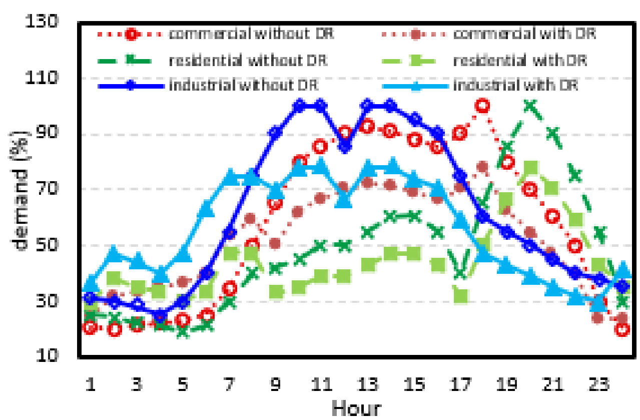

Fig. 8. Daily load profiles of different customers with/without DR

different customers with and without DR implementation [13]. The demand profiles have clearly been flattened by the planned TOU scheme by transferring demand from peak to off-peak periods. End-user procurement expenses are decreased as a result of this. The developed TOU plan may also enable DNO to save money by reducing peak demand and enabling the construction of additional DERs and power delivery systems, especially those reserved for use during peak hours, to be delayed. So, applying DR program is a win-win game that frankly safeguards the interests of both DNO and consumers. Finally, to investigate the potential of the proposed demand flexibility on the important aspects of the problem, e.g., reliability and planning costs, two sensitivity analysis have been performed as illustrated in Fig. 9. With respect to Fig. 9(a), it is clear that by increasing the DR level the values of LOLP is decreased, which is caused by load transfer from peak and critical times to hours when the operating conditions of the system are normal. Additionally, Fig. 9(b) confirms that the DR program can significantly diminish the planning expenditures of system and defer the upgrading of the network. Owing to the fact that the propounded model is run

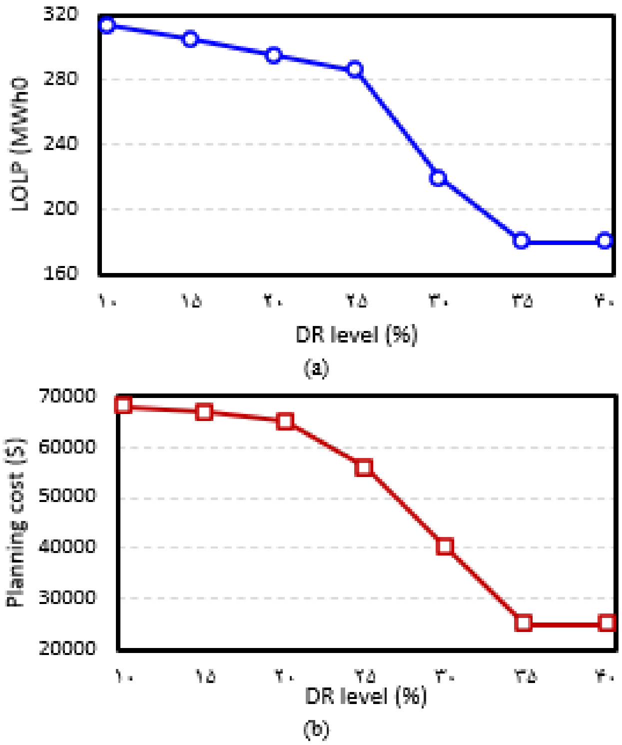

Fig. 9. Sensitivity analysis to investigate the impact of DR on (a) LOLP and (b) planning cost.

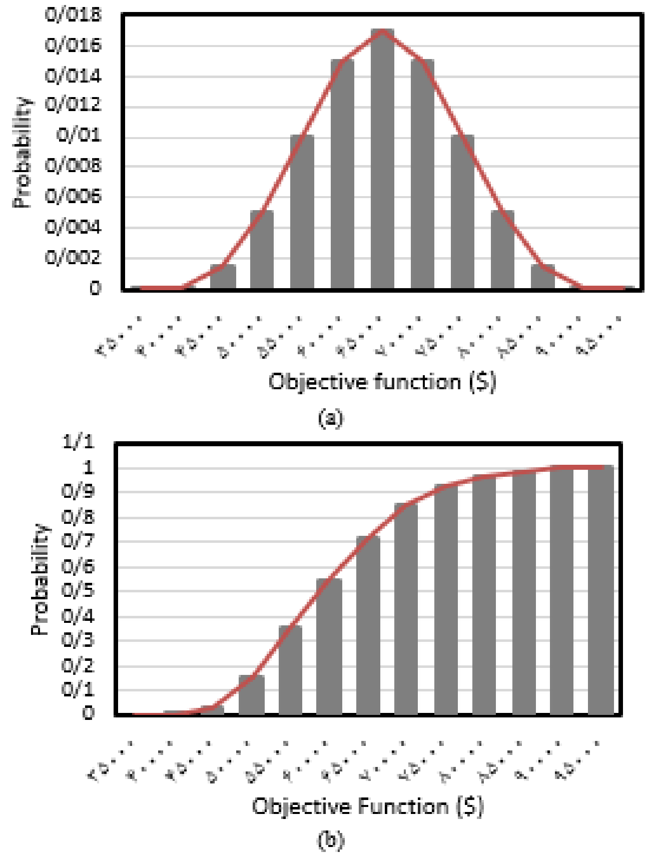

Fig. 10. (a) PDF and (b) CDF of objective function

for all scenarios, therefore, different values will be obtained for the scenarios. Besides, demand management programs may require significant investment by µG operators to participate. For example, µG operators may need to invest in advanced energy management systems or smart grid technology to participate in demand response programs. This can increase the upfront costs of investing in a µG and may deter some potential investors. To demonstrate the variations of the planning costs proportion to the scenarios, the PDF and CDF of objective function are given in Fig. 10. This figure shows that existing the uncertain parameters within the optimization model can vary the optimal value of objective function at different scenarios, which in turn this issue imposes significant risk into the safe operation of system. So, the stochastic modelling of the problem gives a more realistic and reliable solution compared to deterministic one generally. The uncertainty can lead to overinvestment or under-investment in capacity, while supply uncertainty can lead to under-supply or energy shortages. Regulatory uncertainty can affect the availability of funding and incentives, as well as the ability to participate in demand response programs. To mitigate the impacts of uncertainty, µG planners and operators must carefully consider the potential risks and develop strategies to manage uncertainty effectively. This may include using advanced forecasting techniques to predict demand and supply, investing in flexible and scalable infrastructure, and developing contingency plans to manage unexpected events. By doing so, µG planners and operators can improve the reliability and cost-effectiveness of µGs, making them more sustainable and attractive to customers.

5. CONCLUSION

What was discussed in this paper is to outline a novel strategy for analyzing interactions between the DNO and DSM aggregator to maximize the profits of both sides, if act strategically. The case study is performed on an IEEE test-bed and the results obtained from simulations demonstrate that the µG planning problem and DSM schemes are rather complementary from both operator and customer perspectives and their rivalry results in greater cost reductions compared to situations when there is just one enabling technology. The results confirm that participating in the TOU program decreases the installed DER capacity, which in turn leads to lower costs for the DNO. On the contrary hand, the case study discovers that even when the DER siting and size choices are properly optimized, the high availability and low recovery requirements of controlled loads not only improve the profitability of DR aggregator but also dramatically lower profit potential for the DNO. As expected, higher DR participation level considerably improves the reliability of the system, while reducing the planning costs. In conclusion, the DSM programs can have a significant impact on investment decisions in µG. By incentivizing energy reduction during peak periods, the DSM programs can increase the attractiveness of investing in µGs, create new revenue streams, and encourage sustainable design and operation. However, the DSM programs can also pose challenges, such as reducing the need for a µG or increasing upfront costs. As DSM programs continue to evolve, it will be important for µG investors and operators to carefully consider the potential impacts on their investment decisions. By doing so, they can make informed decisions that balance the benefits and challenges of DSM programs and create sustainable, reliable energy systems for communities. In general, the DSM schemes may potentially have a favorable influence on investment choices in μG design. They do this by minimizing capital expenditure, maximizing resource consumption, enhancing grid resilience, delivering cost savings, and simplifying the integration of renewable energy sources.

REFERENCES

1. R. H. Lasseter, "Smart distribution: Coupled microgrids," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 1074-1082, 2011.
2. D. Olivares, A. Mehrizi-Sani, A. H. Etemadi, C. A. Cañizares, R. Iravani, M. Kazerani, A. H. Hajimiragha, "Trends in microgrid control," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, 2014.
3. J. Salehi, A. Namvar, et al, "Effect of power-to-gas technology in energy hub optimal operation and gas network congestion reduction," *Energy*, vol. 240, pp. 122835, 2022.
4. F. Samadi Gazijahani, J. Salehi, M. Shafie-Khah, J. PS Catalão, "Spatiotemporal splitting of distribution networks into self-healing resilient microgrids using an adjustable interval optimization," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5218-5229, 2020.
5. H. Shayeghi, M. Alilou. "Technical-economic management of smart home energy system in the presence of stochastic and seasonal behavior of PV and EV." *Journal of Energy Management and Technology* vol. 6, no. 4, pp. 270-281, 2022.
6. S. Mazaheri Khamaneh, S. Tohidi, M. Reza Feyzi, V. Sohrabi Tabar. "Risk-aware multi-objective planning of a renewable hybrid microgrid incorporating energy storage systems and responsive loads." *Journal of Energy Management and Technology*, vol. 7, no. 3, pp. 125-133, 2023.
7. F. Jabari, M. Nazari-heris, M. Abapour. "Implementation and Investigation of Demand-Side Management Polices in Iran's Industrial and Commercial Sectors." *Journal of Energy Management and Technology* vol. 7, no. 1, pp. 34-42, 2023.
8. H. Fathima, K. Palanisamy, "Optimization in microgrids with hybrid energy systems–A review," *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 431-446, 2015.
9. S. A. Arefifar, Y. A-R. I. Mohamed, T. H. M. EL-Fouly, "Optimum microgrid design for enhancing reliability and supply-security," *IEEE Transactions on Smart Grid*, vol. 4, no 3, pp. 1567-1575, Sep. 2013.
10. F. Samadi Gazijahani, J. Salehi, and M. Shafie-khah, "Benefiting from Energy-Hub Flexibilities to Reinforce Distribution System Resilience: A Pre-and Post-Disaster Management Model," *IEEE Systems Journal*, vol. 16, no 2, pp. 3381-3390, 2022.
11. Z. Wang, et al, "Networked microgrids for self-healing power systems," *IEEE Transactions on Smart Grid*, vol. 2, no 1, pp. 1-10, Apr. 2015.
12. Z. Wang, J. Wang, "Self-Healing resilient distribution systems based on sectionalization into microgrids," *IEEE Transactions on Power Systems*, vol. 3, no 1, pp. 1-10, Oct. 2015.
13. FS. Gazijahani, et al. "Joint energy and reserve scheduling of renewable powered microgrids accommodating price responsive demand by scenario: a risk-based augmented epsilon-constraint approach." *Journal of Cleaner Production*, vol. 262, pp. 121365, 2020.
14. L. Che, X. Zhang, M. Shahidehpour, A. Alabdul-wahab, A. Abusorrah, "Optimal interconnection planning of community microgrids with renewable energy sources," *IEEE Transactions on Smart Grid*, vol. 1, no. 5, pp. 1-10, 2015.
15. A. Khodaei, S. Bahramirad, M. Shahidehpour," Micro-grid planning under uncertainty," *IEEE Transactions on Smart Grid*, vol. 30, no. 5, pp. 2417- 2425, Sep. 2015.
16. L. Che, X. Zhang, M. Shahidehpour, A. Alabdulwahab, Y. A-Turki, "Optimal planning of Loop-Based micro-grid Topology," *IEEE Trans. on Smart Grid*, vol. 2, no. 4, pp. 1-11, Jul. 2016.
17. K. Nekooei, MM. Farsangi, NH. Pour, K. Lee, "An Improved multiobjective harmony search for optimal placement of DGs in distribution systems," *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 557–567, 2013.
18. F. Samadi Gazijahani, J. Salehi, "Robust design of microgrids with reconfigurable topology under severe uncertainty," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 2, pp. 559-569, Apr. 2018.
19. A. Khodaei M. Shahidehpour, "Microgrid-based co-optimization of Generation and transmission planning in power systems," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1582–1590, May 2013.
20. V. Amir, M. Azimian, "Dynamic multi-carrier microgrid deployment under uncertainty," *Applied Energy*, vol. 260, pp. 114293, 2020.
21. J. Wei, Y. Zhang, J. Wang, X. Cao, M. Armoghan Khan, "Multi-period planning of multi-energy microgrid with multi-type uncertainties using chance constrained information gap decision method," *Applied Energy*, vol. 260, pp. 114188, 2020.
22. J. Gao, et al, "A cost-effective two-stage optimization model for microgrid planning and scheduling with compressed air energy storage and preventive maintenance," *International Journal of Electrical Power & Energy Systems*, vol. 125, pp. 106547, 2021.
23. H. Lotfi, A. Khodaei, "AC versus DC microgrid planning," *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 296-304, 2017.
24. F. Samadi Gazijahani, J. Salehi, and M. Shafie-khah, "A Parallel Fast-Track Service Restoration Strategy Relying on Sectionalized Interdependent Power-Gas Distribution Systems," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 3, pp. 1811-1821, 2022.
25. J. Salehi, F. Samadi Gazijahani, and A. Safari, "Stochastic Simultaneous Planning of Interruptible Loads, Renewable Generations and Capacitors in Distribution Network," *Journal of Operation and Automation in Power Engineering*, vol. 10, no. 2, pp. 113-121, 2022.

26. M. Quashie, et al, "Optimal planning of microgrid power and operating reserve capacity," *Applied Energy*, vol. 210, pp. 1229-1236, 2018.

27. Y. Xiang, J. Liu, Y. Liu, "Robust energy management of microgrid with uncertain renewable generation and load," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1034-1043, 2015.

28. S. Pineda, A. Conejo, "Scenario reduction for risk-averse electricity trading," *IET Generation, Transmission and Distribution*, vol. 4, no. 6, pp. 694-705, 2010.

29. M. Baran, F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Power Engineering Review*, vol. 9, no. 4 , pp. 101-102, 1989.

30. The General Algebraic Modeling System (GAMS) Software, [Online]. Available: http://www.gams.com.

31. https://www.gams.com/latest/docs/S_BARON.html.

32. S. Najafi Ravadanegh, M-R. Jannati-Oskuee, and Gevork B. Gharehpetian. "Resiliency-oriented dynamic expansion planning of MG-based distribution networks." *Journal of Energy Management and Technology* vol. 6, no. 1, pp. 44-53, 2022.