Signal Processing and Renewable Energy
March 2021, (pp. 97-113)
ISSN: 2588-7327
eISSN: 2588-7335

Demand Response Potentials for the Economic Deployment of Multi-Carrier Microgrids

Mahdi Azimian[1], Vahid Amir[1*], and Saeid Javadi[1]

[1] Department of Electrical and Computer Engineering, Kashan Branch, Islamic Azad University, Kashan, Iran.

Received: 11-Oct-2020, Revised: 28-Nov-2020, Accepted: 01-Dec-2020.

Abstract

Multi-carrier microgrids integrated by multiple energies can provide high energy supply flexibility for not only electrical end-users but thermal or gas consumers. Thus, this paper inspects the technical and economic viability of multi-carrier microgrid expansions and helps investors decide whether to invest in multi-carrier microgrid installations. The proposed model's solution determines the optimal mixture of distributed energy resources and identifies potential customers' ideal demand response intensity within a real-life industrial multi-carrier microgrid. The developed model aims at minimizing the total planning cost comprising distributed energy resources' investment and replacement, demand response enabling technology, operation, maintenance, energy demand shifting, peak demand charge, CO2e emission, and load curtailment. The design problem is formulated as mixed-integer programming and solved by GAMS 24.1. Numerical simulations reveal the proposed model's efficacy and investigate the impact of various factors on multi-carrier microgrid planning results.

Keywords: Demand Response, Distributed Energy Resources, Multi-Carrier Microgrid, Planning.

1. INTRODUCTION

Microgrids (MGs) as key players in smart grids, comprised of distributed energy resources (DERs) and responsive loads, have attracted significant attention in recent years due to providing reliable and cost-effective energy solutions for energy consumers [1], [2]. Although the advent of smart grid technologies has propelled the integration of demand response programs (DRPs), the impact of advanced infrastructure cost on enabling the potential responsive users as a promising tool in smart grids' territories has

*Corresponding Authors Email: v.amir@iaukashan.ac.ir

been dismissed in the literature. Thus, a cost-effective planning model incorporating demand response (DR) is required for ensuring the financial feasibility of MG deployments.

Numerous studies have been conducted on MG design. An isolated MG's optimal formation regarding DR's direct load control is achieved using an innovative metaheuristic optimization method [3]. The model ensures the power reliability of a remote community by introducing a reliability index. As a new class of MGs, the efficient deployment of provisional MGs is explored to guarantee the prompt integration of renewable energy resources (RERs) and provide economic and environmental benefits for local consumers and the entire system [4]. The financial viability of a campus MG is investigated, incorporating pre- and after-tax cash flows [5]. The model also employs investment-based incentives to proliferate renewable energy penetrations and improve low-emission MGs' financial attractiveness. A comprehensive battery sizing model for MG applications is proposed in [6], which determines the optimal energy and power ratings, technology, and maximum depth of discharge of the battery. The battery lifetime is reflected in the model by means of degradation, which relates to the battery's depth of discharge and lifecycle. Reference [7] proposes a model to optimally size and site photovoltaic (PV) and battery units within an isolated community MG. The model further analyzes the impact of deployed units on power quality and system loss. A generic storage sizing methodology is provided to determine feasible mixtures of short, medium, and long-term storage units within an islanded PV-based MG [8]. The objective is to minimize the annualized life cycle cost of a remote village comprising 20 households. MGs' application at maritime ports is explored considering inherent uncertainties associated with RERs and power outages [9]. The results advocate that port MGs with multiple stakeholders can contribute to various economic aspects, such as avoiding critical facility downtime, energy savings, energy dependency, and emission reduction. A procedure for partitioning smart distribution systems into self -sufficient MGs is proposed by optimally allocating DERs and reclosers [10]. Reference [11] designates a hybrid RER-based system to supply the energy requirement of a zone in Bushehr city. The hybrid system units' optimum capacity is determined using a meta-heuristic algorithm to minimize the overall costs and cost of load losses.

An economic and technical solution for rural electrification of a village is provided by the optimal sizing of RERs [12]. It is declared that the levelized cost of energy of the MG reduces by using the demand shifting strategy of non-essential loads and RER penetrations. A bi-objective model has been proposed to optimally site and size batteries within a 33-bus MG. The model's objective is to improve the MG's economic and reliability performances considering time-of-use DRP. A methodology for optimal sizing of an MG is presented, accounting for the battery and generator units' lifetime based on the usage [13]. The model also incorporates electric vehicles and pumped water storage as dynamic loads to participate in DRPs. Reference [14] presents a joint multi-

objective optimization approach to optimize a grid-connected MG design and operation.
An efficient DR model is employed in the model, resulting in an intense reduction in the system's total cost without compromising customers' satisfaction. A two-stage planning method considering price-based DRPs is proposed for multi-energy systems [15]. The upper-stage is designed to minimize the annual capital and operation costs by deploying DERs. In the lower stage, shiftable customers' load patterns are revised based on the nodal energy price calculated in the upper stage, thereby minimizing users' consumption expenditure using an integrated DRP. The paper in [16] designates an efficient stochastic planning model for self-sufficient ac/dc MGs. The objective is to minimize the planning costs comprising the DERs investment, operation, and electronic converters. Reference [17] proposes a probabilistic dynamic planning procedure for residential energy systems intending to minimize costs over the planning horizon. Controllable electrical and thermal appliances are employed in the model to tackle PV oscillations. An extended work of the previous publication is proposed in [18], which considers the possible PV energy curtailment cost. The results declare that PV curtailment consideration in the objective function significantly proliferates PV installations within residential communities. A bi-objective model is proposed to optimally site and size electrical storage units within a 33-bus MG [19]. The model's objective is to improve both the MG's economic and reliability performances, considering the time-of-use DRP. The work in [20] investigates the long-term planning of renewable-based MG intending to minimize the reliability and lifecycle costs. Critical peak and time-ahead pricing of DRPs are incorporated into the model to enhance energy management.

To the best of the authors' knowledge, investigating the impact of advanced infrastructure cost on enabling the potential responsive customers has not been addressed in the literature. Thus, this paper aims to propose a generic multi-carrier microgrid (MCMG) deployment model to optimally size DERs and identify the ideal DR ratio of a group of industrial customers. The main contributions of the paper are listed as follows:

- Determining the ideal mix and size of DERs from economic, reliability, and environmental perspectives.
- Minimizing the costs associated with the DERs investment and replacement, DR enabling technology, operation, maintenance, energy demand shifting, peak demand charge, emission, and unserved energy;
- Inspecting the effects of the capital investment fund (CIF) extents on the optimal sizing and DR intensity of the proposed MCMG.

2. MODEL OUTLINE AND FORMULATION

The MCMG is an advanced technology that provides economic benefits for its stakeholders. It is also typically formed of a low- or medium-voltage electrical network together with networks of other energy carriers [21]. Smart grid technologies such as distributed energy resources and DRPs can be indisputably integrated within MCMGs to provide salient complementary value propositions to their customers. The proposed model aims to minimize the MCMG total planning cost (1) comprising the investment and replacement costs of DERs, DR enabling technology cost, operation and maintenance costs, energy demand shifting cost, peak demand charge, emission, and unserved energy cost.

$$OF = \sum_{y} \omega_y \cdot \left(IC_y + RC_y + DC_y + OC_y + MC_y + SC_y + PC_y + EC_y + UC_y \right) \tag{1}$$

The investment cost of DERs (2) comprises the investment cost of dispatchable and non-dispatchable distributed generations (DGs), and the investment cost of storage systems associated with installed power and energy capacities [6]. The replacement cost is calculated using (3), which denotes the capital replacement cost of DERs times their installed power/energy capacities. The DR enabling technology cost (4) represents the cost of smart appliances and efficient information and communication technologies for enabling the potential responsive customers and is defined herein as the DR enabling capital cost times the DR intensity. The operation cost (5) denotes the cost or benefit of exchanged power with the electric and natural gas utility companies. The maintenance cost of deployed dispatchable and non-dispatchable units is given in (6). The energy demand shifting cost (7) denotes the energy demand shifting up or down for the potential enabled responsive customers multiplied by the hourly energy demand shifting price. The peak demand charge is calculated in (8), which is interpreted as the peak demand price multiplied by the highest amount of purchased electricity from the power utility company during a billing period. The utility grid and deployed DGs' emission cost are calculated in (9), derived from the emission tax times the equivalent produced emission by utility grid and DGs. Equation (10) represents the load shedding cost for unserved electrical and thermal demand, which is defined as the amount of load shedding multiplied by the value of lost loads.

$$IC_y = \sum_{u \in \{G,W\}} CC_u \cdot P_u^{\max} + \sum_{u \in S} (CP_u \cdot P_u^{\max} + CE_u \cdot E_u^{\max}) \qquad \forall y = 1 \tag{2}$$

$$RC_y = \sum_{u \in \{G,W\}} CCr_u(r_{uy}) \cdot P_u^{\max} + \sum_{u \in S} \left(CPr_u(r_{uy}) \cdot P_u^{\max} + CEr_u(r_{uy}) \cdot E_u^{\max} \right) \tag{3}$$

$$DC_y = CD \cdot LPF \cdot \max(D^e_{(y=Ny)sdh}) \qquad \forall y = 1 \tag{4}$$

$$OC_y = \sum_{s} \sum_{d} \mu_{sd} \cdot \sum_{h} \left(+P_{ysdh}^{Net,e} \cdot \pi_{yh}^{Net,e} + P_{ysdh}^{Net,g} \cdot \pi_{y}^{Net,g} \right) \tag{5}$$

$$MC_y = \sum_{s} \sum_{d} \mu_{sd} \cdot \sum_{h} \sum_{u \in \{G,W\}} P_{uysdh} \cdot \alpha_u^{main} \tag{6}$$

$$SC_y = \sum_s \sum_d \mu_{sd} \cdot \sum_h \pi_{yh}^{shifting} \cdot \left(D_{ysdh}^{shup,e} - D_{ysdh}^{shdo,e} \right) \tag{7}$$

$$PC_y = \sum_s \eta_s \cdot \pi^{peak} \cdot \max(P_{ysdh}^{Net,e,+}) \tag{8}$$

$$EC_y = \sum_s \sum_d \mu_{sd} \cdot \sum_h \pi^{em} \cdot \left(P_{ysdh}^{Net,e} \cdot EF^{Net,e} + \sum_{u \in \{G,W\}} P_{uysdh} \cdot EF_u \right) \tag{9}$$

$$UC_y = \sum_s \sum_d \mu_{sd} \cdot \sum_h P_{ysdh}^{ens,l} \cdot \pi^{ens,l} \; \forall l \in \{e,t\} \tag{10}$$

Equation (11) denotes the present-worth value factor.

$$\omega_y = 1 \big/ (1+i)^{y-1} \tag{11}$$

Equation (12) ensures the electrical demand balance in which the power generation by DERs, and the exchanged power with the utility company, plus the curtailed electricity demand are equal to the electrical demand regarding the demand shifting potential plus the energy consumed by the electric heat pump (EHP). Likewise, the system's thermal demand balance constraint is represented by (13), where the produced thermal energy by DERs plus the curtailed thermal demand is greater than or equal to the customers' thermal demand. The total natural gas consumption dedicated to the combined heat and power (CHP) and gas boiler units is declared as (14).

$$\begin{aligned} &\sum_{u \in \{G,W\}} P_{uysdh}^{e} \pm \sum_{u \in ess} P_{uysdh}^{dch/ch} + P_{ysdh}^{Net,e} + P_{ysdh}^{ens,e} \\ &= D_{ysdh}^{e} + D_{ysdh}^{shup,e} - D_{ysdh}^{shdo,e} + \sum_{u \in \{ehp\}} PD_{uysdh}^{e} \end{aligned} \tag{12}$$

$$\sum_{u \in G} P_{uysdh}^{t} \pm \sum_{u \in tss} P_{uysdh}^{dch/ch} + P_{ysdh}^{ens,t} \geq D_{ysdh}^{t} \tag{13}$$

$$P_{ysdh}^{Net,g} = \sum_{u \in \{chp,boiler\}} \upsilon_{uysdh} \tag{14}$$

The energy generation by deployed units comprising gas-fired units, EHP, and PV is modeled respectively (15)–(17). The hourly generated power by dispatchable and non-dispatchable units is limited by their required and optimized installed capacities (18).

$$\begin{aligned} &P_{uysdh}^{l} = \upsilon_{uysdh} \cdot \alpha_u^{ef,l} \cdot A_u \\ &\qquad \forall u \in \{chp, boiler\}, \forall l \in \{e,t\} \end{aligned} \tag{15}$$

$$P_{uysdh}^{t} = PD_{uysdh}^{e} \cdot \alpha_{ush}^{ef} \cdot A_u \;\; \forall u \in ehp \tag{16}$$

$$\begin{aligned} P_{uysdh} = &\Big(P_u^{\max} \cdot \alpha_{uy}^{ef} \cdot A_u \cdot pp_{uh} \cdot G_s^{ing} \\ &\cdot \big(1 + \kappa \cdot (Tc - Tr_s) \big) \Big) \Big/ G^{stc} \quad \forall u \in pv \end{aligned} \tag{17}$$

$$0 \leq P_{uysdh} \leq P_u^{\max} \cdot V_{uysdh} \quad \forall u \in \{G,W\} \tag{18}$$

The energy storage constraints are represented in (19)–(22). The hourly stored energy is calculated in (20) as the stored energy in the previous hour, energy loss, and the net charged/discharged power. The stored energy at the beginning and the end of each day is presumed to be equal in storage systems to obtain sustainable storage utilization (20). The energy storage power in both charging and discharging modes is restricted by its installed power capacity (21). Constraint (22) limits the available energy amount of energy storage to prevent overcharging.

$$E_{uysdh} = \left(E_{uysd(h-1)} - E_{uysdh} \cdot \alpha_u^{loss} + P_{uysdh}^{ch} - P_{uysdh}^{dch} / \alpha_u^{ef} \right) \cdot A_u \qquad \forall u \in S \tag{19}$$

$$E_{uysd\,(h1)} = E_{uysd\,(h24)} \qquad \forall u \in S \tag{20}$$

$$0 \le P_{uysdh}^{dch/ch} \le P_u^{\max} \qquad \forall u \in S \tag{21}$$

$$E_u^{\max} \cdot (1 - DOD_u) \le E_{uysdh} \le E_u^{\max} \qquad \forall u \in S \tag{22}$$

The installed power and energy capacity of the MCMG's units should be within their allowable installation capacity (23)–(24).

$$0 \le P_u^{\max} \le \overline{P_u^{cap}} \quad \forall u \in \{G, W, S\} \tag{23}$$

$$0 \le E_u^{\max} \le \overline{E_u^{cap}} \quad \forall u \in S \tag{24}$$

In this paper, the shiftable load DR model of paper [22] is employed to enable the demand-side management, as formulated in (25)–(28). It is noteworthy that the maximum hourly amount of demand shifting is constrained by the determined participation rate of enabled shiftable customers. Herein, only the customers equipped with smart appliances can participate in shifting strategies of DRPs.

$$\sum_h D_{ysdh}^{shup,e} = \sum_h D_{ysdh}^{shdo,e} \tag{25}$$

$$0 \le D_{ysdh}^{shup,e} \le D_{ysdh}^{e} \cdot LPF \cdot IS_{ysdh}^{shup,e} \tag{26}$$

$$0 \le D_{ysdh}^{shdo,e} \le D_{ysdh}^{e} \cdot LPF \cdot IS_{ysdh}^{shdo,e} \tag{27}$$

$$0 \le IS_{ysdh}^{shup,e} + IS_{ysdh}^{shdo,e} \le 1 \tag{28}$$

Amounts of exchanged electricity and natural gas with the utility network are respectively constrained by network capacities (29)–(30).

$$\left| P_{ysdh}^{Net,e} \right| \le \overline{P^{Net,e}} \tag{29}$$

$$0 \le P_{ysdh}^{Net,g} \le \overline{P^{Net,g}} \tag{30}$$

A load shedding scheme is utilized to ensure the balance of power between the generation and consumption in the MCMG (31). The equivalent loss factor is utilized in this paper to assess the reliability level of the MCMG (32), which is commonly considered below 0.01% for developed countries.

$$0 \le P_{ysdh}^{ens,l} \le (D_{ysdh}^{l} + D_{ysdh}^{shup,l} - D_{ysdh}^{shdo,l}) \qquad \forall l \in \{e, t\} \tag{31}$$

$$ELF_y = \left(\sum_s \sum_d \mu_{sd} \cdot \sum_h P_{ysdh}^{ens,e} / D_{ysdh}^{e}\right) / \left(N_h \cdot \sum_s \sum_d \mu_{sd}\right) \le \overline{ELF_y} \tag{32}$$

The online reserve constraint (33) is imposed to compensate for any sudden change either in generation or demand to ensure the MCMG's reliable operation.

$$\left(\sum_{u \in ess} \alpha_u^{ef} \cdot \min\left(E_{uysdh} / N_h, P_u^{\max}\right) \right) + \left(\sum_{u \in \{chp, fc\}} (P_u^{\max} \cdot A_u - P_{uysdh}^{e}) \right) \ge R_{ysdh} \tag{33}$$

3. SIMULATIONS RESULTS AND DISCUSSIONS

This study deploys an MCMG test system based on a real-life industrial park in Golpayegan, Iran. It is worth pointing out that the premises' customers are presumed to be the assets' stakeholders. Thus, the model is solved regarding cooperative energy scheduling and planning of different assets. The initial aggregated electrical and thermal loads of the industrial park are forecasted in Fig. 1. Herein, two typical days of three typical seasons involving summer, transitional (spring/autumn), and winter are selected to represent the whole year. The hourly electricity market price is acquired from the online ISO-New England data repository [23]. The natural gas market price of $0.00344/kWh, based on the Henry Hub Natural Gas data repository, is utilized in this paper [24]. The characteristics of candidate DERs are given in Table. 1 and 2. The required parameters for the MCMG deployment are represented in Table. 3. Twenty-four hours of islanding per year is considered on average based on historical outages data obtained from the Golpayegan Electric Utility Company. The problem was formulated by mixed-integer programming (MIP) and solved by GAMS 24.1.2. The following cases are studied:

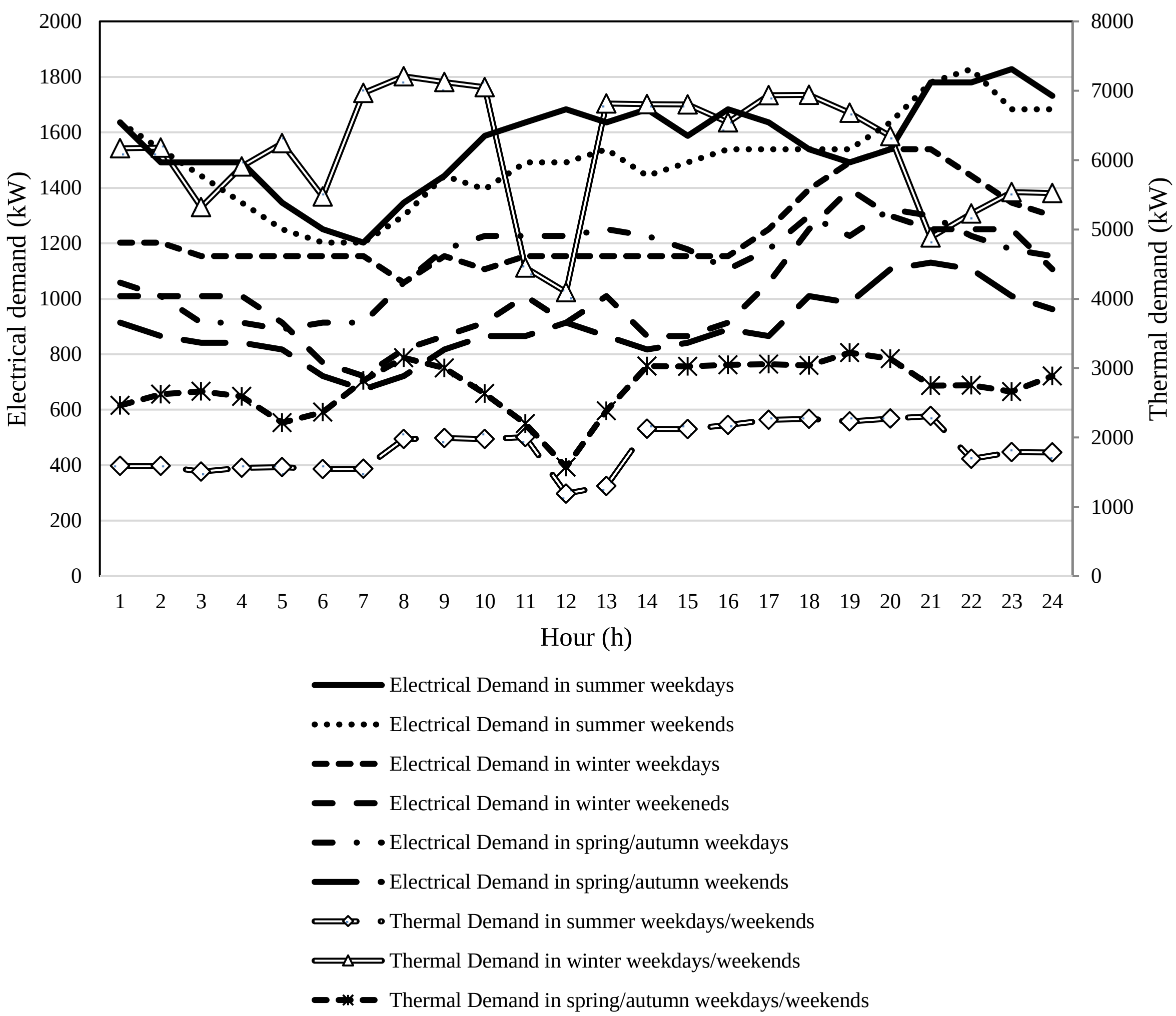

Fig. 1. Average value of loads in the initial year.

Table 1. *Dispatchable and nondispatchable units characteristics.*

Unit	Capital investment/ replacement costs ($/kW)	Maintenance coefficient ($/kWh)	Electrical/thermal efficiency (%)	Availability (%)	Lifetime (year)
CHP	300/300	0.01258	35/50	96	20
Boiler	45/45	0.00870	0/90	97	10
EHP	250/250	0.00300	97/0	98	15
PV	550/550	0.00310	-	96	25

Table 2. *Energy storage characteristics.*

Unit	Capital investment / replacement costs		Efficiency (%)	Loss efficiency (%)	Depth of discharge (%)	Availability (%)	Lifetime (year)
	Power ($/kW)	Energy ($/kWh)					
ESS	30/20	75/37	93	5	80	96	5
TSS	5/5	33/30	90	5	100	100	15

Table 3. *Required parameters for the mcmg planning*

Discount rate (%)	5	**Value of lost load ($/kWh)**	**Electricity**	3.65
Annual load growth rate (%)	2.9		**Heat**	0.107
Annual electricity price growth rate (%)	2.5	**Emission factor ($/kg.CO2e)**	**Utility**	0.2556
Monthly demand charge ($/kW)	6.192		**CHP**	0.17606
Required reserve margin (%)	10		**Boiler**	0.226
Equivalent loss factor (%)	0.01		**FC**	0.287
Demand response capital cost ($/kW)	1200	**CO2e tax price ($/kg.CO2e)**		0.0276

Case 1: MCMG planning as a function of CIF

MCMG planning is solved for various CIFs. Herein, the CIF denotes the available budget that can be put into the project by MCMG stakeholders. The optimal size and generation mix of deployed DERs with respect to the CIF variations are depicted in Fig. 2. It can be perceived from the results that the CHP would always be installed as the main supplier of electrical and thermal demands. Besides, the planning solution would install a PV unit with a large capacity to fulfill a big part of the demand and sell the excess profitable electricity to the utility company. The planning solution would install a thermal storage system (TSS) in conjunction with heat suppliers as if its energy rating is almost 2.33 times the power rating. However, by limiting the CIF progressively, the energy rating of deployed TSS decreases monotonically. Likewise, the

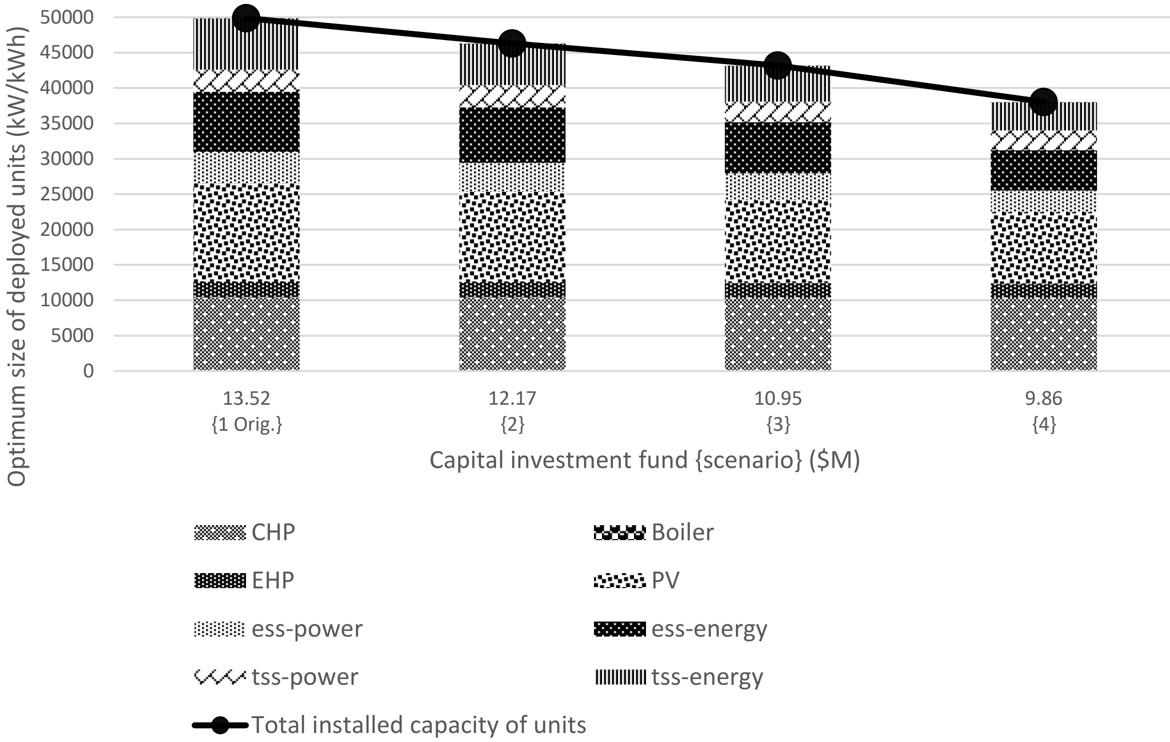

Fig. 2. Results of Technologies Optimum Size as a Function of CIF.

ESS with larger capacity would be installed to store the PV unit's surplus generation. It is worth pointing out that the ESS energy rating is calculated to be about two times than its power rating. Besides, a low-sized EHP is required to fulfill a part of thermal demand in conjunction with the CHP unit. All in all, dispatchable units would be preferably utilized in all scenarios to ensure an uninterruptable supply of demands during normal and emergency circumstances.

Fig. 3 illustrates the costs associated with the planning of the MCMG as a function of the CIF. According to the figure, the investment cost of deployed units keeps dropping by limiting the CIF. The same is perceived for the replacement cost. The result also advocates that enabling responsive users are justifiable only if the CIF is larger than $10.95M in such a network. Herein, potential responsive users, by participating in incentive-based DR programs, gain roughly half of the financed DR enabling technology cost and contribute energy savings by shifting their demands from peaks to off-peaks. Moreover, by decreasing the CIF, the accrued operational cash inflows decrease by about 5.2% for each scenario, whereas the maintenance cost slightly increases by about 0.9%. According to the figure, decreasing the CIF would increase the planning project's emission cost due to the PV unit's lower proliferation. On the other hand, the peak demand charge is zero, denoting the customers rather supply their demand by local DERs instead of the utility network.

Besides, the load shedding cost for partially curtailing low-prioritized thermal demands increases from \$0.4M to \$0.5M by decreasing the CIF. Overall, the economic feasibility of MCMG-based systems is verified for all scenarios since the accumulated revenue streams surpass the investment costs.

The demand response intensity and levelized cost of energy changes with respect to the CIF variations are shown in Fig. 4. Results show that, by decreasing the CIF, the levelized cost of energy would increase trivially, which could turn the project into an unattractive case. However, the financial feasibility of the MCMG deployment is verified since the determined levelized cost of energies is lower than the average retail rate of \$0.086/kWh. Besides, the DR intensity of only the first three scenarios is settled to be 27%, 13%, and 1% since the DR capability merit of the proposed model would be justified merely for that CIF which is larger than \$10.95M.

Case 2: Impact of DR enablement capital cost on MCMG planning

The planning solution's sensitivity with respect to DR, enabling technology capital cost is studied for a boundless CIF in this case. Fig. 5 shows the results and illustrates that a decline in DR enablement's capital cost would increase the DR intensity. The change in DR intensity also directly impacts the optimal size and mixture of deployed DERs and consequently affects the planning cost (see Fig. 6-7). According to Fig. 6, units' overall installed capacity would be affected by changes in DR intensity and reduced by 7.4% from 51.8 MW to 47.9 MW. The results advocate that higher PV unit proliferation

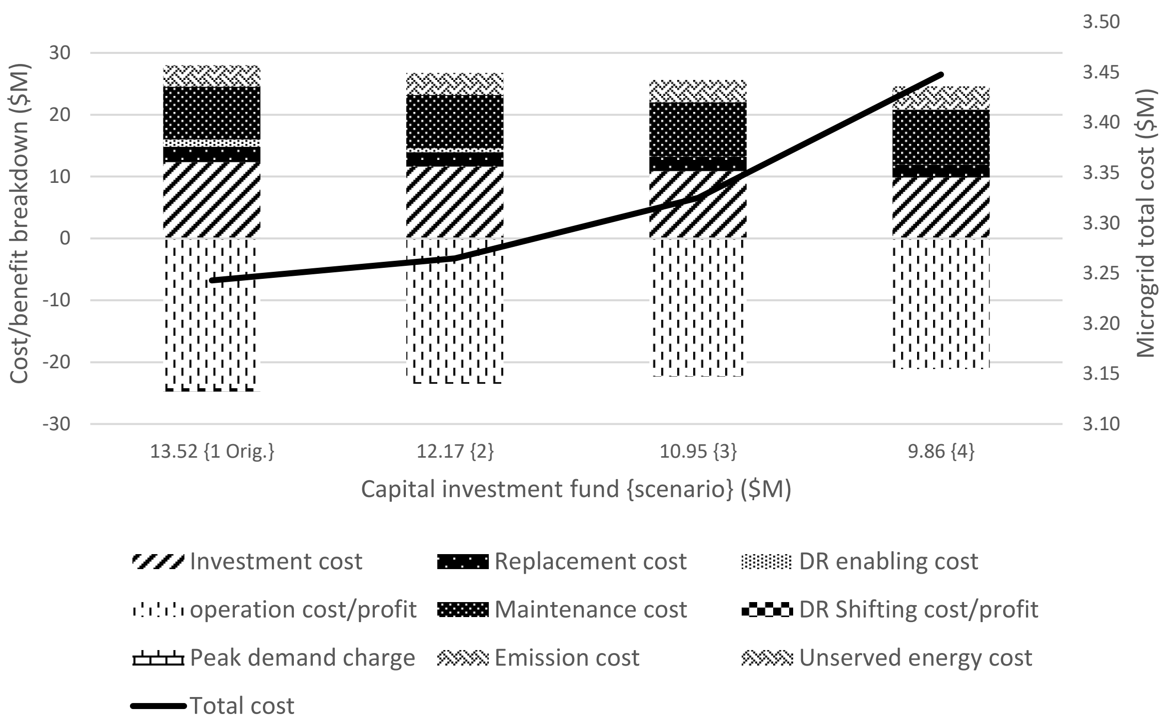

Fig. 3. Cost breakdown of deployed MCMG as a function of CIF.

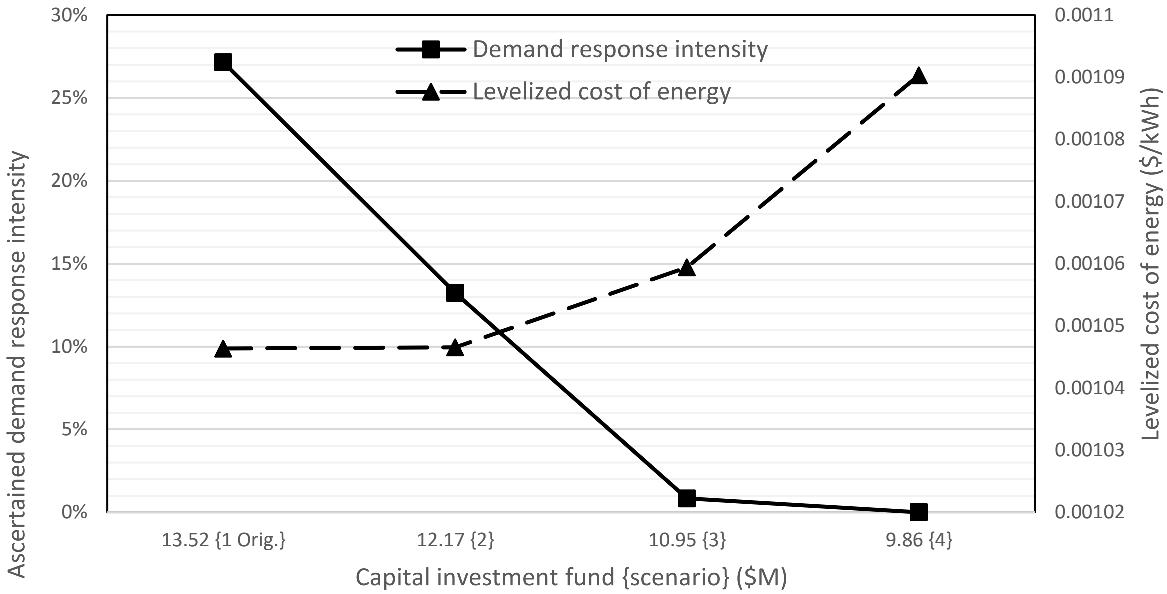

Fig. 4. Effect of CIF variations on MCMG economic metrics.

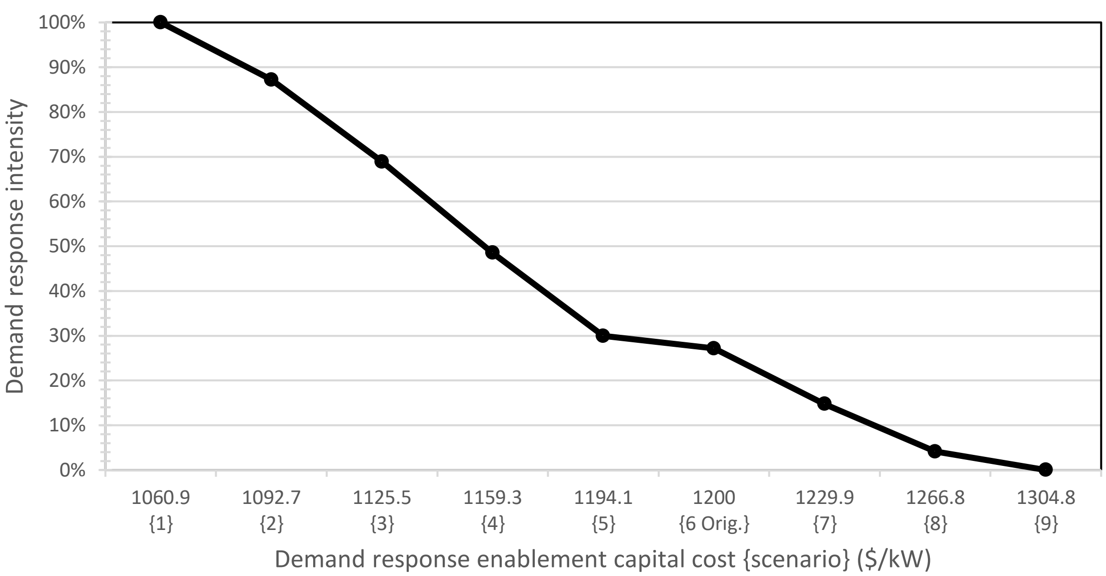

Fig. 5. Effect of changes in DR enablement cost on DR intensity.

would be realized by higher DR intensity. Besides, by higher DR intensity, the size of CHP and EHP decreases trivially. According to Fig. 7, the total planning cost would vary between $2.91M–$3.28M regarding DR intensity. In detail, the investment on DERs, particularly renewables, elevates by DR intensity of over 68.9%, which consequently leads to a significant reduction in emission and load shedding costs. By and large, the results advocate that the DR enabling technology cost is a decisive factor for enabling potential responsive users.

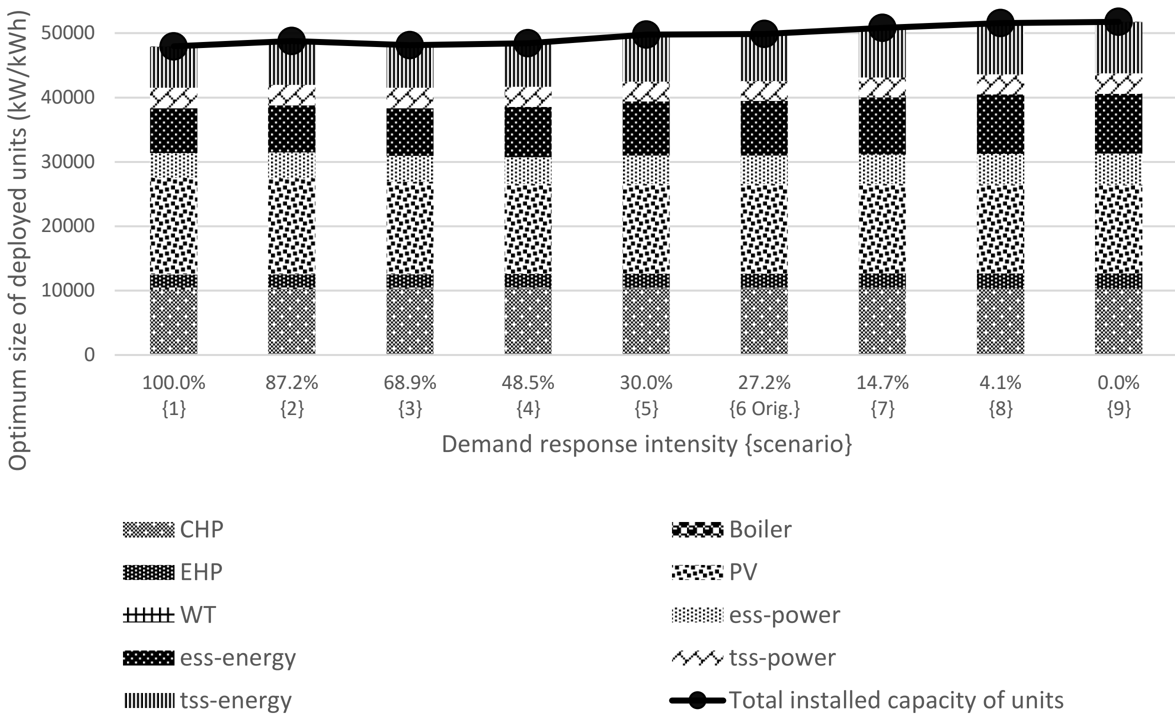

Fig. 6. Optimum size of technologies as a function of DR intensity.

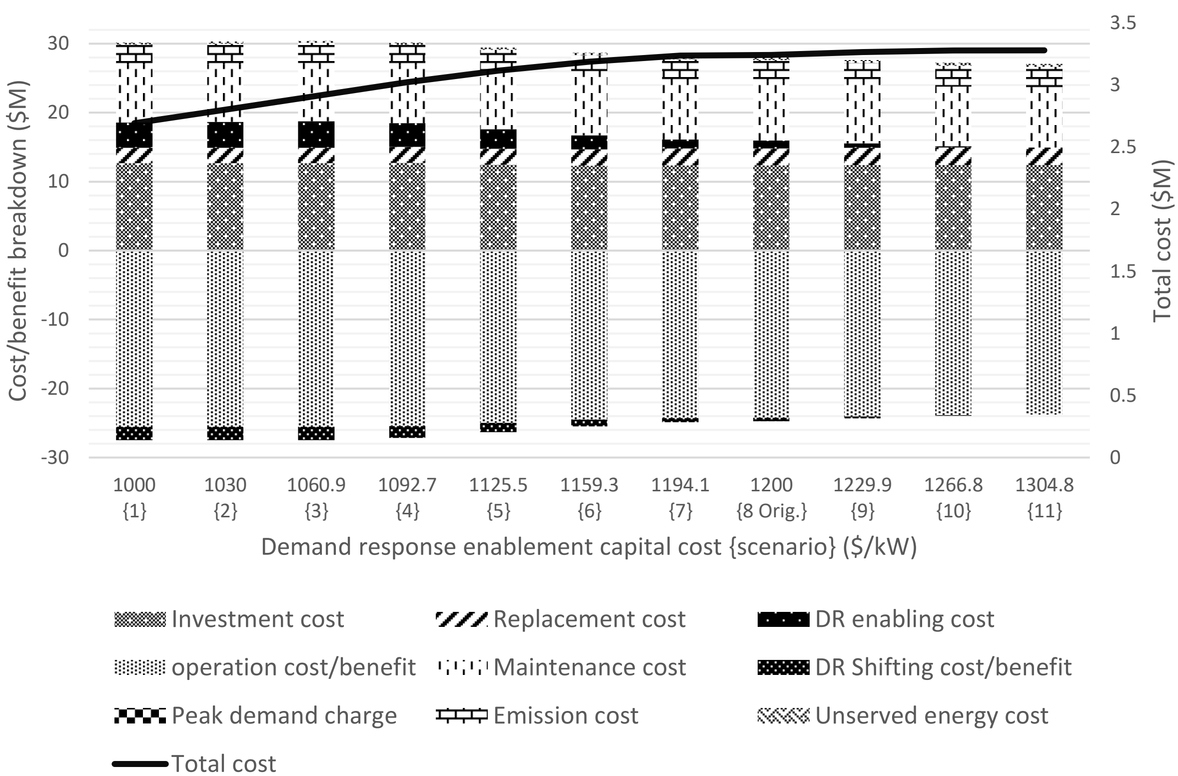

Fig. 7. Cost breakdown of MCMG as a function of DR intensity.

4. CONCLUSION

This paper presents an efficient and generic framework for designing multi-carrier microgrids considering technical, economic, and reliability criteria. The optimal configuration mix of DERs and the ideal ratio of enabled responsive customers are determined within the proposed MCMG while ensuring the desired level of reliability. The problem was formulated as a mixed-integer programming model that minimizes the overall planning cost subject to prevailing planning, operation, and reliability constraints. Herein, the proposed model was comprehensive in incorporating and mixing various terms with different time scales in one problem. Numerical simulations were represented to inspect the impact of the changes in CIF and smart appliances cost on MCMG planning solutions. It was verified that potential responsive customers together with DERs would be enabled only as a last resort to tackle price fluctuations. Hence, a profound drop in advanced infrastructure tools' capital cost is essential for encouraging customers to install modern equipment and, consequently, participate in DRPs. Lastly, numerical simulations exhibited the proposed model's economy and reliability merits through various scenarios.

NOMENCLATURE

Indices

boiler	Index for gas boiler unit
chp	Index for combined heat and power unit
d	Index for days
ehp	Index for electric heat pump unit
ess	Index for electrical storage system
fc	Index for fuel cell unit
h	Index for hours
l	Index for carrier comprising *{e: electricity, t: heat}*
pv	Index for photovoltaic unit
s	Index for seasons
tss	Index for thermal storage system
u	Index for distributed energy resources

α^{main}	Maintenance coefficient of units
π^{em}	CO2e tax price
π^{ens}	Value of lost load
$\pi^{Net,e}, \pi^{Net,g}$	Electricity and natural gas price
π^{peak}	Peak demand price
$\pi^{shifting}$	Energy demand shifting price
κ	Maximum power temperature coefficient
μ / η	Number of days/months per season
ω	Present-worth value factor

Variables

$D^{shup/shdo}$	Shifted up/down electricity demand
DC	Microgrid demand response enabling cost

y	Index for years

Sets

G	Set of dispatchable units
S	Set of storage system units
W	Set of nondispatchable units

Parameters

A	Availability coefficient of units
CC	Capital cost of distributed generation
$CCr(r)$	Capital replacement cost of distributed generation
CD	Capital cost of demand response enablement
CE	Capital cost of storages – energy
$CEr(r)$	Capital replacement cost of storages – energy
CP	Capital cost of storages – power
$CPr(r)$	Capital replacement cost of storages – power
D	Load demand
DOD	Depth of discharge of storages
E^{cap}	Installation energy capacity of storages
EF	CO2e emission conversion factor
EL	Economic lifetime of units
$\overline{ELF}$	Maximum equivalent loss factor
G^{ing}	Solar irradiation forecast
E	The stored energy of storages
$E^{\max}$	Installed energy capacity of storages
EC	Microgrid emission cost
ELF	Equivalent loss factor
IC	Microgrid investment cost of units
$IS^{shup/shdo}$	Shifting up/down indicator
LPF	Demand response intensity rate (0–1)
MC	Microgrid maintenance cost
OC	Microgrid operation cost/profit
OF	Objective function
P	Output power of distributed energy resources
$P^{dch/ch}$	Energy storage discharging/charging power
P^{ens}	Load curtailment.
$P^{\max}$	Installed power capacity of units
$P^{Net,e/g}$	Exchanged power with the utility company
PC	Microgrid peak demand cost
PD	Input electric energy of units
RC	Microgrid replacement cost of units
SC	Microgrid energy demand shifting cost/profit
UC	Microgrid unserved energy cost
V	Commitment state of dispatchable units

α^{ef}	Efficiency of units
α^{loss}	Energy loss coefficient of storages
υ	Natural gas consumption by gas-fired units

REFERENCES

[1] H. Razmi, H. Doagou-Mojarrad, and J. Olamaei, "Comparative study of optimization algorithms for sizing of Wind Turbine/ Fuel Cell/ Electrolyzer/ Hydrogen Tank in the hybrid stand-alone power system," *Signal Process. Renew. Energy*, vol. 4, no. 3, pp. 81–94, Sep. 2020, Accessed: Oct. 10, 2020. [Online]. Available: http://spre.azad.ac.ir/article_676126.html.

[2] M. Azimian, V. Amir, and S. Javadi, "Economic and Environmental Policy Analysis for Emission-Neutral Multi-Carrier Microgrid Deployment," *Appl. Energy*, vol. 277, p. 115609, Nov. 2020, doi: 10.1016/j.apenergy.2020.115609.

[3] S. Mohseni, A. C. Brent, and D. Burmester, "A demand response-centred approach to the long-term equipment capacity planning of grid-independent micro-grids optimized by the moth-flame optimization algorithm," *Energy Convers. Manag.*, vol. 200, p. 112105, 2019, doi: 10.1016/j.enconman.2019.112105.

[4] A. Khodaei, "Provisional Microgrid Planning," *IEEE Trans. Smart Grid*, vol. 8, no. 3, pp. 1096–1104, 2017, doi: 10.1109/TSG.2015.2469719.

[5] M. Husein and I. Y. Chung, "Optimal design and financial feasibility of a university campus microgrid considering renewable energy incentives," *Appl. Energy*, vol. 225, pp. 273–289, 2018, doi: 10.1016/j.apenergy.2018.05.036.

[6] I. Alsaidan, A. Khodaei, and W. Gao, "A Comprehensive Battery Energy Storage Optimal Sizing Model for Microgrid Applications," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3968–3980, 2018, doi: 10.1109/TPWRS.2017.2769639.

[7] F. Nejabatkhah, "Optimal Design and Operation of a Remote Hybrid Microgrid," *CPSS Trans. Power Electron. Appl.*, vol. 3, no. 1, pp. 3–13, Mar. 2018, doi: 10.24295/CPSSTPEA.2018.00001.

[8] A. S. Jacob, R. Banerjee, and P. C. Ghosh, "Sizing of hybrid energy storage system for a PV based microgrid through design space approach," *Appl. Energy*, vol. 212, pp. 640–653, Feb. 2018, doi: 10.1016/j.apenergy.2017.12.040.

[9] A. Molavi, J. Shi, Y. Wu, and G. J. Lim, "Enabling smart ports through the integration of microgrids: A two-stage stochastic programming approach," *Appl. Energy*, vol. 258, p. 114022, Jan. 2020, doi: 10.1016/j.apenergy.2019.114022.

[10] M. Barani, J. Aghaei, M. A. Akbari, T. Niknam, H. Farahmand, and M. Korpas, "Optimal Partitioning of Smart Distribution Systems Into Supply-

Sufficient Microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2523–2533, May 2019, doi: 10.1109/TSG.2018.2803215.

[11] E. Ansari Nezhad and M. Najafi, "Optimal and Intelligent Designing of Stand-alone Hybrid Photovoltaic/Wind/Fuel Cell System Considering Cost and Deficit Load Demand Probability, Case Study for Iran (Bushehr City)," *Signal Process. Renew. Energy*, vol. 4, no. 2, pp. 87–106, 2020.

[12] J. Kumar, B. V. Suryakiran, A. Verma, and T. S. Bhatti, "Analysis of techno-economic viability with demand response strategy of a grid-connected microgrid model for enhanced rural electrification in Uttar Pradesh state, India," *Energy*, vol. 178, pp. 176–185, 2019, doi: 10.1016/j.energy.2019.04.105.

[13] D. R. Prathapaneni and K. P. Detroja, "An integrated framework for optimal planning and operation schedule of microgrid under uncertainty," *Sustain. Energy, Grids Networks*, vol. 19, p. 100232, Sep. 2019, doi: 10.1016/j.segan.2019.100232.

[14] J. Chen *et al.*, "Optimal sizing for grid-tied microgrids with consideration of joint optimization of planning and operation," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 237–248, 2018, doi: 10.1109/TSTE.2017.2724583.

[15] G. Pan, W. Gu, Z. Wu, Y. Lu, and S. Lu, "Optimal design and operation of multi-energy system with load aggregator considering nodal energy prices," *Appl. Energy*, vol. 239, pp. 280–295, 2019, doi: https://doi.org/10.1016/j.apenergy.2019.01.217.

[16] A. A. Hamad, M. E. Nassar, E. F. El-Saadany, and M. M. A. Salama, "Optimal Configuration of Isolated Hybrid AC/DC Microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2789–2798, 2019, doi: 10.1109/TSG.2018.2810310.

[17] S. Senemar, M. Rastegar, M. Dabbaghjamanesh, and N. D. Hatziargyriou, "Dynamic structural sizing of residential energy hubs," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1236–1246, 2019.

[18] S. Senemar, A. R. Seifi, M. Rastegar, and M. Parvania, "Probabilistic Optimal Dynamic Planning of Onsite Solar Generation for Residential Energy Hubs," *IEEE Syst. J.*, vol. 14, no. 1, pp. 832–841, Mar. 2020, doi: 10.1109/JSYST.2019.2901844.

[19] S. Nojavan, M. Majidi, and N. N. Esfetanaj, "An efficient cost-reliability optimization model for optimal siting and sizing of energy storage system in a microgrid in the presence of responsible load management," *Energy*, vol. 139, pp. 89–97, Nov. 2017, doi: 10.1016/j.energy.2017.07.148.

[20] M. K. Kiptoo, O. B. Adewuyi, M. E. Lotfy, T. Senjyu, P. Mandal, and M. Abdel-Akher, "Multi-Objective Optimal Capacity Planning for 100% Renewable Energy-Based Microgrid Incorporating Cost of Demand-Side Flexibility Management," *Appl. Sci.*,

vol. 9, no. 18, p. 3855, Sep. 2019, doi: 10.3390/app9183855.

[21] V. Amir, S. Jadid, and M. Ehsan, "Operation of networked multi-carrier microgrid considering demand response," *COMPEL - Int. J. Comput. Math. Electr. Electron. Eng.*, vol. 38, no. 2, pp. 724–744, Mar. 2019, doi: 10.1108/COMPEL-07-2018-0276.

[22] V. Amir and M. Azimian, "Dynamic Multi-Carrier Microgrid Deployment Under Uncertainty," *Appl. Energy*, vol. 260, p. 114293, Feb. 2020, doi: 10.1016/j.apenergy.2019.114293.

[23] ISO-NE, "ISO New England - Real-Time Maps and Charts," 2015. http://www.iso-ne.com/isoexpress/ (accessed Feb. 25, 2020).

[24] U.S Energy Information Administration, "Henry Hub Natural Gas Spot Price (Dollars per Million Btu)," *Eia*, 2016. https://www.eia.gov/dnav/ng/hist/rngwhhdm.htm (accessed Feb. 26, 2020).

[1]