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ORIGINAL PAPER

Probabilistic optimization of planning and operation of networked microgrids with renewable energy resources considering demand response programs

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Abstract
Recently, demand response programs (DRPs) have been introduced as a potential solution to effectively enhance both energy systems and consumers participating in DRP due to the reduction in investment and energy cost of systems as well as the energy cost of consumers. This paper proposes an optimal framework for microgrid planning that integrates renewable energy sources, storage systems, uncertainty, and DRPs. Not only the lifetime and uptime of renewable resources and storage systems are considered by optimizing the life cycle costs, but also the rated power of devices with discrete values are integrated into the model by binary variables. The uncertain parameters are modeled by probability density functions then they are divided into states by the clustering technique. Scenarios are generated by the scenario matrix and then the number of scenarios is reduced to 10 to decrease the computational burden. A case study with a test system demonstrates the effectiveness of the proposed method and the potential of DRPs to avoid device investment and reduce energy costs.

Keywords Demand response programs · Life cycle cost · Micro-grid planning · Renewable sources · Uncertainty

List of symbols

Acronyms

BESS	Battery energy storage system
CCP	Pritical peak pricing
DRP	Demand response program

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MIP	Mixed-integer programming
LCC	Life cycle cost
PDF	Probability distribution function
PV	Photovoltaic
RS	Renewable energy sources
RTP	Real-time price
WT	Wind turbine
$C_t^{inv}, C_t^{ope}, C_t^{emi}$	Investment, operation, emission cost
C_t^{drp}	Cost of the incentive-based DRPs
CD	Cost of disposal of the equipment

Sets and indices

N_k	Number of parameters X
N_s^x	Number of states of parameter X
N_w	Number of scenarios
w	Scenario ($w \in N_w$)
H	Number of hours on day
h	Hour ($h \in H$)
T	Overall planning period
t	Planning year ($t \in T$)
K	Number of RS's technology
k	Technology of RS ($k \in K$)

Parameters

I_{ir}	Solar irradiance
μ, σ	Mean and standard deviation of the stochastic variable
v	Wind speed
c	Scale index of Rayleigh pdf
X_s,	λ_sSpecific value and probability of stochastic parameters
k_{shif}	Maximum shiftable load factor
$P_{t,h}^d$	Demand of consumers
k_w^d	Factor of load
C_k^{RS}	Capital cost of RS
C_P^{BE}, C_C^{BE}	Capital costs under the power and capacity of BESS
$C_{OM.t}^{RS}$	Operation and maintenance coefficient of RS
$\pi_{h,w}^e$	Electrical prices
$\pi_{\max}$	Maximum electrical price
k^e, k^{RS}	Coefficients of electrical prices and output powers of RS
ξ_{RS}, ξ_{UG}	Emission coefficients of RS and traditional sources
π^{emi}	Emission taxes
π^{DR}	Incentive cost of DRPs
T_c, t_I	Life cycle and investment year of equipment
$P_{\max}^{UG}$	Maximum power of connected tranformer
$P_{r.k,i}^{RS}$	Rated power of RS, type k

$P_{r.i}^{BE}$, $E_{r.i}^{BE}$	Rated power and capacity of BESS
$k_{soc}^{\min}$, $k_{soc}^{\max}$	Lower and upper bounds of state of charge
$E_{t,h}^{BE}$, $E_{t,0}^{BE}$	Stored energy level at final and initial time

Variables

$P_{t,h}^{DR-}$, $P_{t,h}^{DR+}$	Decreased and increased power variables of DRP
$I_{t,h}^{DR+}$, $I_{t,h}^{DR-}$	Binary variables
$P_{k,t}^{RS}$	Invested power variables of the RS
$P_{k,t,h,w}^{RS}$	Generated power of RS
$P_{t,h}^{BE+}$, $P_{t,h}^{BE-}$	Charge/discharge powers of BESS
P_{t}^{BE},	E_{t}^{BE}Invested power and capacity of BESS
$\alpha_{k.j}$, β_i, γ_i	Binary variables
$P_{t,h,w}^{UG}$	Received power from the utility grid

1 Introduction

Micro-grid is a scaled-down version of the power system comprising the low-voltage grid with distributed generators, and storage systems to supply electricity for consumers [1]. Micro-grids can operate independently known as islanded mode or can be connected to a utility grid known as grid-connected or networked mode. In the networked mode, the loads are simultaneously supplied from both the utility grid and distributed generators that often use renewable energy types. This structure offers several advantages and benefits including increased reliability, improved energy efficiency, cost and loss reduction, and emission reduction [2]. However, several challenges have arisen regarding the operation, control, and protection of micro-grid. Indeed, the uncertainty of distributed generators using renewable energies is a major challenge to effective planning and operating of the micro-grids. Therefore, modern optimization methods can be applied to micro-grids planning and operation to improve the efficiency, economics, and resiliency of the system.

1.1 Literature review

RS are considered as green energy sources including solar, wind, geothermal, and bioenergy. Indeed, RS with various technologies such as PV, WT, and mini-hydropower are popularly applied in the fact micro-grids [3]. When RS is integrated into the micro-grid, the optimal use of these resources enhances the efficiency of the system in both planning and operation problems because of providing necessary complementary power sources, increasing the overall system reliability and flexible, reducing capital and operation costs as well as the reducing pollutant emissions and climate changes [4]. However, the natural intermittent of the RS power, load, and energy prices…, bring a lot of challenges to both the operation and planning of micro-grids. Recently, probabilistic approaches and multi-scenario-based approaches are the most common methods to cope with these multiple aspects of uncertainties [5]. Besides, energy storage can help to control new challenges emerging from integrating intermittent renewable energy such as WT and PV, enhance the flexibility of micro-grid, promote the use of RS, and relieve grid congestion [6]. BESS with mature technologies such as the lead-acid battery, nickel-based battery, sodium-sulfur battery, lithium-based battery, and flow battery is successfully applied in the micro-grid and different electric power systems [7–9]. In electric power systems, BESS can enhance the effectiveness of the system in short-term to ensure the stability, robust operation, and reliability of the electrical grid or manage the customer energy to enhance the power quality of systems such as supply interruptions and voltage dips. Besides, the efficiency of the system or RS in the long term also can be enhanced due to a reduction of energy and investment costs [10]. Hence, RS integration in micro-grids should be paired with BESS and it is an effective solution always considered at both the operational and planning stages to improve their performance and flexibility.

Additionally, DRP has been used as a tool to balance the demand and supply of energy systems in recent years. It is a useful check to shift the demand of consumers. It can effectively increase the energy use of consumers, the flexibility of the energy systems and the competitiveness [11]. DRP can be defined as changes in electricity usage by end-use customers from their usual consumption pattern in response to changes in prices called price-based DRP. Within price-based DRPs, fluctuations in electricity prices are the main tool used to modify consumer energy use with three main programs consisting of time of use, CPP, and RTP [11, 12]. In time of use programs, electricity prices often increase during periods of high demand or reduce during periods of low demand to shift consumer behavior. This leads to a reduction in typical peak demand and the energy usage is shifted to other periods thus the investment in generation and distribution systems can be deferred. Besides, DRP also can be established to incentivize end-use customers to change their normal consumption in return for monetary value based on the financial incentives for consumers to reduce peak use and provide load flexibility [13]. In emergency response programs, incentives are made available for customers who participate voluntarily in load shedding during reliability-triggered events. Similarly, the direct load control program is remotely controlled by the operator to large energy consumption appliances of voluntary consumers to respond to the demand. Other incentive-based programs have been created to meet the needs of various kinds of consumers under different conditions, such as curtailable service, demand bidding, and buyback [14, 15]. DRPs positively impact both the DRP participator and distribution companies and it is a developable trend in the future of energy systems.

Several studies have been conducted and proposed models for planning, designing, and operating the micro-grids integrated renewable energy resources and storage systems. To investigate the effectiveness of DRPs in micro-grid operation, [16] proposes a stochastic scheduling model for demand response-enabled microgrids with renewable generations and develops a hybrid analytic-heuristic solution approach. Similarly, a novel bi-level optimal dispatching model for the community integrated energy system with an electric vehicle charging station in multi-stakeholder scenarios is established in [17] with the aim of minimizing the operating costs and providing a new way to improve the energy efficiency and reduce the environmental pollution. The simulation results verify the effectiveness of the proposed methods. DRP not only guides users to actively take part in micro-grid scheduling but also significantly mitigates the effects of renewable generation uncertainties, which provides a way of promoting the ongoing low-carbon transition towards sustainable production.

Recently, several pioneering works have attempted to combine the DRPs with the parameter uncertainty in energy system planning. A stochastic optimization framework for power generation system planning integrating uncertainty is introduced in [18]. The optimization framework is also proposed for investment planning of distributed generation resources in coordination with demand response [19] and considering RS [20]. The results show the benefits of the proposed planning framework including the reduction of investment power of distributed generators, storage systems, and total cost of micro-grids. Similarly, energy hub optimization with the participation of RS and DRPs is introduced with a scheduling framework [21] and a planning model [22]. Besides, the effect of DRPs in cost optimization of micro-grid considering uncertain parameters is shown with the reduction of the total cost, electricity purchased from the market, and emission cost. The uncertainty of parameters can be modeled by Monte Carlo simulation, linearization-based technique, and technique based on the approximation of pdf. They are divided into different discrete states by the clustering technique and then are integrated into different scenarios [18, 23]. Besides, a federated deep generative learning framework, that integrates federated learning and least square generative adversarial networks, is proposed in [24] for renewable scenario generation. The experiment results verify the robustness of the above method.

Life cycle cost refers to the total cost consumed during the entire life cycle of an engineering project from the decision-making design stage to the end-of-life disposal including initial investment costs, operation and maintenance costs, and decommissioning and disposal costs. The LCC has been applied in several studies and demonstrates its feasibility and effectiveness in distributed energy storage planning of distribution grids, and micro-grids. In [25], a two-stage heuristic planning strategy has been proposed, which determines the optimal sitting and sizing of the ESSs in the distribution grids with the participation of PV and WT. Similarly, the LCC objective is also utilized to plan micro-grids integrated with the uncertainty of parameters [26] or RS [27]. LCC includes the total monetary cost of installing and operating the micro-grid for the duration of its entire life.

In general, the previous works in the area have shown the effectiveness of DRP and RS in planning micro-grids and energy systems. However, the planning frameworks have not fully considered the effects of various types of RS, the parameter uncertainty, investment cost, operation and emissions, and the lifetime of the equipment. In this context, a probabilistic planning framework for the networked micro-grids is proposed to investigate the coordination of DRPs and uncertainties of multiple renewables (i.e., PV and WT). The scope of introduced models in literature and the scope and contribution of this paper is summarized in Table 1.

Table 1 Literature review and contribution of this paper

References	Stochastic	PV	WT	BESS	DRP	Emission	O&M cost	Capital cost	LCC
[26]		√				√	√	√	√
[24]	√	√	√	√		√	√	√	√
[18]	√	√	√			√	√	√	
[20]		√	√	√	√		√	√	
[28]	√						√	√	√
[19]		√		√	√		√	√	
[22]	√		√		√	√	√		
Proposed model	√	√	√	√	√	√	√	√	√

1.2 Main contributions of this work

This study presents a probabilistic planning framework for the networked micro-grids. The contributions of this work are summarized as follows:

- Proposing a probabilistic planning framework to simultaneously optimize the invested sizing and timing of both RS and BESS in networked micro-grids under the impact of DRPs and uncertain parameters. The objective function is to minimize the expected LCC of the micro-grid which includes the investment cost, operation cost, emission cost, cost of the incentive-based DRPs, and cost of disposal of the equipment at the end of the planning time.
- Considering the uncertainty of output power of RS, energy demand of consumers, and electrical price along with DRPs in the optimal model. Additionally, not only the lifetime and uptime of RS and BESS are considered by the objective function LCC but also their rated power of them with discrete values are integrated into the model by binary variables and thus reduce the error of planning results.
- Evaluating the possible feasibility and efficiency of the proposed planning framework with the impact of DRPs and the obtained results have been compared to existing approaches.

1.3 Organization of this paper

The other sections of this paper are organized as follows. The problem formulation is given in Sect. 2. After that, Sect. 3 presents the simulation of different cases. At last, the conclusive remarks and a few insights for future work are discussed in Sect. 4.

2 Problem formulation

2.1 Uncertain parameters modeling

The stochastic parameters are often modeled by pdfs and then they are divided into different states by the k-mean clustering technique. Where the generated power of PV depends on solar irradiance which always varies due to various climate changes and other conditions. The random change of solar irradiance is often modelled by a suitable pdf such as normal, gamma, beta, or Gaussian pdf. In this study, the beta pdf is selected and presented as Eq. (1) with the solar irradiance I_{ir}, mean μ, and the standard deviation σ of the stochastic variable [18, 21].

$$\begin{gathered} f_b(I_{ir}) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}.I_{ir}^{(\alpha-1)}.(1-I_{ir})^{(\beta-1)} & if 0 \le I_{ir} \le 1 \\ 0 & else \end{cases} \\ \beta = (1-\mu).\left(\frac{\mu.(1+\mu)}{\sigma^2} - 1\right); \quad \alpha = \frac{\mu.\beta}{1-\mu} \end{gathered} \tag{1}$$

Similarly, the Weibull or Rayleigh pdf is generally utilized to describe the probability distribution of wind speed due to the great flexibility. The Rayleigh pdf for modeling the wind speed v is represented as the Eq. (2) with the scale index c [29].

$$f_r(v) = \left(\frac{2v}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{2}$$

Moreover, the electricity price is also a stochastic value with a high deviation and the normal pdf is generally utilized to model this parameter [21, 30]. Similarly, the stochastic load of the micro-grid is also modeled by normal pdf and shown in Eq. (3). Where, μ is the mean of the distribution, σ is the standard deviation and σ^2 is the variance of the random variables that are the electricity price and loads.

$$P(X = x|\mu, \sigma^2) = f(x) = \frac{1}{\sqrt{2\pi\sigma}}\exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \tag{3}$$

Then, the clustering technique is utilized to divide the pdf into different states under historical data. In each state, there is a specific value with the related probability which are denoted by X_s and λ_s [23], respectively. These parameters are integrated into a hybrid model as Eq. (4) [31]. Where, the C_w and $\lambda_w\{C_w\}$ are the matrices that enumerate the possible values and probability of parameters. λ_s^x is the probability of parameter X at state s integrated into scenario w. N_k is the number of parameters X and N_s^x is the number of states of parameter X.

$$\begin{gathered} M = \{C_w,\ \lambda_w\{C_w\}\} \\ \lambda_w\{C_w\} = \prod_{k=1}^{N_k} \lambda_s^x\{X_s\}\ ;\ N_w = \prod_{k=1}^{N_k} N_s^x \end{gathered} \tag{4}$$

The number of generated scenarios by the scenario matrix is very large and thus scenario reduction methods are applied to reduce the number of scenarios in order to reduce the computational burden [29, 32].

2.2 The generated power of RS

In each scenario, the generated power of PV and WT is calculated as expressions (5) and (6), respectively [18, 21]. In which, P_r^{pv}, I_r are rated power and solar irradiance of PV, respectively. I_w, θ_w are operation irradiance and temperature in scenario w while $\alpha_\theta, \theta_{am}$ are the power temperature coefficient and standard ambient temperature, respectively. P_w^{wt}, P_r^{wt} are output and rated power together with cut-in speed v_{ci}, rated speed v_{cr}, and cut-off speed v_{co} of WT.

$$P_w^{pv}(I,\theta) = P_r^{pv}.\frac{I_w}{I_r}\left[1 + \alpha_\theta\left(\theta_w - \theta_{am}\right)\right] \tag{5}$$

$$P_w^{wt}(v) = \begin{cases} 0 & v_w \le v_{ci} \text{ or } v_{co} \le v_w \\ P_r^{wt}.\frac{(v_w - v_{ci})}{(v_r - v_{ci})} & v_{ci} \le v_w \le v_r \\ P_r^{wt} & v_r \le v_w \le v_{co} \end{cases} \tag{6}$$

2.3 Incentive-based DRP formulation

The DRPs can be classified into two types price-based DRP and incentive-based DRP [33]. Where the incentive-based DRP through the shifting capability of electrical loads provides flexibility to the system. Hence, the incentive-based mechanism is applied with the incentive subsidy cost for the consumers participating DRPs. In Eq. (7), the constraints are established to limit the shiftable demand. Where, k_{shif} is the maximum shiftable load factor of each consumer and $P_{t,h}^d$ is the demand of consumers at the calculated time. $P_{t,h}^{DR-}, P_{t,h}^{DR+}$ are the decreased and increased power quantities of DRPs. The increase or decrease of the power of DRP are decided by binary variables $I_{t,h}^{DR+}, I_{t,h}^{DR-}$ [21, 22]. The total load curtailment must be shifted to other times and hence total increased energy must equilibrate total decreased energy in a calculated cycle as Eq. (8).

$$\begin{aligned} 0 \le P_{t,h}^{DR+} \le k_{shif}.P_{t,h}^d.I_{t,h}^{DR+} \\ 0 \le P_{t,h}^{DR-} \le k_{shif}.P_{t,h}^d.I_{t,h}^{DR-} \end{aligned} \tag{7}$$

$$\sum_{h=1}^{H} P_{t,h}^{DR+} = \sum_{h=1}^{H} P_{t,h}^{DR-}; \quad I_{t,h}^{DR+} + I_{t,h}^{DR-} = 0 \tag{8}$$

2.4 Planning framework

The networked micro-grids planning framework is designed to minimize the expected LCC of the project during the analyzed period. The objective function includes the investment cost (C_t^{inv}), expected operation cost (C_t^{ope}), expected emission cost (C_t^{emi}), cost of the incentive-based DRPs (C_t^{drp}), and cost of disposal of the equipment at the end of planning time, CD, as shown in Eq. (9). Total cost of the project is converted to the base year by discount rate r.

$$OF = \min \sum_{t=1}^{T} \frac{1}{(1+r)^t} \left[C_t^{inv} + C_t^{ope} + C_t^{emi} + C_t^{drp} - CD \right] \tag{9}$$

where C_t^{inv} consist of the investment cost of RS and BESS represented in Eq. (10). C_k^{RS} is capital cost and $P_{k,t}^{RS}$ is selected power variable of the RS. C_P^{BE},C_C^{BE} are capital costs under the power and capacity of BESS, respectively. Similarly, P_t^{BE},E_t^{BE} are invested power and capacity of BESS, respectively.

$$\begin{aligned}
C_t^{inv} &= \sum_{k=1}^{K} C_k^{RS}.P_{k,t}^{RS} + \left(C_P^{BE}.P_t^{BE} + C_E^{BE}.E_t^{BE} \right) \\
C_t^{ope} &= 365 \sum_{h=1}^{H} \sum_{w=1}^{N_w} \lambda_w \left(\pi_{h,w}^{e}.P_{t,h,w}^{UG} + \sum_{k=1}^{K} C_{OM.k}^{RS}.P_{k,t,h,w}^{RS} \right) \\
C_t^{emi} &= 365 \sum_{h=1}^{H} \sum_{w=1}^{N_w} \pi^{emi}.\lambda_w \left(P_{t,h,w}^{UG}.\xi_{UG} + \sum_{k=1}^{K} P_{k,t,h,w}^{RS}.\xi_{RS} \right) \\
C_t^{drp} &= 365 \sum_{h=1}^{H} \pi^{DR} (P_{t,h}^{DR+} + P_{t,h}^{DR-})
\end{aligned} \tag{10}$$

In addition, C_t^{ope} consists of the operation cost of RS and costs for energy purchasing from the utility grid. Where, $C_{OM.t}^{RS}$ is operation and maintenance coefficient of RS and $P_{t,h,w}^{UG}$ is the received power from the utility grid. $\pi_{h,w}^{e}$ is electrical prices purchased from the market while $P_{k,t,h,w}^{RS}$ is the generated power of RS determined as Eq. (11). k^e, k^{RS} are coefficients of electrical prices and output power of RS in operation each hour or scenario.

$$\pi_{h,w}^{e} = k_h^e.k_w^e.\pi_{\max}; \quad P_{k,t,h,w}^{RS} = k_h^{RS}.k_{k,w}^{RS}.P_{k,t}^{RS} \tag{11}$$

The emission costs of RS and the utility grid are calculated under emission coefficients of RS and traditional sources denoted by ξ_{RS}, ξ_{UG}, respectively. π^{emi} is emission taxes and λ_w is probability at scenario w. $P_{t,h}^{DR-}$, $P_{t,h}^{DR+}$ are the decreased and increased power quantities of DRPs at any available time while π^{DR} is the incentive cost of DRPs for the increased or decreased power quantities [18, 34]. The cost of disposal at the end of the project is calculated by expression (12) with the life cycle, investment year of equipment denoted by T_c and t_I, respectively.

$$CD = \sum_{k=1}^{K} \left(1 + t_{I.k}^{RS}/T_{c.k}^{RS}\right) C_k^{RS} P_{k,t}^{RS} + \left(1 + t_I^{BE}/T_c^{BE}\right)\left(C_P^{BE}.P_t^{BE} + C_E^{BE}.E_t^{BE}\right) \tag{12}$$

The power balance constraint in each operation state w is shown in Eq. (13) with profile and factor of load denoted by $P_{t,h}^d$ and k_w^d, respectively. $P_{t,h}^{BE+}, P_{t,h}^{BE-}$ are the charge/discharge powers of BESS. Similarly, the selection of sizes of RS and BESS is limited by constraints in Eq. (14). The discrete rated powers of RS are selected by binary variables $\alpha_{k.j}$ while discrete rated powers and capacities are selected by binary variables β_i, γ_i [31]. The operation powers of RS and BESS are constrained by invested sizes while the operation power of the utility grid is constrained by the maximum power of connected equipment,P_{max}^{UG}. Where, $P_{r.k,i}^{RS}$ is rated power of RS with different types. $P_{r.i}^{BE}$, $E_{r.i}^{BE}$ are rated power and capacity of BESS with different types.

$$P_{t,h,w}^{UG} + \sum_{k=1}^{K} P_{k,t,h,w}^{RS} = k_w^d.P_{t,h}^d - \eta_{\mathrm{BE}}.I_{\mathrm{t,h}}^{BE-}.P_{t,h}^{BE-} + I_{\mathrm{t,h}}^{BE+}.P_{t,h}^{BE+} - P_{t,h}^{DR-} + P_{t,h}^{DR+} \tag{13}$$

$$\begin{aligned} &P_{k,t}^{RS} = \sum_{i=1}^{n} \alpha_{k,i}.P_{r.k,i}^{RS}; \quad P_t^{BE} = \sum_{i=1}^{m} \beta_i.P_{r.i}^{BE}; \quad E_t^{BE} = \sum_{i=1}^{m} \gamma_i.E_{r.i}^{BE} \\ &P_{t,h,w}^{UG} \le P_{\max}^{UG}; \qquad P_{t,h}^{BE-} \le P_t^{BE}; \qquad P_{t,h}^{BE+} \le P_t^{BE} \end{aligned} \tag{14}$$

The BESS can charge at hours with low electrical price and load, and then it generates back to the system at peak hours with the high electrical price. The energy balance of BESS in the calculated cycle is constrained as Eq. (15) [19, 25]. The charge/discharge of them is decided by two binary variables $I_{\mathrm{t,h}}^{BE+}$ and $I_{\mathrm{t,h}}^{BE-}$.

$$\begin{aligned} &\sum_{h=1}^{H} \eta_{BE}.I_{t,h}^{BE-}.P_{t,h}^{BE-} = \sum_{h=1}^{H} I_{t,h}^{BE+}.P_{t,h}^{BE+} \\ &I_{t,h}^{BE+} + I_{t,h}^{BE-} = 1 \end{aligned} \tag{15}$$

To ensure the lifetime of BESS, the stored energy is limited by lower and upper bounds of state of charge denoted by $k_{soc}^{\min}, k_{soc}^{\max}$, respectively, as shown in Eq. (16). The state of charge displays the stored level of BESS which increases in charge time and decreases in discharge time. $E_{t,h}^{BE}$ and $E_{t,0}^{BE}$ are the stored energy level at final and initial time, respectively.

$$\begin{aligned} &E_{t,h}^{BE} = E_{t,h-1}^{BE} + I_{t,h}^{BE-}.P_{t,h}^{BE-}.\eta_{BE} - I_{t,h}^{BE+}.P_{t,h}^{BE+} \\ &k_{soc}^{\min}.E_t^{BE} \le E_{t,h}^{BE} \le k_{soc}^{\max}.E_t^{BE} \\ &E_{t,H}^{BE} = E_{t,0}^{BE} \end{aligned} \tag{16}$$

The planning framework is a mixed-integer problem.

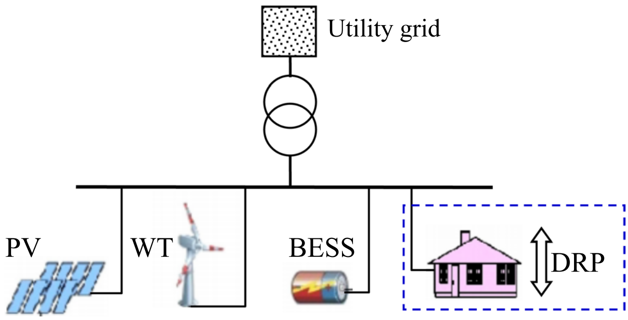

Fig. 1 The structure of test micro-grid

Table 2 Data of uncertain parameters

State	PV		WT		Load		Price	
	k_s^{pv}	λ_s^{pv}	k_s^{wt}	k_s^{wt}	k_s^{d}	λ_s^{d}	k_s^{e}	λ_s^{e}
1	0	0.001	0	0.199	0.351	0.033	0.3	0.023
2	0.15	0.018	0.15	0.266	0.406	0.047	0.4	0.069
3	0.30	0.037	0.35	0.273	0.451	0.091	0.45	0.092
4	0.40	0.068	0.45	0.152	0.510	0.163	0.5	0.116
5	0.50	0.123	0.55	0.077	0.585	0.163	0.55	0.138
6	0.60	0.165	0.65	0.051	0.650	0.165	0.65	0.134
7	0.70	0.186	0.75	0.045	0.713	0.166	0.75	0.215
8	0.80	0.163	0.85	0.033	0.774	0.106	0.8	0.115
9	0.90	0.138	0.95	0.025	0.853	0.056	0.9	0.076
10	1	0.101	1	0.078	1	0.010	1	0.022

3 Case study

3.1 Structure and parameters of test micro-grid

In this paper, a structure of the networked micro-grids is utilized to investigate the feasibility and efficiency of the proposed framework shown in Fig. 1. The load is simultaneously supplied from both RS and utility grid. The RS consisting of PV and WT are selected and applied in this structure because of improving the efficiency, and reliability and reducing the investment cost of the micro-grid [19, 22]. Besides, not only BESS is utilized but also incentive-based DRP is considered to improve the effectiveness of micro-grid.

The randomness of solar radiation and wind speed is expressed by beta and Rayleigh pdf, respectively. Then, they are divided into different states with specific values and probabilities in each state as assumed in Table 2.

Similarly, the randomness of loads and electrical prices are modeled by normal pdf and divided into different states [18, 21]. These parameters are integrated into a hybrid model by Eq. (4) then GAMS/SCENRED program using the fastback

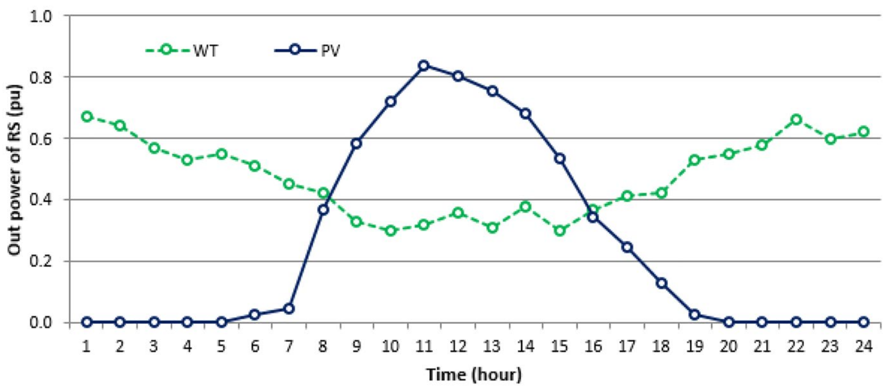

Fig. 2 Mean out power profiles of RS for a typical day

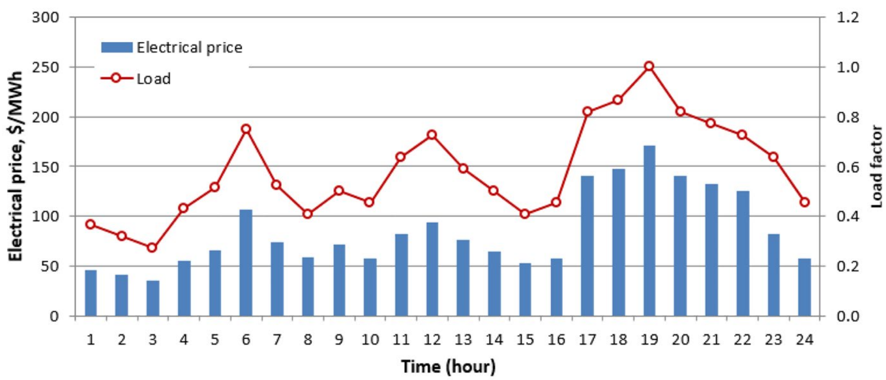

Fig. 3 Profiles of mean electrical price and load for a typical day

forward method is employed to reduce the number of scenarios to 10, decreasing the computational burden [21, 22].

The mean out power profiles of RS is analyzed under typical characteristic of the day as in Fig. 2. Similarly, mean load and energy price profiles for a typical day at base year are assumed as in Fig. 3 with the annual growth factor of the load of about 3%.

The input data includes capital cost and lifetime as in Table 3 [29, 33]. The emission tax of CO_2 is 10$/ton. The planning period is assumed for 10 years and the discount rate is 10%. The emission coefficient of PV, WT, and utility grid is 0.25, 0.27, and 0.65 kg/kWh, respectively. η of BESS is about 0.9 [35, 36]. O&M cost PV and WT is 2.5$/MWh and 3.5$/MWh, The incentive cost of DRPs for the increased or decreased power quantities is 0.01$/kW [18, 34]. The maximum shiftable load factor of consumers by DRP is about 50%. The mean active and reactive power of the load is assumed about 500 kW and 242 kVAr, respectively.

Table 3 Input data

	P_r/E_r, kW/kWh	C_P/E_P, \$/kW/\$/kWh	T_c, year
PV	100; 150; 180; 210; 255; 360; 390; 450; 480; 495; 510	1500	20
WT	100; 150; 200; 250; 300; 350; 375; 400; 430; 475; 500	1800	20
BESS	(40; 60; 80; 100; 135; 160; 185; 200)/(100; 200; 300; 400; 450; 500; 550; 600)	200/100	10

3.2 Simulation cases

In this work, two cases are considered to study the effect of incentive-based DRP on the optimal design of micro-grid. The micro-grid is planned without DRP and with DRP. Besides, the obtained results are compared to existing approaches to evaluate the efficiency of the proposed planning framework and the impact of DRPs. The GAMS/CPLEX solver is utilized to find out the optimal solution.

3.3 Analysis of invested size and time of RS and BESS

The type, size, and invested time of the PV, WT, and BESS are selected and shown in Table 4. In both cases, the rated power of WT and PV is invested at about 400 kW and 480 kW corresponding with types 8 and 9, respectively. WT is always invested in the first year while PV is only selected in the 7th year at the case without DRP and 8th year at the case with DRP. Similarly, BESS is invested in the 2nd year in the case without DRP and in the 7th year in the case with DRP. The rated power of BESS invested in the case with DRP reduces about 40 kW corresponding to 20%. The deferment of BESS investment on the case with DRP is due to the impact of DRP in the power reduction of the load in peak hours.

3.4 Economic cost analysis

Economic and technical indicators of micro-grid are optimized and shown in Table 5. A comparison between cases with DRP and without DRP shows that the invested cost of equipment reduces 90×10^3\$ corresponding to 8.91% due to the deferment of RS investment in the case with DRPs. The cost of DRPs increases about 7.48×10^6\$ during the planning period. The deferment of RS investment leads

Table 4 Comparison of invested size and time of RS and BESS

	Without DRP			With DRP		
	Types	*P_r/E_r, kW/kWh*	*T_I, year*	*Types*	*P_r/E_r, kW/kWh*	*T_I, year*
PV	9	480	7	9	480	8
WT	8	400	1	8	400	1
BESS	8/6	200/500	2	6/6	160/500	7

Table 5 Comparison of economic and technical indicators of micro-grid

Economic and technical indicators	Without DRP	With DRP	Comparison
Total expected LCC, 10^6 $	1.81	1.62	− 0.19
Invested cost, 10^6 $	1.01	0.92	− 0.09
Cost of DRPs, 10^3 $	0	7.48	7.48
Purchased electricity from utility grid, 10^6 kWh	21.01	20.61	0.6
Expected cost for purchasing electricity, 10^6 $	1.37	1.17	− 0.2
CO_2 emission, 10^3 tons	15.13	15.27	0.14
Emission taxes cost, 10^3 $	94.71	95.67	0.96

to an increase in the electricity amount purchased from the utility grid and thus emission tax costs increase 965.2$ corresponding to 1.01% due to the high emission coefficient of traditional resources. Although the purchased electricity amount from the utility grid increases 600×10^3kWh, the cost for purchasing electricity reduces by $200 \times 10^3$$ corresponding with 14.6% because of the reduction in electricity amount purchased in high price hours. Hence, the expected value of LCC reduces by about $190 \times 10^3$$ corresponding to 10.5% under the impact of DRP compared with without DRP case.

The simulation results show that the incentive-based DRP has been significantly effective in planning the networked micro-grids due to reducing the invested cost of devices, energy cost, and LCC. Moreover, the load curve is shifted with peak load shaving and thus the peak valley difference of the load reduces, and the stability of the load curve increase. This leads to the investment cost for devices to connect with the utility grid also decreases. This means that the proposed planning framework considering the stochastic parameters greatly enhances the accuracy of calculation results and the effectiveness of an investment project.

Additionally, to evaluate the efficiency of the proposed planning framework and the impact of DRPs, the obtained LCC of micro-grid are compared to existing studies as presented in Table 6. LCC computed under the introduced method in [18] is the largest because of ignoring the participation of BESS and the impact of DRP. The peak load is maximum in this context and thus the invested power of RS (i.e., PV and WT) increases, leading to an increase in the capital cost and LCC. In contrast, LCC calculated according to the method introduced in [20] is the lowest, but this result has significant errors and does not properly evaluate the effectiveness of the planning problem of micro-grid due to no consideration of uncertainty and emission costs. This is not consistent with the inherent volatility and intermittency

Table 6 Expected LCC comparison between the proposed model and other alternative models in the literature

References	[22]	[20]	[19]	[18]	Proposed model
LCC, 10^6 $	1.635	1.532	1.764	1.815	1.621

of parameters and the emission cost of actual micro-grids. When BESS is not integrated into the micro-grid planning framework [22], LCC increases 14×103$ corresponding to 0.86% compared to the proposed model. Similarly, the proposed method in [19] only considers PV and ignores the influence of WT and thus LCC is 1,764×106$, which increases 143×103$ equivalent to 8.82%. Therefore, it can be shown that the proposed planning framework is suitable and efficient for networked micro-grids integrated into RS and DRPs.

3.5 Impacts of DRP

The optimal scheduling of the incentive-based DRP is also determined on each operation day as shown in Fig. 4. The DRP impacts the demand of consumers with the decreased power quantity of DRP in peak hours. In hours 6, 11, and 12, loads are reduced by about 157.5 kW, 120 kW, and 182.5 kW, respectively. Similarly, the decreased power quantity of DRP from 183 to 250 kW in hours 17–22. On the contrary, the impact of DRP in off-peak hours leads to an increase in the demand of consumers in hours from 1 to 5, from 7 to 10, from 13 to 16, 23, and 24. The increased power quantity due to the impact of DRP is maximum in hour 5 with about 127.5 kW and minimum in hour 3 with 67.5 kW. Hence, the peak demand of consumers in the case with DRP reduced from 500 kW in the case without DRP to 413 kW corresponding with a reduction of about 17.4%. Also, loads in low hours of the case with DRP increase from 136 to 181 kW corresponding with an increase of about 32.8%. This leads to the reduction of invested power of devices and the peak valley difference of the load together with more stability of the load curve.

Similarly, the operation power of devices such as BESS, PV, WT, and the received power from the utility grid in all scenarios and cases is also determined. Figure 5 displays the operation power of BESS at the 10th year in both cases. BESS charges from hour 1 to hour 4 in the case with DRP while it only charges from hour 1 to hour 3 in case without DRP with a maximum power of about 200 kW. The participation of DRP in the case with DRP also reduces the discharge duration of BESS

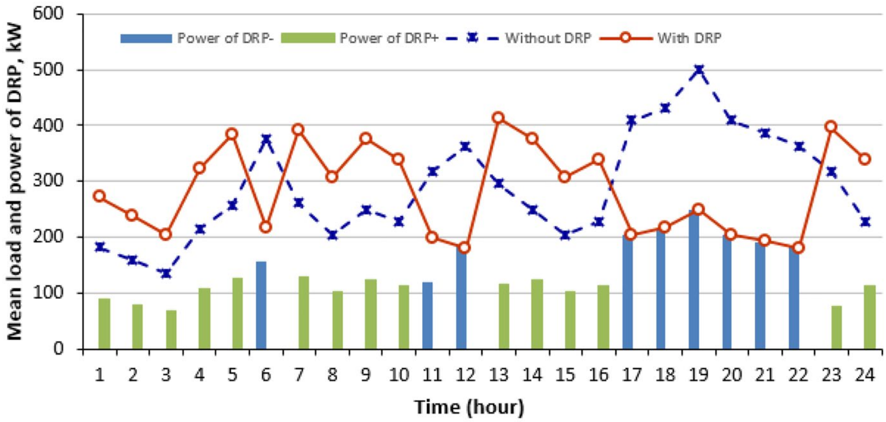

Fig. 4 Mean load value and power of DRP

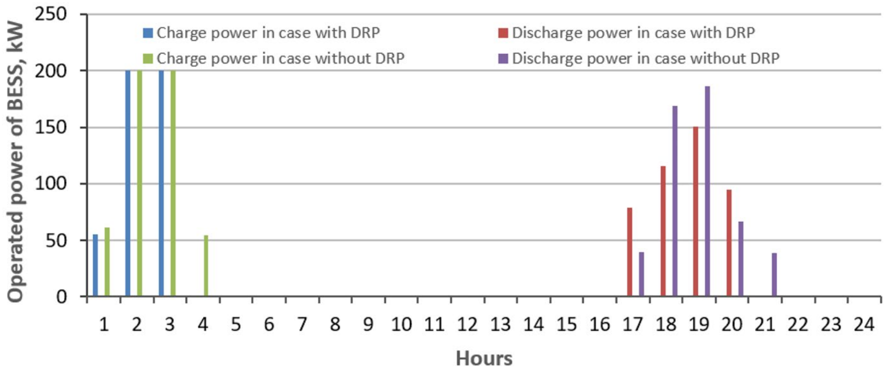

Fig. 5 Operated power of BESS in cases, 10th year

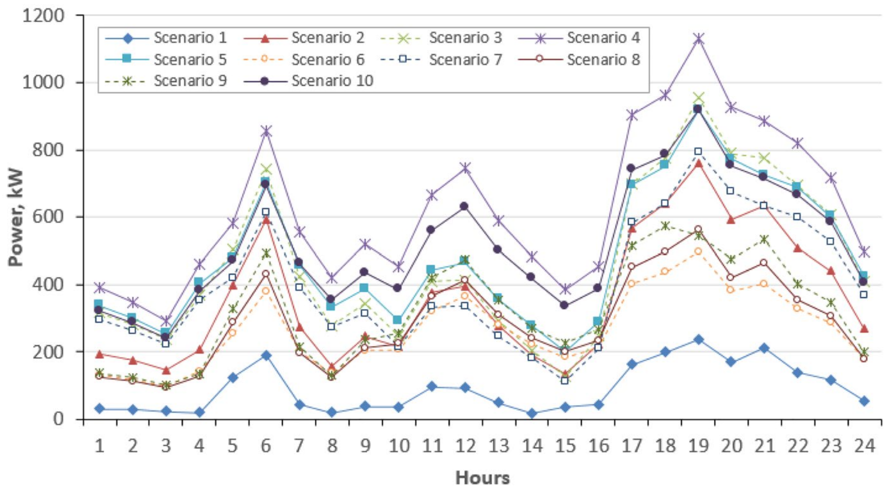

Fig. 6 Received power from utility grid in scenarios at the 10th year of case without DRP

from 5 h in the case without DRP to 4 h. In the case without DRP, the maximum discharge power is 186 kW at the 19th hour while the minimum discharge power is 39.3 kW at the 17th hour.

The received power from the utility grid in scenarios in the 10th year of both cases is presented in Figs. 6 and 7. The participation of DRP in the case with DRP also reduces the peak valley difference of the power curves from 839 to 521.2 kW in scenario 4. The maximum power received power from the utility grid in scenario 4 reduces from 1130.3 kW in the case without DRP to 883 kW in the case with DRP. In contrast, the minimum power value in scenario 1 increases from 91.2 kW in the case without DRP to 294.5 kW in the case with DRP.

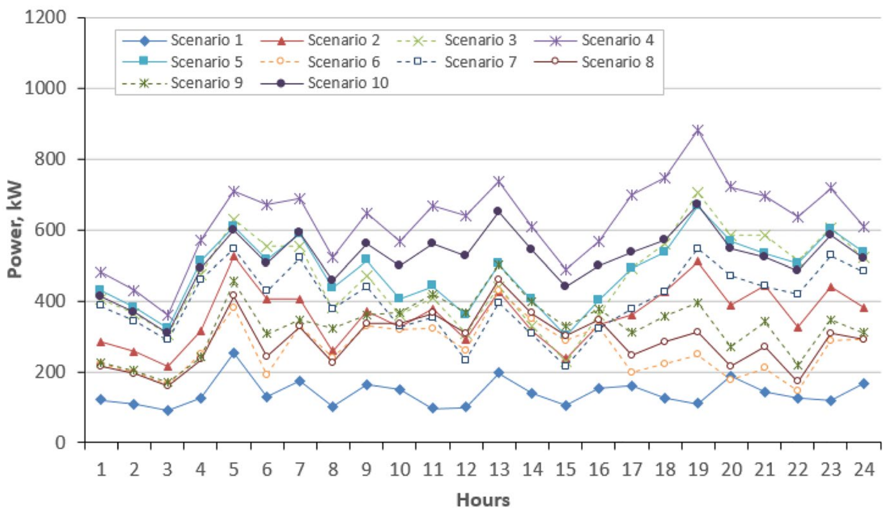

Fig. 7 Received power from utility grid in scenarios at the 10th year of case with DRP

3.6 Sensitive analysis of expected LCC

Moreover, the sensitivity of the expected LCC of the project is analyzed with respect to the different values of the maximum shiftable load factor and incentive cost of DRP shown in Fig. 8. The LCC reduces rapidly when the maximum shiftable load factor increases. The value of LCC is about 1.81 M$ when the maximum shiftable load factor is 0% and the incentive cost of DRP is 0.01$/kW. It reduces to 1.62 M$ and 1.54 M$ corresponding to increases in the maximum shiftable load factor of about 50% and 100%, respectively. Similarly, the LCC of the project is impacted by the incentive cost of DRP and increases under the incentive cost of DRP. When

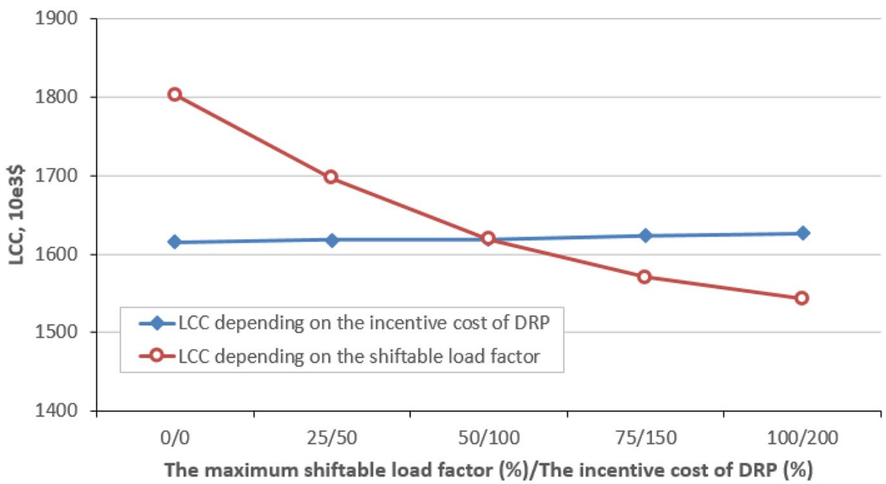

Fig. 8 Sensitive analysis on maximum shiftable load factor and incentive cost of DRP

the maximum shiftable load factor is 50% and the incentive cost of DRP is 0.01$/kW, the LCC of the project is about $1619.1 \times 10^3$$. It reduces to $1618.4 \times 10^3$$ and $1615.3 \times 10^3$$ when the incentive cost of DRP reduces by 50% and 100%, respectively. When the incentive cost of DRP increases by 150% and 200%, LCC also increases to $1623.1 \times 10^3$$ and $1626.5 \times 10^3$$, respectively.

4 Conclusion

In response to the growing energy demand for energy systems, DRP can become a significant potential solution in the operation and planning of micro-grids due to the reduction of investment and energy costs, an increase in the flexibility of systems as well as the reduction in the energy cost of consumers. In this paper, a probabilistic planning model of networked micro-grids has been proposed under minimization expected LCC which allows considering the lifetime, uptime, and the discrete rated power of devices as well as the impact of the DRP and uncertainty parameters. The simulation results for the test micro-grid show the feasibility of the proposed framework and the solution obtained with DRP is more efficient than the case without DRP. The incentive-based DRP can significantly improve the effectiveness of micro-grids such as the investment deferment of devices from 1 to 5 years, the reduction of expected LCC by about 10.5%, and the purchased electricity from the market by about 14.6%. In addition, the planning framework can be extended by integrating electrical vehicles or different energy forms of multi-energy systems in future works.

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