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Optimizing Sustainable Multi-Microgrid System Considering Uncertainties and Seasonal Factor

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Abstract:- This study proposes the multi-microgrid (MMG) system as a solution to address the challenges posed by the intermittent nature of renewable energy sources and demand uncertainty. The objective is to find the optimal choices regarding the quantity, site, and size of renewable distributed generation sources, as well as the battery charging state in each microgrid. Additionally, the model aims to manage the electricity flows between microgrids, demand areas, the main grid, and nearby microgrids within the MMG system. The proposed model also considers energy trading within the peer-to-peer (P2P) intra-trading framework, considering the simultaneous connection of microgrids to both the main grid and neighboring microgrids within the MMG under various types of uncertainty and impacted factors. The objective function is to maximize the overall financial gain, minimize the cumulative cost related to the environment while meeting customer demand. A combination of Genetic algorithm and CPLEX is developed to solve the proposed model. The experimental findings demonstrate the effectiveness and fulfillment of the proposed model and algorithm.

Keywords*: Multi-microgrid system, GA-CPLEX, P2P intra-trading, Uncertainties.*

1. Introduction

A. Motivation

Recently, renewable energy generation has been increasingly utilized as a means to reduce the environmental impact associated with conventional energy sources [1-3]. Microgrid is widely regarded as a fundamental solution for enabling the integration and utilization of renewable generation within the distribution system. Microgrids are systems that generate and distribute heat and power, incorporating different generators and distributed storage units. Their purpose is to ensure adequate power quality and reliability for multiple demand loads within the system [4, 5]. These systems have the capability to operate either as part of a larger energy system or independently in island mode. They are designed to deliver sufficient energy with consistent quality and reliability to meet the demands of various load requirements [6]. With the growing concern for environmental issues and the emphasis on sustainable development, microgrids are gaining increasing significance and playing a larger role in the energy sector.

In the future, energy systems will consist of multiple microgrid systems, collectively forming a multi-microgrid (MMG) system. These MMG systems will have the ability to interact with each other as well as with the main grid [7]. The intermittent nature of renewable energy generation presents challenges for microgrids when it comes to connecting to the main electricity grid and engaging in peer-to-peer (P2P) energy trading with other nearby microgrids [8]. Therefore, it is imperative to focus on the design and energy management of MMG systems in order to achieve economic, environmental, and social objectives simultaneously.

B. Literature Review

Previous research has examined the design considerations of microgrids with regards to economic factors, meeting demand requirements, and environmental objectives. A strategy for P2P energy trading was devised to achieve emission reduction and exploit energy-saving opportunities within microgrids [9]. A multi-stage scenario-based approach was proposed to address the optimal scheduling of microgrids while taking into account the uncertain nature of renewable energy sources [10]. A multi-layer framework was developed to optimize the management of microgrids by considering both demand-side management and the carbon trading market [11]. The proposed model primarily addressed the operational scheduling of an individual microgrid, without taking into account the interactions among neighboring microgrids. The application of Particle Swarm Optimization (PSO) algorithms and Genetic Algorithms (GA) was investigated for the economic dispatch of MMG systems. The objective was to minimize operational costs while ensuring compliance with the constraints of the distribution system [12]. A stochastic-chance constraint approach was developed to address the uncertainty associated with renewable energy sources and enhance the integration of green energy within microgrids. The aim was to increase the penetration of renewable energy in microgrids while effectively managing the associated uncertainties [13]. A multi-objective tri-stage decision-making framework was introduced, aiming to simultaneously optimize the operating cost, generation flexibility, and demand-side flexibility of MMG [7]. However, these studies have not considered seasonal factor for determining the electricity pricing. Besides, the electricity flows between entities, sites, and size of renewable distributed generation (RDG) sources were not invested in detail in any these researches. Previous research did not take into account the method for managing energy trading within P2P intra trading. Additionally, the economic index including price coefficient, elasticity coefficient, profit margin, and discount rate were not taken into the consideration in related studies.

C. Research Contribution

In order to address the limitations observed in prior studies, this research examines the design problem of sustainable MMG system. The objective is to make optimal decisions regarding the quantity, placement, and size of RDG sources, as well as the movement of electricity among demand areas, the main grid, microgrids, and P2P interactions within a sustainable MMG framework. The contributions of this study are outlined as follows:

1. The objective of this proposed model is to assist investors in making optimal decisions concerning the quantity, placement, and size of RDG sources, the charging state of battery in each microgrid as well as managing the electricity flows between microgrids, demand areas, the main grid, and additional nearby microgrids within the MMG system.
2. Furthermore, the proposed model considers energy trading within the P2P intra-trading framework and takes into account the MMG system, where microgrids are connected to both the main grid and neighboring microgrids simultaneously.
3. This research suggests the combination of a GA and CPLEX as a solution approach to address a multi-objective mixed-integer linear programming model (MMILPM). This proposed approach effectively handles different types of uncertainties related to the decision problem, such as demand uncertainty and variability in electricity generated from RDG sources, as well as variability in constraints and objectives.

The subsequent sections of this paper are structured as follows. Section 2 descrips the considered problem and formulates the MMILPM. The solution method is shown in section 3. Section 4 proposes the experimental results to evalutate the effectiveness of the suggested model. Section 5 illustrates the important conclusions.

2. Problem Description And Mmilpm Development

A. Problem Description

The proposed sustainable MMG system in Fig. 1 including MMG and main grid. Each microgrid has battery and a group of several RDG sources consisting of wind and solar power that are established nearby demand areas. The demand load of customers is supplied from MMG system and main grid. Microgrids in MMG can trade in P2P intra-trading if these microgrids has sufficient or insufficient energy. Each microgrid in MMG do not directly serve electricity to demand areas in other nearby microgrids in the same MMG system. MMG system makes strategic decisions relating to the quantity, placement, and size of RDG sources in each microgrids; the movement of electricity (i.e, the volume of electricity distributed to demand areas from MMG and main grid); and prices for selling electricity to demand areas and trading P2P market.

This research aims to design sustainable MMG system to maximize overall profitability and minimize the cumulative costs associated with environmental impacts while ensuring the fulfillment of the demand load under consideration of uncertainties, and the limitations and restrictions imposed by societal and operational factors. Demand load, possible sites, and size of RDG sources are assumed to be predefined. The level of CO2 emissions depends on the quantity of electricity generated and the length of its distribution. Due to the benefit of renewable energy generation on the reliability, environment and economy, the utilization of these generation has increased recently [1]. Microgrids are recognized as a fundamental approach to promote the integration of renewable generation into the distribution system [3, 7]. Therefore, this paper take into the consideration of renewable energy sources in the MMG system to achieve optimal profit and reduce environmental cost. The microgrid is connected with other nearby microgrids and main grid to limit the uncertain nature of RDG sources. These factors are crucial in improving the effectiveness of the proposed sustainable MMG design and promoting a flexible and sustainable energy supply balance. The problem of designing the sustainable MMG is expressed as a mathematical model called a multi-objective mixed integer linear programming model (MMILPM).

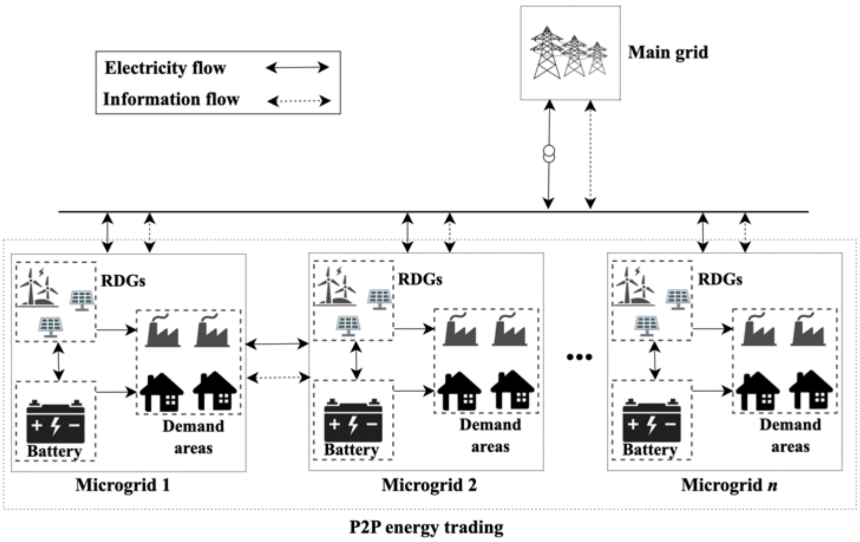

Fig. 1 Structure of proposed multi-microgrids system

B. Model Development

Sets

N	Set of microgrids, $N = \{1,2,..,|N|\}$
I	Set of potential placements for RDG sources, $I = \{1,2,..,|I|\}$
J	Set of renewable types of RDG sources, $J = \{1,2,..,|J|\}$
B	Set of batteries, $B = \{1,2,..,|B|\}$
D	Set of demand areas, $D = \{1,2,..,|D|\}$
T	Total time periods, $T = \{1,2,..,|T|\}$

Decision variables

m_{njd}^{t} electricity selling price from microgrid n with renewable type j to demand area d at time t

p_{n}^{t} electricity selling price for intra-trading in among microgrids at time t

v_{njd}^t amount of electricity produced and delivered from microgrid n with renewable type j to demand area d at time t

l_{dnj}^t amount of electricity delivered from main grid to demand area d belong to microgrid n with renewable type j at time t

$$x_{ijn} = \begin{cases} 1 & \text{if potential location for RDG } i \text{ with renewable} \\ . & \text{type } j \text{ of microgrid } n \text{ is establised} \\ 0 & \text{otherwise} \end{cases}$$

$$y_n^t = \begin{cases} 1 & \text{if there is intra} - \text{trading in among microgrid} \\ . & n \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

$$z_{bn}^t = \begin{cases} 1 & \text{if batery } b \text{ in microgrid } n \text{ charges energy at} \\ . & \text{time } t \\ 0 & \text{otherwise} \end{cases}$$

Parameters

A_{dn}^t demand load of demand area d in microgrid n at time t [kWh] (uncertainty)

vl_n^t amount of electricity sold from microgrid n to microgrids $n-1$ and $n+1$ at time t [kWh] (uncertainty)

f_n^t quantity of electricity that microgrid n buys from P2P intra-trading at time t [kWh] (uncertainty)

g_n^t amount of electricity sold from microgrid n to main grid at time t [kWh] (uncertainty)

pc price for buying electricity from P2P intra-trading [$]

e lifetime of microgird [year]

Y the total count of operational days within a year[day]

fk_{nj} fixed cost of microgrid n with renewable type j [$]

dk_n distance for delivering electricity from main grid to microgrid n [km]

ac_{nj} the cost incurred for maintenance activities on an annual basis of microgrid n with renewable type j [$/year]

am the cost incurred for maintenance activities on an annual basis of main grid [$/year]

gc the cost of producing electricity per unit of main grid [$/kWh]

dc the cost associated with distributing electricity per unit of main grid [$/kWh. km]

uc_{nj} the cost of producing electricity per unit of microgrid n with renewable type j [$/kWh]

fc_n the cost associated with delivering electricity per unit of microgrid n [$/kWh. km]

ub unit charging cost of battery [$/kWh]

kd_{njd} distance for delivering electricity from microgrid n with renewable type j to demand area d in the same microgrid n [km]

dm_n distance for delivering electricity from main grid to microgrid n [km]

bc^t electricity purchase price from P2P intra-trading [$/kWh]

ve_n^t volume of electricity delivered from P2P intra-trading to microgrid n at time t [kWh]

id_n distance for delivering electricity from P2P intra-trading to microgrid n [km]

ps price for selling electricity to main grid [$/kWh]

pb	price for selling electricity from main grid [\$/kWh]
lc_{ij}	environmental cost of the land used to establish RDG sources i with renewable type j [m. u/mWh]
ec	unit CO_2 emission cost [\$/kg]
ao_{ijn}	quantity of CO_2 emission for opening RDG sources i with renewable type j of microgrid n [kg/kWh]
uo_{nj}	unit CO_2 emission for each kWh electricity produced from microgrid n with renewable type j [kg/kWh]
do	unit CO_2 emission for delivering each kWh electricity [kg/kWh]
mo	unit CO_2 emission for each kWh electricity generated from main grid [kg/kWh]
eb	unit CO_2 emission for each kWh electricity charged from battery [kg/kWh]
Ω_{bn}	the amount of energy storage of battery b in microgrid n at the end of day [mW]
C_{nj}	the highest limit of capacity for the microgrid n with renewable type j [mW]
Q	capacity of main grid [mW]
G_{max}	maximum capacity level of battery [mW]
G_{min}	minimum capacity level of battery [mW]
h_{bn}^t	amount of electricity is stored in battery b of microgrid n at time t [mW]
τ_{bn}	amount of electricity is stored in battery b of microgrid n in its initial state[mW]
γ_{bn}^t	time-varying state of charge stage for battery b in microgrid n
μ_{bn}^t	hourly energy storage of battery b in microgrid n [h]
S_n^t	the ratio between the electricity generated and the demand within microgrid n during the specific time period t [number]
P_n	the highest quantity of electricity that microgrid n is allowed to buy from P2P intra-trading [kWh]
CM_{max}	the upper bound on CO_2 emission in possible site of multi-microgrid system [kg]
α	price coefficient
ζ	elasticity coefficient
ϵ	profit margin [%]
η	discount rate [%]

The first objective function is to maximize the overall profitability while the second objective function aims to minimize the cumulative costs associated with environmental impacts. The overall profitability is obtained by the gap between system's revenue (IC_{MMG}) and total costs that include the costs for P2P intra-trading (C_{trade}), main grid (C_{main}), and MMG system (C_{MMG}) as shown in Eq. (1). The annual cost calculated by dividing this cost to total number of generation days per year (N).

$$Max\ W_1 = IC_{MMG} - C_{trade} - C_{main} - C_{MMG} \quad (1)$$

Income of MMG (IC_{MMG}) comes from the electricity sold to demand areas, P2P intra-trading and main grids as calculated in the first, second and last term of Eq. (2).

$$IC_{MMG} = \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T} m_{njd}^t A_{dn}^t x_{ijn} + \sum_{n=1}^{N}\sum_{t=1}^{T} p_n^t\, vl_n^t + \sum_{n=1}^{N}\sum_{t=1}^{T} g_n^t ps \quad (2)$$

The cost for trading electricity (C_{trade}) in Eq. (1) is from costs for buying electricity from P2P intra-trading as shown in the Eq. (3).

$$C_{trade} = \sum_{n=1}^{N}\sum_{t=1}^{T} f_n^t\, pcy_n^t \tag{3}$$

The costs for main grid (C_{main}) in Eq. (1) consists of cost for maintaining system in the first term and costs for buying electricity and producing and delivering electricity from main grid to demand areas d of microgrids n as formulated by Eq. (4).

$$C_{main} = \sum_{t=1}^{T}\frac{am}{N} + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T} l_{dnj}^t(pb + dcdk_n + gc) \tag{4}$$

The electricity costs of MMG (C_{MMG}) in Eq. (1) is formulated by Eq. (5) including the fixed cost for installation and purchasing all required components of RDG sources, annual maintenance cost in the first term, cost for charging energy of battery in the second term, costs for producing and delivering electricity from MMG to demand areas and to main grid and from main grid to demand areas in the third, fourth, fifth, and last term, respectively.

$$\begin{aligned} C_{MMG} = &\sum_{n=1}^{N}\sum_{j=1}^{J} fk_{nj}\frac{\eta(1+\eta)^e}{(1+\eta)^e-1}\frac{1}{Y} + \frac{ac_{nj}}{Y} + \sum_{n=1}^{N}\sum_{b=1}^{B}\sum_{t=1}^{T} z_{bn}^t ub(h_{bn}^t - \tau_{bn}) \\ &+ \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} g_n^t(uc_{nj} + fc_n dm_n) \\ &+ \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T} v_{njd}^t(kd_{njd} fc_n + uc_{nj}) \\ &+ \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T} l_{dnj}^t(dcdk_n + gc) \end{aligned} \tag{5}$$

The second objective function in Eq. (6) is to minimize the cumulative costs associated with environmental impacts that come from the CO_2 emission costs for establishing MMG system (C_{land}), charging electricity of battery (C_{bat}), producing and delivering electricity from MMG to demand areas and main grid (C_{cm}), form main grid to MMG system (C_{om}), and from MMG to P2P intra-trading (C_{ot}).

$$Min\ W_2 = C_{land} + C_{bat} + C_{cm} + C_{om} + C_{ot} \tag{6}$$

The CO_2 emission costs for establishing MMG system are shown in Eq. (7) that comes from the environmental cost of land used and CO_2 emission costs for opening RDG sources.

$$C_{land} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{N}(lc_{ij} + ao_{ijn}ec)C_{ijn}x_{ijn} \tag{7}$$

The CO_2 emission cost for charging electricity of battery b in MMG system is calculated by Eq. (8).

$$C_{bat} = \sum_{n=1}^{N}\sum_{b=1}^{B}\sum_{t=1}^{T} eceb(h_{bn}^t - \tau_{bn})z_{bn}^t \tag{8}$$

The CO_2 emission costs for producing and delivering electricity from MMG to demand areas and to main grid are formulated in the first and second term, respectively in Eq. (9).

$$C_{cm} = \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T} ec\left(uo_{nj} + dokd_{njd}\right) v_{njd}^{t} + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} g_n^t ec\left(uo_{nj} + dodm_n\right) \tag{9}$$

The CO_2 emission costs for generating and distributing electricity from main grid to MMG system are formulated by Eq. (10).

$$C_{om} = \sum_{n=1}^{N}\sum_{d=1}^{D}\sum_{t=1}^{T} ec(mo + dodm_n)\, l_{dnj}^{t} \tag{10}$$

The CO_2 emission costs for generating and distributing electricity from MMG to P2P intra-trading are shown in Eq. (11).

$$C_{om} = \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} ec\left(uo_{nj} + id_n do\right) l_{dnj}^{t} vl_n^t \tag{11}$$

Constraint (12) estimates electricity demand by considering the seasonal electricity pricing $\left(m_{njd}^{t}\right)$ and the primary energy usage of the electrical equipments (br_{rs}^{t}) in demand areas. Constraint (13) ensures that the total energy generated from microgrid n at time t does not overcome its capacity level. Constraint (14) warrants that the amount of electricity distributed from main grid at time t is not greater than its capacity level. Constraint (15) warrants the amount of electricity that microgrid n can buy from P2P intra-trading at time t. Constraint (16) ensures that customer demands load is full fill at time t. Constraint (17) warrants that CO_2 emission released from establishing and operating MMG system meets government regulation. Constraint (18) ensures the non-negativity of the decision variable.

$$\sum_{d=1}^{D} A_{dn}^{t} = \sum_{d=1}^{D}\sum_{s=1}^{S} br_{rs}^{t} - \alpha\left(m_{njd}^{t}\right)^{\zeta}, \forall n \in N, \forall t \in T \tag{12}$$

$$\sum_{d=1}^{D} v_{njd}^{t} + vl_n^t + g_n^t \le C_{ijn} x_{ijn}, \forall n \in N, \forall i \in I, \qquad \forall j \in J, \forall t \in T \tag{13}$$

$$\sum_{d=1}^{D}\sum_{n=1}^{N}\sum_{j=1}^{J} l_{dnj}^{t} \le Q, \forall t \in T \tag{14}$$

$$0 \le f_n^t \le P_n y_n^t, \forall n \in N, \forall t \in T \tag{15}$$

$$\sum_{d=1}^{D} v_{njd}^{t} + \sum_{d=1}^{D} l_{dnj}^{t} + f_n^t \ge \sum_{d=1}^{D} A_{dn}^{t}, \forall n \in N, \forall j \in J, \forall t \in T \tag{16}$$

$$\begin{aligned}
&\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{N} ao_{ijn} C_{ijn} x_{ijn} + \sum_{n=1}^{N}\sum_{b=1}^{B}\sum_{t=1}^{T} eb(h_{bn}^{t} - \tau_{bn}) z_{bn}^{t} \\
&\quad + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T}\left(uo_{nj} + dokd_{njd}\right) v_{njd}^{t} \\
&\quad + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} g_n^t\left(uo_{nj} + dodm_n\right) + \sum_{n=1}^{N}\sum_{d=1}^{D}\sum_{t=1}^{T}(mo + dodm_n)\, l_{dnj}^{t} \\
&\quad + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\left(uo_{nj} + id_n do\right) l_{dnj}^{t} vl_n^t \le CM_{max}
\end{aligned} \tag{17}$$

$$m_{njd}^{t}, p_n^t, v_{njd}^{t}, l_{dnj}^{t} \ge 0 \tag{18}$$

C. Battery Storage

The hourly energy storage profile is shown in Eq. (19). Where, $\mu_{bn}^{t}(+), \mu_{bn}^{t}(-) \geq 0$ present the hourly charging and discharging profile of battery b in microgrid n at time t, respectively. The state of charge (SoC) of battery b has time-varying states γ_{bn}^{t} for the storage component as shown in Eq. (20). The hourly storage profile (μ_{bn}^{t}) of battery b in microgrid n at time t is a rate of change in the SoC that varies over time. In which: 0: idle state of battery battery b in microgrid n at time t.

The amount of energy storage in battery b at time t relies on factors such as SoC, charging/discharging rate, and the initial storage condition. Besides, the total energy storage in battery battery b at time t has to meet the following generation constraint that it is constrained by the maximum capacity threshold of the battery as shown in Eq. (21). SoC by the conclusion of the day (Ω_{day}) is calculated by Eq. (22). The value of Ω_{day} is flexible and remain in its initial state.

The battery battery b in microgrid n will charge energy at time t if this microgrid has surplus energy $(S_{n}^{t} > 1)$. So that, this microgrid will sell its surplus energy to main grid or to other nearby microgrids through P2P intra-trading at time t. On the other hand, if battery b in microgrid n discharges energy at time t, there are two situations. The first situation is this microgrid has enough electricity to full fill customer demand $(S_{n}^{t} = 1)$. The second situation is this microgrid has insufficient electricity so that it has to buy electricity from main grid or other local microgrids through P2P intra-trading at time $(S_{n}^{t} < 1)$.

$$\mu_{bn}^{t} = \mu_{bn}^{t}(+) - \mu_{bn}^{t}(-) \tag{19}$$

$$G_{min} \leq \gamma_{bn}^{t} \leq G_{max} \tag{20}$$

$$0 \ll \tau_{bn} + \sum_{t=1}^{T} \mu_{bn}^{t} \ll G_{max} \tag{21}$$

$$\sum_{t=1}^{T} \mu_{bn}^{t} = \Omega_{day} \tag{22}$$

D. P2P intra-trading

Equation (23) calculates the generation to demand ration of microgrid n at time t. This value is used to evaluate the ability that microgrid n will join to P2P intra-trading if it has surplus or deficient electricity at time t. In the given time period $t \in T$, If $S_{n}^{t} = 1$, microgrid n $(n \in N)$ will not joint to P2P intra-trading.

If $S_{n}^{t} > 1$, the values of S_{n-1}^{t} and S_{n+1}^{t} are considered. In which, if $S_{n-1}^{t} = S_{n+1}^{t}$, microgrid n $(n \in N)$ will sell its surplus energy to main grid with the volume calculated by Eq. (24). By contrast, if $S_{n-1}^{t} < 1$ or $S_{n+1}^{t} < 1$, microgrid n $(n \in N)$ sells its surplus energy to P2P intra-trading with amount determined by Eq. (25).

If $S_{n}^{t} < 1$, $S_{n-1}^{t} \leq 1$ and $S_{n+1}^{t} \leq 1$, microgrid n buys electricity from main grid with amount formulated by Eq. (26). If $S_{n}^{t} < 1$ and $S_{n-1}^{t} > 1$ or $S_{n+1}^{t} > 1$, microgrid n buys electricity form P2P intra-trading with amount determined by Eq. (27).

$$S_{n}^{t} = \frac{\sum_{d=1}^{D} v_{njd}^{t}}{\sum_{d=1}^{D} A_{dn}^{t}}, \forall n \in N, \forall j \in J, \forall t \in T \tag{23}$$

$$g_{n}^{t} = (S_{n}^{t} - 1) \sum_{d=1}^{D} A_{dn}^{t}, \forall n \in N, \forall t \in T \tag{24}$$

$$vl_{n}^{t} = (1 - S_{n}^{t}) \sum_{d=1}^{D} A_{dn}^{t}, \forall n \in N, \forall t \in T \tag{25}$$

$$\sum_{d=1}^{D} l_{dnj}^{t} = (1 - S_n^t) \sum_{d=1}^{D} A_{dn}^{t}, \forall n \in N, \forall t \in T \quad (26)$$

$$f_n^t = (1 - S_n^t) \sum_{d=1}^{D} A_{dn}^{t}, \forall n \in N, \forall t \in T \quad (27)$$

3. Proposed Solution

The framework for making decisions on MMG system design suggested in this study is given in Fig. 2. The integration between Genetic algorithm-CPLEX solver (GA-CPLEX) is applied to solve the MMILPM to propose optimal structure of sustainable MMG system.

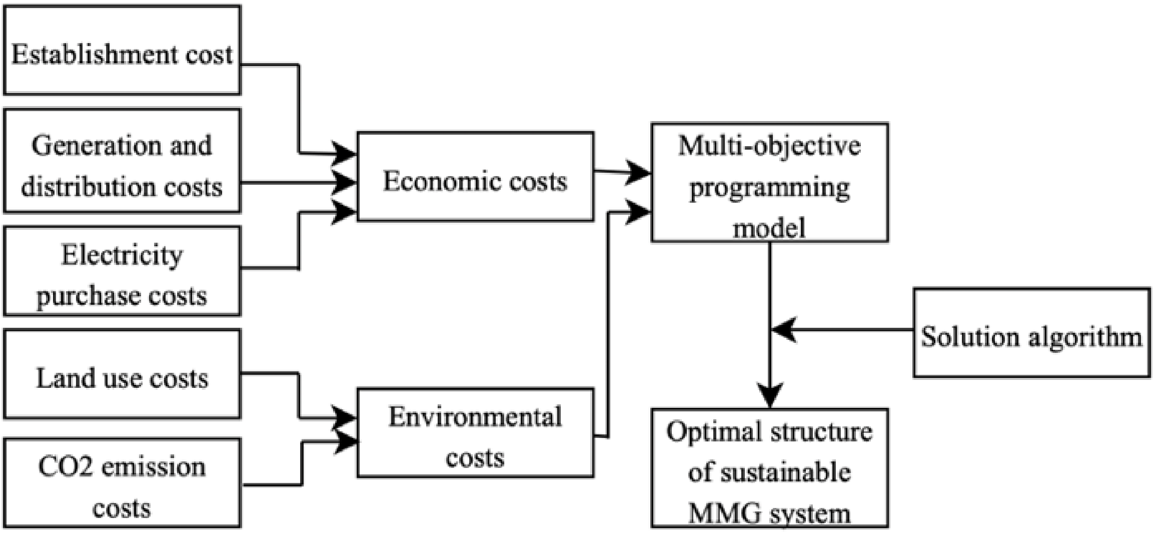

Fig. 2 The suggested approach for optimizing the sustainable MMG system

Traditional methods may not be sufficient to solve the intricate network design problems. Soleimani and Kannan suggested that GA could be a suitable alternative for addressing these optimization problems. GA is frequently employed to explore and find high-quality solutions by incorporating operators inspired by biological mechanisms, such as mutation, crossover, and selection. In order to solve the local optimization of GA, CPLEX solver is to find the optimal solution. In which, the GA solution is applied in CPLEX serving as the lower bound for the overall financial gain and upper bound the cumulative cost related to the environment

Procedure GA-CPLEX: Summary of the proposed solution algorithm

Step 1. Define chromosome for GA. There are two types of chromosomes: establishing chromosomes for RDG sources and the exchange of electricity chromosomes between entities in the MMG system

Step 2. Define the fitness function. During the planning phase, the chromosomes must initially comply with the constraints of the MMG. Subsequently, the two objective functions are employed to evaluate the fitness. For every value of $r \leq population\_size$, feasible chromosomes are randomly generated and stored along with their corresponding objective function values, as defined by Eqs. (1) and (6). Feasibility is determined by ensuring that the chromosomes satisfy all relevant constraints. Among the randomly generated feasible chromosomes, select, and save the one that has the highest value of the objective function (1) and the lowest value of the objective function (6) as the current solution for the problem defined by MMILPM.

Step 3. Determine selecting strategy, crossover, and mutation. The roulette wheel method is employed to select parents for crossover, while random selection is used for mutation.

Step 4. Apply GA solution as a lower and upper bound for each objective function in CLPEX to determine optimal solution.

4. Results

Experimental scenarios are employed to assess the efficacy of the proposed model and algorithm. The MMG system consisting of a solitary main grid, three microgrids composed of ten potential sites, a battery, and ten demand areas is taken a consideration in this research. In each microgrid, every RDG has two size levels and a lifespan of ten years. A one-day period (24 hours), represented by $T = \{1,2,3, \ldots ,24\}$, is utilized to determine the electricity generation of each RDG in the microgrid and determine the selling price of electricity. The Python 3.8.5 programming language was used to implement the proposed GA, while the CPLEX solver was implemented using AMPL. The experiments were performed on a computer with a processing speed of 3.60GHz and a RAM capacity of 16.0 GB.

A. In put Data

In the experimental scenarios, the financial investment and size of each RDG are derived from the data provided by [14]. The costs associated with the production of energy, maintenance, and CO2 emissions are based on the data found in the technical reports published by [15]. The electricity demand load and the information pertaining to weather conditions is from [16] and [17], respectively.

B. Configuration and Sensitivity of Parameters

The variables incorporated in the developed model, such as elasticity coefficient, price coefficient, and profit margin are determined based on the preferences and requirements of the decision-maker. The values assigned to the parameters of the recommnended algorithm, including the crossover and mutation rates, as indicated in Table 1, are derived from the works of [18] and [19].

Table 1 Paramters of the suggested model and GA

Parameters	Values
Elasticity coefficient (ζ)	0.6
Profit margin (ϵ)	0.2
Crossover rate	0.5
Mutation rate	0.5
Mutation selection rate	0.5
Number of iteration	2,000

To evaluate the robustness of the proposed GA and ensure that the chosen parameters yield the best results, the performance of the GA was analyzed by comparing the results obtained with varying mutation and selection rates. The results depicted in Fig. 3 and Fig. 4 demonstrate that the proposed GA, utilizing a mutation rate of 0.5% and a selection rate of 0.5%, outperforms other solutions achieved with different mutation and selection rates. Hence, the proposed GA, employing a mutation rate of 0.3% and a selection rate of 0.5%, has demonstrated greater effectiveness in solving the presented problem. The result in Fig. 3 demonstrates that the overall financial gain experiences an average increase of over 5% and the cumulative cost related to the environment decreases by approximately 10% when compared to alternative mutation rates. Similarly, in Fig. 4, it can be observed that the proposed selection rate leads to an increase in the overall financial gain by nearly 5.77% and a reduction in the cumulative cost related to the environment reduce by approximately 4.01% compared to any other selection rates.

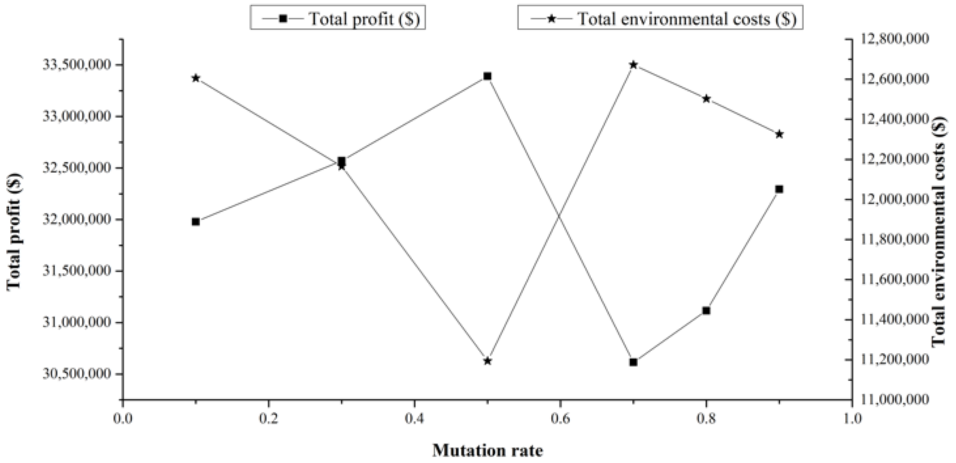

Fig. 3 The assessment of the overall financial gain and cumulative cost related to the environment across various mutation rate values

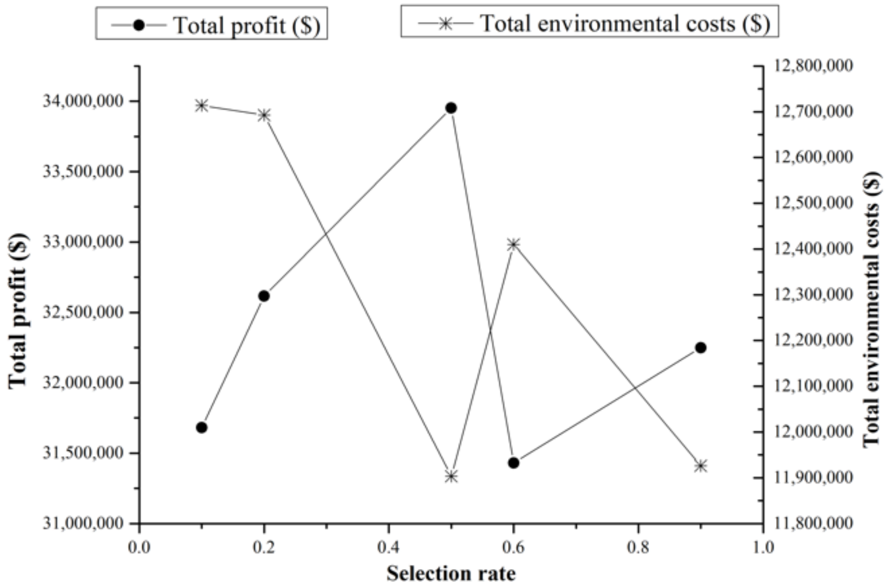

Fig. 4 The assessment of the overall financial gain and cumulative cost related to the environment across various selection rate values

In order to conduct a more comprehensive assessment of the developed model's sensitivity and performance, flexible parameters such as the elasticity coefficient (ζ), profit margin (ϵ), and discount rate (η) are investigated using various values as shown in Fig. 5, Fig. 6, and Fig. 7, respectively. In comparison to the other elasticity coefficients, when the elasticity coefficient (ζ) is 0.6, the overall financial gain raises by on average, a rate of 3.42%, while the cumulative cost related to the environment drops by 8.06%. Additionally, the result in Fig. 6 indicates that if the profit margin for participating in P2P energy trading increases from 0.05 to 0.2, the overall financial gain raises by 1.58% and the cumulative cost related to the environment reduce by 5.85% on average. The recommended model attains the highest overall financial gain and the lowest cumulative cost related to the environment when the discount rate (η) is set to 0.1 as shown in Fig. 7. Typically, increasing the discount rate from 0.1 to 0.2 results in a drop of over 2.31% the overall financial gain and an rise of 4.86% in the cumulative cost related to the environment.

According to the aforementioned results, the proposed model exhibits sensitivity to changes in the flexible parameters and proves to be more effective compared to other parameter values.

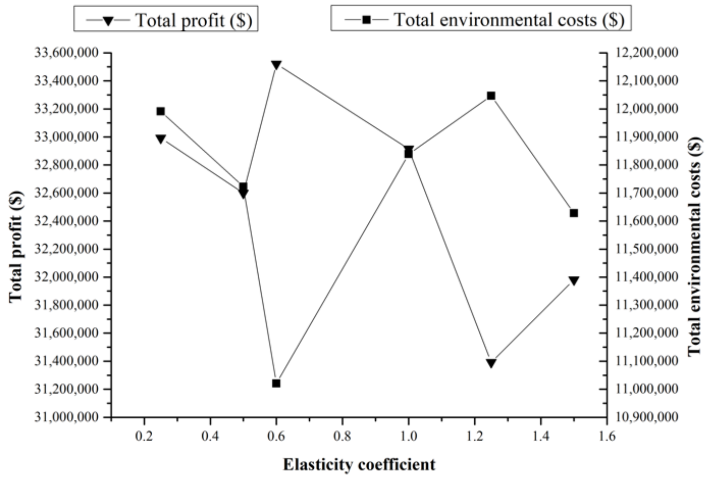

Fig. 5 The assessment of the overall financial gain and cumulative cost related to the environment across various elasticity coefficient values

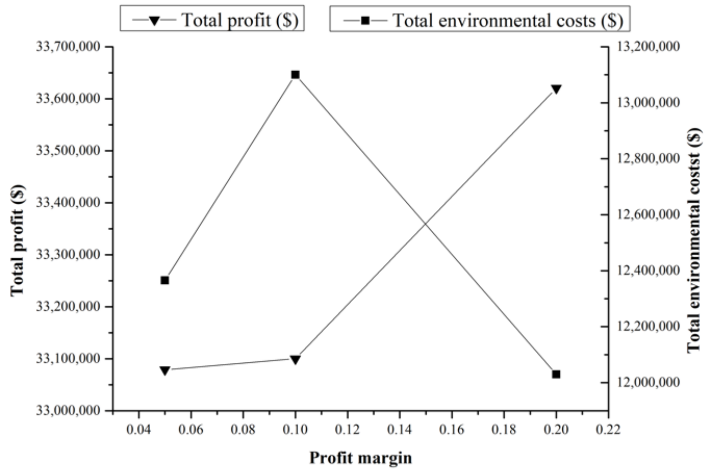

Fig. 6 The assessment of the overall financial gain and cumulative cost related to the environment across various profit margin values

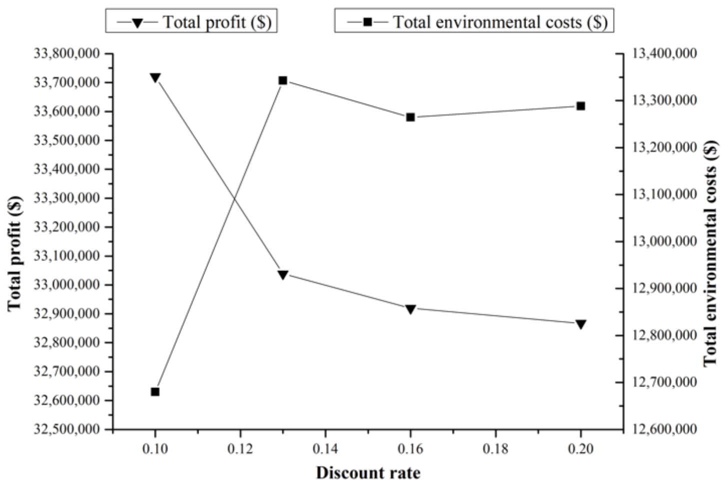

Fig. 7 The assessment of the overall financial gain and cumulative cost related to the environment across various discount rate values

C. Sustainable MMG system

The distribution of electricity from microgrids, the main grid, and P2P intra-trading to the respective demand areas are highlighted in Fig. 8. The findings depicted in Fig. 8 indicate a general trend of increasing total electricity demand from approximately 4:00 to around 13:00. After that, the demand gradually decreases until approximately 20:00, followed by another increase until around 22:00. Finally, the demand starts decreasing again until approximately 3:00. Furthermore, the microgirds actively participates in P2P intra-trading by selling more than 20% of its surplus electricity during specific time periods: 1:00, 4:00, and 5:00, from 13:00 to 16:00, and from 21:00 to 24:00. Conversely, the micorgids procures inadequate electricity acquired through P2P intra-trading across three separate time intervals: from 6:00 to 8:00, from 10:00 to 12:00, and from 17:00 to 20:00.

Table 2 displays the maximum capacity of the five RDG units for the establishment of the microgrid 1, 2 and 3 with the related type of renewable and capacity. In the proposed model, the selection of RDG locations for maximizing the overall financial gain and minimizing the cumulative cost related to the environment is determined based on the distance between RDG placements and demand areas.

The distribution of electricity from microgrids, the main grid, and P2P intra-trading to the respective demand areas are highlighted in Fig. 8. The findings depicted in Fig. 8 indicate a general trend of increasing total electricity demand from approximately 4:00 to around 13:00. After that, the demand gradually decreases until approximately 20:00, followed by another increase until around 22:00. Finally, the demand starts decreasing again until approximately 3:00. Furthermore, the microgirds actively participates in P2P intra-trading by selling more than 20% of its surplus electricity during specific time periods: 1:00, 4:00, and 5:00, from 13:00 to 16:00, and from 21:00 to 24:00. Conversely, the micorgids procures inadequate electricity acquired through P2P intra-trading across three separate time intervals: from 6:00 to 8:00, from 10:00 to 12:00, and from 17:00 to 20:00.

Table 2 The size and placement of the deployed RDG sources

				Microgrid 1						
Placement	1	2	3	4	5	6	7	8	9	10
Size *(mW)*	300	-	400	300	-	-	300	-	400	-
Type of renewable	W		PV	W			W		PV	
				Microgrid 2						
Placement	1	2	3	4	5	6	7	8	9	10
Size *(mW)*	300	300	-	-	400	-	300	-	-	400
Type of renewable	W	PV			PV		W			PV
				Microgrid 3						
Placement	1	2	3	4	5	6	7	8	9	10
Size *(mW)*	-	400	-	400	-	300	-	300	400	-
Type of renewable		PV		W		W		W	PV	

Based on Figure 9, it is evident that 85.7% of the electricity supplied to demand areas originates from the MMG. The remaining demand load is met by sourcing 6,1% from the main grid and 8,2% from P2P intra-trading. These findings highlight the feasibility of accommodating the uncertain size of RDG sources, as renewable sources have intermittent availability, necessitating the use of electricity delivered from the main grid and P2P intra-trading.

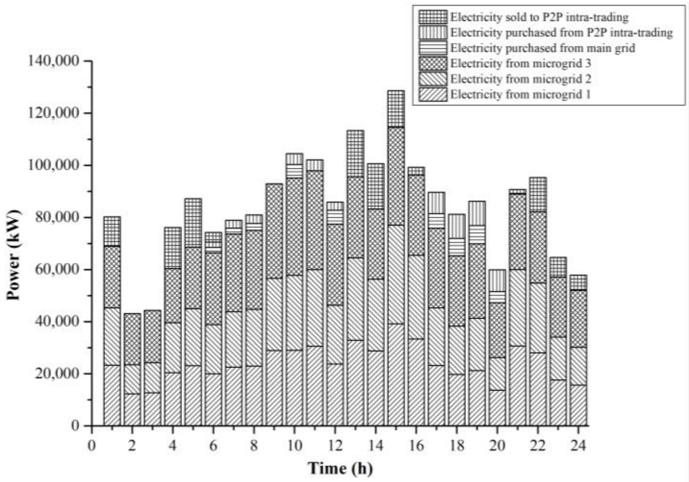

Fig. 8 Power flows in 24 hours

The charging states of battery in microgird 1, 2 and 3 are shown in Fig. 9. As can be seen that, batteries in microgrid 1 and 3 charge energy within the specified time frame: 1:00, 4:00, 5:00, 13:00 to 15:00, and 21:00-24:00. Battery in microgrid 2 charges energy from 4:00 to 6:00, 13:00 to 16:00, and 21:00 to 22:00. The energy stored in each battery is utilized to fulfill the demand load within the corresponding microgrid and any excess energy is sold through P2P intra-trading.

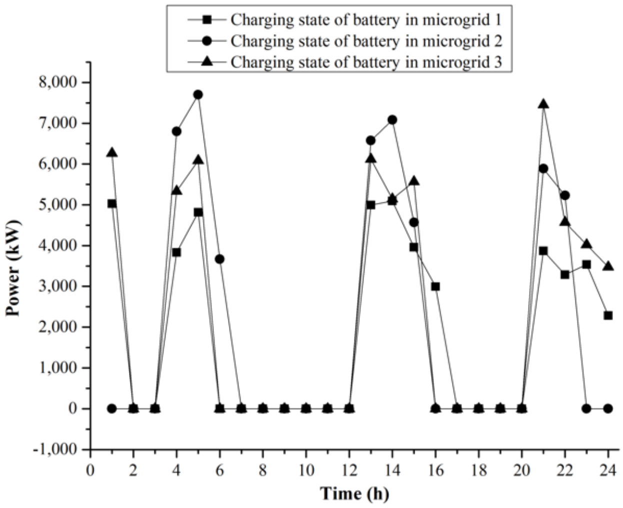

Fig. 9 Charging state of battery in the MMG system

Considering the computational outcomes presented above, it can be concluded that the proposed MMG design is effective in managing the grid during uncertain weather conditions. Additionally, the majority of electricity produced from RDG sources is supplied to the demand areas, with only the surplus energy being sold through P2P market. Consequently, to maximize profitability for the MMG, greater emphasis is placed on meeting demand through RDG sources rather than relying heavily on P2P market. This arrangement is vital for maintaining the sustainability of the grid. The MMG system attains an optimal total profit of $33,520,187 and a total environmental cost of $11,029,476.

5. Conclusion

The study proposed the optimal MMG system that encompasses decisions concerning the quantity, placement, and size of RDG sources, battery charging states, and the efficient management of electricity flows among microgrids, demand areas, the main grid, and neighboring microgrids within the MMG system. The proposed framework incorporates P2P intra-trading concept and considers the MMG system, wherein microgrids are interconnected with both the main grid and nearby microgrids concurrently. The proposed solution approach involves combining a Genetic GA and CPLEX to tackle MMILPM. This approach effectively handles various uncertainties associated with the decision problem, including demand uncertainty, variability in electricity generated from RDG sources, as well as fluctuations in constraints and objectives. The experimental results validate the effectiveness and success of the proposed model and algorithm.

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