Solar Energy 262 (2023) 111861

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

Novel sustainable urban management framework based on solar energy and digital twin

Jianhe Xu [*], Jiajun Gong

School of Architecture, Changsha University of Science & Technology, Changsha 410076, China

ARTICLE INFO

Keywords:
Sustainable urban management
Digital twin
Solar and wind renewable energy resources
Time-of-use
Microgrid

ABSTRACT

This paper proposes a sustainable energy management method for microgrids (MGs) in the urban area while taking into account energy storage systems (ESSs) and renewable energy (RE). This study integrates RE, such as solar and wind energy production, into the power grid, and formulates the optimum dispatch scheme of hybrid energy production, based on ESS charge and discharge planning using their digital models. Electricity is exchanged among the MG systems and the utilities on a daily basis. MG systems' cost-effective dispatch per day is solved by an improved pigeon-inspired optimization algorithm (IPIOA) considering the time-of-use (TOU) and other technical limitations. IPIOA can be modified in various ways for finding possible spaces with greater efficiency. This study uses IPIOA to manage power costs economically for Islanding and non-Islanding cases and compares the outcomes with other methods. Additionally, it uses micro-turbines as well as REs, ESSs, and Islanding and non-Islanding cases to schedule MGs optimally. In comparison to a number of existing algorithms, the new approach has proven to be more robust, reliable, and efficient.

1. Introduction

A number of countries have adopted energy-efficient policies for sustainable energy management in the urban areas. In addition to promoting the utilization of plug-in electric vehicles (PEVs), renewable energy resources (RERs), and hybrid electric vehicles (HEVs), the programs also encourage power efficiency [1]. Nevertheless, as distributed generation (DG) from RERs spreads, resulting in more power production from the power plant to the distribution levels, as well as commercializing PEVs and stations for the charge, power grids experience more fluctuations and two-way communication. For adequate management of this phenomenon, interruptions must be minimized, service quality and reliability assured, and massive electrical grids avoided from being stressed. As an example, ref [2] outlined the issues associated with a large surplus of PV power in Germany, forcing coal-fired units to temporarily close. Ref [3] examined the effect of the Fast and Ultra PEV charging station on distribution grids, while ref [4] urged stronger cooperation among the transmission system operator and distribution system operator (DSO).

Moreover, the U.S. consistently emphasizes the need for the demand response (DR) program as of the early 2000 s in an effort to enhance distribution network flexibility, including, by releasing specific electricity prices and incentives [1] that affect users' decisions [5]. Additionally, the DR program ought to help users control, schedule, and manage individual loads, particularly when using Energy Storage Systems (ESSs) and generators.

Microgrids (MGs) are defined by the United States Dept. of Energy to be a set of interlinked loads and distributed power sources inside precisely outlined limits, acting as one controllable unit on the grids. MGs are able to be operated in either islanded mode or non-Islanding mode by connecting and disconnecting from the grids. In this way, under disruptions, MG generations and the local load would be separated from distribution networks without damaging the reliability of distribution networks [6]. It is possible to design an MG to accommodate any number of houses up to a whole neighborhood. Furthermore, HEVs are classified as MGs due to their auxiliary or multiple-production power systems that support enhanced dynamic response. Nano-grids typically run in the islanded modes, in other words, separate from the charge stations, due to their small dimensions.

MG electric architectures typically have a main bus, called the backbone that connects the convertors of a distributed energy system to the upstream grids. As well as being constructed in AC and DC modes, it could also be constructed in the radial or ring modes. Ref [7] discussed the benefits of using DC MGs over AC MGs because of their simplicity

* Corresponding author.
E-mail address: xjhwork523@sina.com (J. Xu).

https://doi.org/10.1016/j.solener.2023.111861
Received 2 March 2023; Received in revised form 27 May 2023; Accepted 12 July 2023
Available online 27 July 2023

and fewer conversion steps, particularly in the PV, ESS, and DC load, such as PEV charge. In addition, these benefits result in a smooth transition to a DC network. In recently published papers, combined AC-DC MGs have been shown to have greater potential because of their security, robustness, and power quality, in addition to the possibilities of combining the advantages of AC and DC MGs. In fact, combined AC-DC systems are more suitable for home MGs since they do not require modifying the electric system [8].

A crucial duty of MG is claimed in ref [9] when it comes to MG power flow management, so MG energy management systems (EMSs) are part of the smart network control model's 2nd layer. An energy appliance's control system is the 1st layer of a smart network control model, whereas MG energy management systems (EMS) must manage multiple MGs through the MG EMSs of one smart network. As a result, the EMSs are responsible for implementing an actual decision-making method for controlling and managing the MG power flow and grid link. Therefore, it ensures that the local MG subsystems meet the preferences of end users and DSOs in accordance with a precise formulation of the Objective Function (OF). Additionally, the duration of the operation depends on the sampling interval of the smart meter, ranging from a couple of minutes to a period of an hour [5].

In response to the simulation case examined, the OF formula may include penalties (rewards). Typically, they have been employed for evaluating the impact of variations in the power flow, self-usage by MGs, reducing peak demand, and the profits from grid-traded energy on the distribution network [10]. A variety of techniques are explored by researchers regarding the modeling of EMS, which range from rule-driven approaches using expertise to information-based approaches and machine learning. Ref [11] defined 3 types of EMSs: stochastic model, soft calculating-driven model, and heuristic model, though most solutions described in academic papers combine the 3 types of models. A reinforcement learning approach is also being investigated [12]. Information-based solutions in the EMS are investigated because just rarely does the EMS create the optimum plan of the local MG power flow in the actual world. Typically, research reports on the implementation of (pseudo)deterministic algorithms according to Dynamic Programming (DP), greedy algorithms, Mixed Integer Linear Programming (MILP), and Linear Programming (LP). Ref [13] proposes a constant power cost program for buying and selling energies and formulates the OF for maximizing income from trades in power. As a result, an LP formula can simply solve EMS. For optimizing the MG power flow, with its random and unpredictable features, EMS must be aware of the upcoming power system's time series, as explained in published research. EV EMSs may have a similar issue with knowing automobile routes and traffic data in applications related to automobiles. Thus, according to [14], the optimization algorithm should not be directly applied to EMS; instead, it should be used for the analysis of benchmark results, EMS reference solution assessment, and power system sizing [15]. As a means of more effectively coping with the uncertainty associated with the MG power system, ref [10] examined a probability-based planning method. Metaheuristic methods were likewise found to be useful. In contrast, ref [15] compares an NN-driven EMS with a less complex rule-driven EMS. Despite this, EMS schemes remain difficult to interpret in such situations.

Technically, MG energy management (EM) involves a variety of limitations in a complicated and multidimensional environment. The current study proposes a novel framework for the sustainable energy management of the microgrids in the urban areas. To this end, digital twin is used as a powerful tool for modeling the realistic behavior of the physical devices. Moreover, an improved pigeon-inspired optimization algorithm (IPIOA) would addresses the nonlinear nature of the problem. This paper proposes changes to the IPIOA's movement pattern in order to efficiently find possible spaces. IPIOA aims at improving MG power performance and optimizing DG utilization for maximizing income in a sustainable way. A comparison is made between the outcomes of the algorithm and earlier outcomes carrying out optimization on a number of scenarios. It is evident from the outcomes that the suggested approach would be practical, reliable, and better in comparison to existing algorithms. The rest of paper is organized as follow: System model and problem formulation are presented in sections 2 and 3, respectively. The Pigeon-inspired optimization algorithm (PIOA) and its improvement are introduced in section 4. Case studies and simulation results are reported in section 5. Finally, the main conclusion is presented in section 6.

2. System scheme

The study develops the optimization scheme to generate MG schedules, considering RER and ESS availability in an urban area. Throughout the 24 h, energy is exchanged among the utilities and the MG by means of the electrical connection making a sustainable power delivery system. MG is able to sell surplus energy to the utilities based on time-of-use (TOU). As well as operating Islanding, the MG could also be connected to the network. A specified load requirement can be met by optimally dispatching energy from various resources and ESS in accordance with the EM approach. It would be possible to use IPIOA as a non-Islanding unit and as a Islanding unit for cost-effective EM. As well as adequate production capacities, IPIOA provides operating methods and control systems. All microturbines (MT), wind turbines (WT), photovoltaics (PV), and ESS schemes need to be developed.

2.1. MT model

MTs are referred to as DGs because they produce fixed amounts of energy. Eq.1 represents the price of fuel for a micro-gas turbine to be a quadratic function:

$$F_i(P_i(t)) = a_i P_i^2(t) + b_i P_i(t) + c_i \tag{1}$$

$F_i(P_i(t)) = a_i P_i^2(t) + b_i P_i(t) + c_i$ shows the price of the fuel for agent i during t. a_i, b_i, c_i show the generation price coefficients for agent i. $P_i(t)$ shows the output of a committed agent i during t.

2.2. WT model

In a WT, wind power is converted into mechanical energy using complicated aerodynamics. As a randomly selected parameter, wind speed nearly completely determines wind energy practically. Eq.2 describes the relationship between wind speed and mechanical energy derived [16]:

$$P_w(t) = \frac{1}{2}\rho v^3(t) C_p(\lambda,\theta) A_w \tag{2}$$

Where $P_w(t)$ defines the output power from the WT at time t. θ is the rotor blades' pitch angle (deg). λ is the tip velocity coefficient. ρ shows the density of air (kg/m^3). $v(t)$ is the wind velocity (m/s) at time t. A_w defines the area covered via the rotor (m^2). C_p is the proficiency ratio of wind power. $C_p(\lambda,\theta)$ has been allocated in the following manner:

$$\begin{gathered} C_p(\lambda,\theta) = 0.73 \times \left(\frac{151}{\lambda_i} - 0.58\theta - 0.002\theta^{2.14} - 13.2\right) \times e^{-\frac{18.4}{\lambda_i}} \\ \lambda_i = \frac{1}{\dfrac{1}{\lambda - 0.02\theta} - \dfrac{0.003}{\theta^3 + 1}} \end{gathered} \tag{3}$$

Eq. 4 has been used to explain the OFF/ON state for the WT:

$$\begin{gathered} v(t) = v_i(t) if v_{start} \le v(t) \le v_{full} \\ v(t) = v_{full} if v_{full} < v(t) < v_{stop} \\ v(t) = 0 if v_{stop} \le v(t) or v(t) < v_{start} \end{gathered} \tag{4}$$

Where v_{stop}, v_{full}, and v_{start} are the stop, rated, and start wind speed (m/s), respectively. $v_i(t)$ is the current wind velocity (m/s) at time t.

2.3. The PV model

PV arrays are formed by combining PV cells in series and parallel. The intensity of sunlight plays a major role in affecting PV panels' output. Eq.5 calculates the output of a PV [17]:

$$P_s(t) = K_{PV} \times P_G(t) \times A_{PV} \tag{5}$$

In which, $P_s(t)$ shows PV output during t; $P_G(t)$ shows global radiation during t; A_{PV} shows the region of the PV array (W/m^2); K_{PV} shows the PV performance.

2.4. The ESS model

By calculating the difference between energy stored in 2 successive steps, it is possible to determine the output of one ESS. The ESS stores power in the following way [18].

(1) When the ESS charges:

$$\eta_C P_B(t) \le Q_{s,max} \tag{6}$$

$$Q_s(t+1) = Q_s(t) + \eta_C P_B(t) \tag{7}$$

(2) When the ESS discharges:

$$\eta_D P_B(t) \le Q_s(t) \tag{8}$$

$$Q_s(t+1) = Q_s(t) + \eta_D P_B(t) \tag{9}$$

In which, η_C shows the charge performance and η_D shows the discharge performance. $P_B(t)$ shows the electric energy for the ESS output during t^{th} hour. $Q_B(t)$ shows the sum capacities of ESSs during t^{th} hour. $Q_{s,max}$ shows the rated maximal storage power.

3. Problem definition

MGs can define energy management to be the optimization function minimizing overall operation costs and meeting inequality and equality restrictions. Here are the objective function and related limitations for the problem:

$$\min Obj(.) = \sum_{t=1}^{H} \left\{ \sum_{i=1}^{N} F_i(P_i(t))U_i(t) + P_{tie}(t) \times \text{price}(t) \right\} \tag{10}$$

Where $P_{tie}(t)$ is the active power sold/ bought to/from the main grid at time t. $price(t)$ defines the TOU amounts. $U_i(t)$ indicates the off/on conditions of agent i at time t.

The system limitations and unit limitations are included in the limitations:

(1) Balancing loads:

$$\sum_{t=1}^{H} \left\{ \sum_{j=1}^{m} P_{load,j}(t) + P_{loss}(t) \right\} = \sum_{t=1}^{H} \left\{ \sum_{i=1}^{N} P_i(t)U_i(t) + \sum_{s=1}^{S} P_s(t) + \sum_{w=1}^{W} P_w(t) + P_{tie}(t) + P_B(t) \right\} \tag{11}$$

Where $P_{loss}(t)$ is the entire loss of grid transmission at time t. N and H show the entire number of micro-gas turbines and the scheduling time, respectively.

(2) Agent power production restriction:

Fig. 1. The TOU ratio for a day.

$$P_{i,min} \le P_i(t) \le P_{i,max} \tag{12}$$

Where $P_{i,max}$ and $P_{i,min}$ are the maximum and minimum production restrictions of agent i, respectively.

(3) Minimal up-time restriction:

$$x_i^{on} \ge T_i^{on} \tag{13}$$

(4) Minimal down-time restriction:

$$x_i^{off} \ge T_i^{off} \tag{14}$$

Where x_i^{off} and x_i^{on} define continued down-time and up-time of agent i, respectively. T_i^{off} and T_i^{on} define the minimum down-time and up-time of agent i, respectively.

(5) Ramp up ratio:

$$\begin{aligned} &P_i(t) - P_i(t-1) \le UR_i, \\ &ifU(i,t) = 1andU(i,t-1) = 1 \end{aligned} \tag{15}$$

(6) Ramp down ratio:

$$\begin{aligned} &P_i(t-1) - P_i(t) \le UR_i, \\ &ifU(i,t) = 1andU(i,t-1) = 1 \end{aligned} \tag{16}$$

Where DR_i and UR_i define ramp down and up of agent i, respectively.

(7) Limitations associated with interchanging with utilities:

$$P_{tie,min} \le P_{tie}(t) \le P_{tie,max} \tag{17}$$

Where $P_{tie,max}$ and $P_{tie,min}$ define maximum and minimum active power generation of the main grid at time t, respectively.

(8) Limitations associated with capacity of the ESS:

$$P_{B,min} \le P_B(t) \le P_{B,max} \tag{18}$$

Where $P_{B,max}$ and $P_{B,min}$ define maximum and minimum storage amount of the ESS, respectively. Fig. 1 shows the 24 h power cost in the system. As mentioned before, this paper uses digital twin to help more accurate charging and discharging management of the ESS. The use of digital twin technology in energy storage systems (ESS) charge and discharge planning can improve the efficiency of the system and reduce energy costs [19]. Digital twin technology allows for the simulation of the system's performance, as well as its interaction with the surrounding environment. This allows for more accurate predictions of ESS performance, which can be used to optimize the system's charge and discharge planning. By analyzing the data from the digital twin, the system can be optimized to reduce energy costs and improve its efficiency. Additionally, digital twin technology can be used to detect potential issues and anomalies, allowing for early detection and prompt action. This can help to reduce the risk of system failures and improve overall system reliability [20].

The scalability of the digital twin hardware design is a critical aspect to consider, particularly when dealing with larger or more complex systems. In the context of the proposed sustainable urban management framework based on solar energy and digital twin, scalability becomes vital for effectively managing microgrids (MGs) in urban areas. As the system expands in size or complexity, the digital twin models need to accommodate and accurately represent the various components, such as renewable energy sources (e.g., solar and wind), energy storage systems (ESSs), and micro-turbines. The hardware design of the digital twin should be capable of handling the increasing volume of data and computational requirements, ensuring efficient modeling and optimization of hybrid energy production and ESS charge and discharge planning. Furthermore, the scalability of the hardware design should enable seamless integration with the power grid, allowing for cost-effective dispatch and electricity exchange between MG systems and utilities. Considerations for scalability include robust algorithms, efficient utilization of computing resources, and adaptability to evolving technical limitations and future expansions.

4. PIOA and its enhancement

Evolutionary algorithms (EAs) offer several advantages for solving nonlinear and nonconvex problems. Their ability to perform global search makes them effective in finding the global optimum, even in the presence of multiple local optima. EAs are flexible and can handle various types of optimization problems without relying on specific assumptions about the problem's structure. Moreover, their robustness enables them to handle noisy and uncertain domains, which are often encountered in nonlinear and nonconvex problems. Overall, EAs provide a powerful and versatile approach for tackling these challenging optimization tasks. Duan first devises the PIOA in 2014 as a heuristic optimization method for solving complex problems. Ref [21] demonstrated that PIO was an efficient algorithm to solve air robot path scheduling problems in comparison to the conventional differential evolution (DE) algorithms. PIO is based on pigeon homing behaviors, akin to the search for optimum solutions.

4.1. Behavior profiles of the natural pigeons

Due to their excellent homing abilities, pigeons are used in the armed forces and communication fields since ancient times. Numerous investigations [22] have shown that pigeons differ in their navigation methods for handling various parts of journeys. Upon starting a journey, pigeons choose directions based on compasses. For detecting variations in magnetic fields, the pigeon uses iron crystals in its beak after taking flight. Pigeons likewise use the sun to navigate, as well as to detect magnetic fields. They appear to be capable of detecting differences in the sun's altitude at the beginning and finishing of their journey. Due to their ability to perceive magnetic fields and the sun's altitude, they find their flight path. They, in contrast, switch their navigation tactics halfway through the journey in order to pay attention to the landmarks and route points, including hills, rivers, and roads, in order to correct and reassess during the journey. Using the homing behavior evaluation of the pigeon, the PIOA can be determined and is close to being optimized.

4.2. An optimization algorithm based on pigeons

This algorithm is represented by 2 operators, one like a compass and one like a landmark, which abstract pigeon homing features. As the altitude of the sun and magnetic fields change, compass-like operators change, and the landmark operators change with landmarks [21]. As they approach their location, they become more independent of compass-like operators and rely more on landmark operators.

a) Compass-like operators

To begin, the PIO algorithm generates several not-real members of a colony of pigeons. Every iteration procedure updates the position and velocity of not-real pigeons using the compass-like operators. The below formulas have been employed by pigeons for updating the position and velocity:

$$V_i(t) = V_i(t-1) \bullet e^{-Rt} + rand \bullet (X_g - X_i(t-1)) \tag{19}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{20}$$

In which, X shows the position and V shows the velocity of the not-real pigeon. *rand* shows a randomly selected actual numbers.R shows the navigation or compass factor. i shows the member indicator and t shows the count of iterations. A comparison of the present locations of pigeons in a total swarm of pigeons yields the optimal location, called X_g. $V_i(t-1)$ represents the previous flight path of the existing pigeon. Accordingly, an updated journey direction depends on its previous flight path and the present global optimum location.

b) Landmark operators

First, a fitness amount must be calculated for all not-real pigeon positions in the Landmark Operator using the below formula:

$$fitness(X_i(t)) = \frac{1}{f_{min}(X_i(t)) + \varepsilon} \tag{21}$$

There is an abandonment of approximately 50% of the members based on fitness value ranking. $X_c(t)$ represents the center pigeon's average amount during t^{th} iterations. There is no doubt that the optimum location would be the best known member for landmarks. Other flyers are following the one to their goal. The below equations are used to determine the updated positions of others:

$$X_c(t) = \frac{\sum X_i(t).fitness(X_i(t))}{N_P \sum fitness(X_i(t))} \tag{22}$$

$$X_i(t) = X_i(t-1) \bullet e^{-Rt} + rand \bullet (X_c(t) - X_i(t-1)) \tag{23}$$

In which, N_p shows the count of members of pigeons.

4.3. PIOA improvement

The PIOA appears similar to various metaheuristic algorithms but also suffers from local optimal trapping. Premature convergences are typically solved using chaotic and quantum evolution methods.

a) Quantum evolution

Swarm-based optimization algorithms use quantum evolution to increase the capacity of stochastic searches. An important feature in quantum evolution algorithms is the quantum rotation gate and is explained in the following way:

Table 1
Rotation angle.

x_i		0	0	0	0	1	1	1	1
$Best_i$		0	0	1	1	0	0	1	1
$f(x) > f(best)$		False	True	False	True	False	True	False	True
θ_i	$\beta_i = 0$	0	0	0	0	0	$\mp 0.05\pi$	$\mp 0.05\pi$	$\mp 0.05\pi$
	$\alpha_i = 0$	0	0	0	$\mp 0.05\pi$	$\mp 0.05\pi$	0	0	0
	$\alpha_i\beta_i < 0$	0	0	0	0.05π	0.05π	-0.05π	-0.05π	-0.05π
	$\alpha_i\beta_i > 0$	0	0	0	-0.05π	-0.05π	0.05π	0.05π	0.05π

$$U(\Delta\theta_i) = \begin{bmatrix} cos\Delta\theta_i & -sin\Delta\theta_i \\ sin\Delta\theta_i & cos\Delta\theta_i \end{bmatrix} \tag{24}$$

$$\begin{bmatrix} \hat{\alpha}_i \\ \hat{\beta}_i \end{bmatrix} = \begin{bmatrix} \cos(\theta_i + \Delta\theta_i) \\ \sin(\theta_i + \Delta\theta_i) \end{bmatrix} \tag{25}$$

In which, θ_i shows the quantum rotations angle for all quantum bits. $U(\Delta\theta_i)$ shows the quantum rotation gate. Below is a complete description of the update procedure:

$$\begin{bmatrix} \hat{\alpha}_i \\ \hat{\beta}_i \end{bmatrix} = U(\Delta\theta_i).\begin{bmatrix} \cos(\theta_i + \Delta\theta_i) \\ \sin(\theta_i + \Delta\theta_i) \end{bmatrix} \tag{26}$$

It is advantageous in comparison to traditional stochastic conversion to change the angle of a quantum bit during all updates and set a direction for the not-real pigeon's optimal location. Table 1 determines the direction and value of θ_i.

Quantum bit strings containing many quantum bits are used to express population members [23]. In the quantum bit strings, all columns represent the quantum bits, in the following way:

$$q = \left[\begin{array}{c|c|c} \alpha_1 & \alpha_1 & \\ \beta_1 & \beta_1 & \end{array}, \cdots, \begin{array}{c|c|c} \alpha_n & \alpha_{n+1} & \\ \beta_n & \beta_{n+1} & \end{array}, \cdots, \begin{array}{c|c} \alpha_{D+1} & \\ \beta_{D+1} & \end{array} \right] \tag{27}$$

There is a random distribution of the i^{th} dimension vector within the predefined U_{max} and U_{min}. The i^{th} dimension is computed in the following way:

$$x_i = U_i^{min} + \left(\sum_{i=1}^{n} b_i.2^{i-1} \right).\frac{U_i^{max} - U_i^{min}}{2^n - 1} \tag{28}$$

The pigeon member $X = (x_1, x_2, \cdots, x_D)$ can be obtained by repeating corresponding steps for all dimensions of the problems.

4.4. Chaotic local search

In chaos theory, small changes in primary circumstances result in large differences over time. In the metaheuristic algorithm, the chaotic quest method has been employed for avoiding early convergence. Swarm-based algorithms reduce local optimal traps as a result of chaotic searching processes. The system's convergence time could be reduced accordingly.

The study suggests replacing the low fitness amounts of members with better ones using Chebyshev map [24]. Chebyshev maps are classical chaotic models iterating continuously as follows:

$$z_m^{t+1} = \cos\left(k.cos^{-1}z_m^t\right), t = 0, 1, 2, \cdots, \tag{29}$$

In which, k shows the control variable, in this case $k = 2$ and $z_m^t \in (-1, 1)$. Substituting the variables into Eq.29, a chaotic sequence is obtained corresponding to the dynamic characteristics. With the introduction of Chebyshev map, the chaotic local quest in the PIO algorithm aims to find the best location closest to the X_{best}. The details of instructions for Chebyshev chaotic quest are given below:

Stage one: The number of iterations N_c is adjusted and a randomly selected number $z_m^0 \in (-1, 1)$ is created for forming the Chebyshev sequences.

Stage two: Iteration numbers i are related to control variable k through the below formula.

$$k = \frac{N_e + 1 - i}{N_e} \tag{30}$$

Stage three: The below formula has been used to determine the updated members:

$$V = (1 - k).X_p + k.X_{new} \tag{31}$$

Stage four: Fitness of the updated members is calculated and the optimal one to X_p is recorded.

Stage five: A chaotic local quest ends if the present iteration times i correspond with the overall number of iterations N_c. If not, continue to search.

5. Simulation results with different scenarios

The suggested method is applied to a standard lower voltage MG, based on Fig. 2. It includes a group of DG units: 3 MTs, one WT, one PV, and ESS. A common coupling connects the system with the network. Figs. 3–5 show the overall load demands, the expected WT speed, and the expected PV irradiation during 24 h. The paper considers a 24-hour time interval on an hourly basis. Active power was generated at the unity power factor by each DG.

5.1. Outcomes of various case studies

It was possible to simulate both a non-Islanding and a Islanding case study for analyzing and comparing the MG system's efficiency. MG systems and utilities are able to trade energy anytime when they are non-Islanding. Using DGs, WT, PV, and ESS for load management was investigated in a Islanding case study. As a result of higher utilization levels of DGs, power fluctuations are greater in the two case studies.

The power supply model in the non-Islanding case study is shown in Fig. 6. DGs and utilities supply 44.7% and 55.3% of the overall production, with a 3.1% loss. Approximately 47.7% of the load demand is met by the PV and the WT, while the MG is entirely adequate for meeting

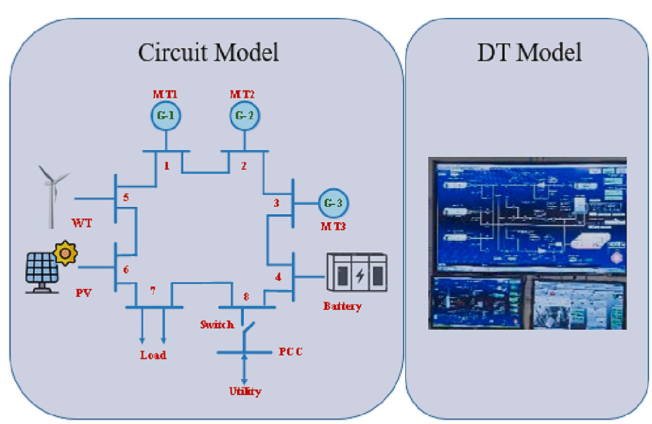

Fig. 2. Standard lower voltage MG system diagram and modeling in DT system.

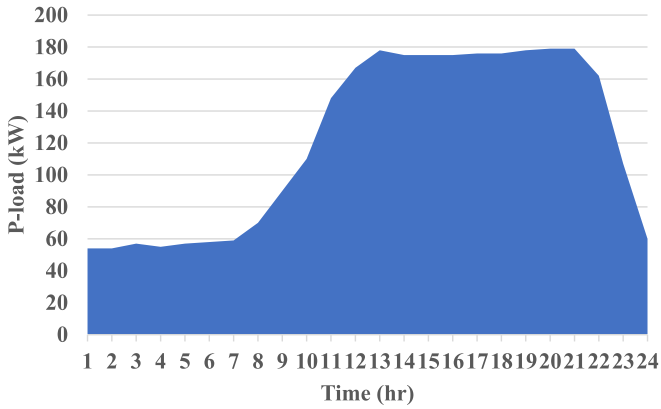

Fig. 3. Load demands during 24 h.

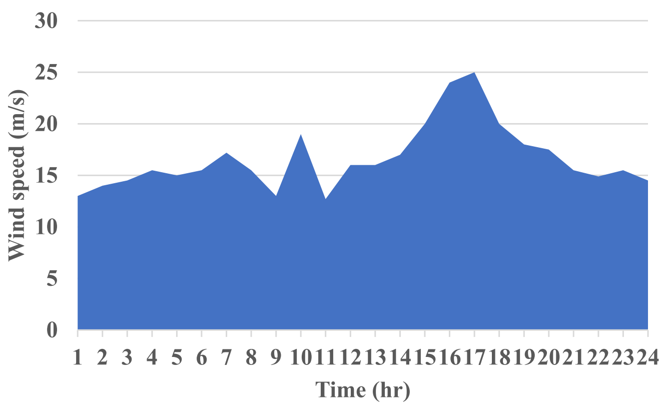

Fig. 4. The expected WT speed during 24 h.

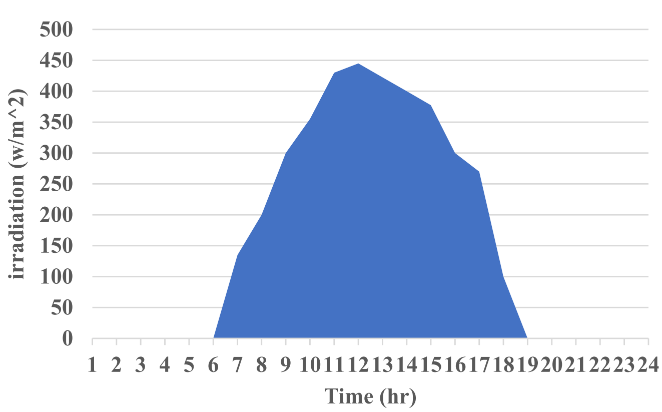

Fig. 5. The expected PV irradiation during 24 h.

load demands.

A Islanding power supply model is shown in Fig. 7. In this model, MT supplies 55.0% of energy production, WT supplies 34 %, and PV supplies 11.1% of energy production. There is a reduction of 3.1% in loss to 2.5%. Due to the breakdown of energy from the utility for the Islanding case study, additional energy is needed from the MTs. MTs generate 50% of the power for the Islanding case study.

The outcomes of the simulations for various case studies are shown in Table 2. All scenarios are tested for one hundred runs. Table 2 shows that the suggested algorithm performs well for finding solutions, the number of productions to convergence, and the average running time. The average running time for case one equals 0.8 and for case 2 equals 2.4 s. The IPIOA is clearly capable of solving the problem efficiently and often

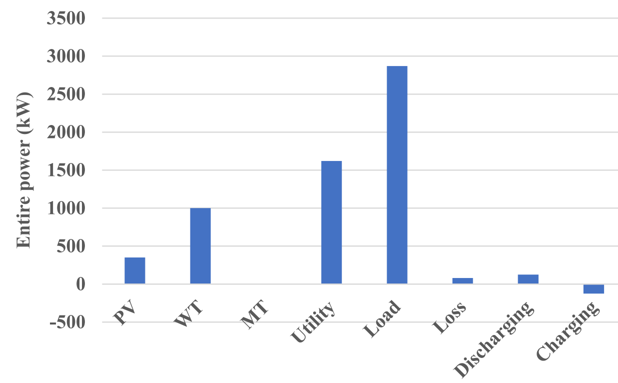

Fig. 6. The power supply model for the non-Islanding case study.

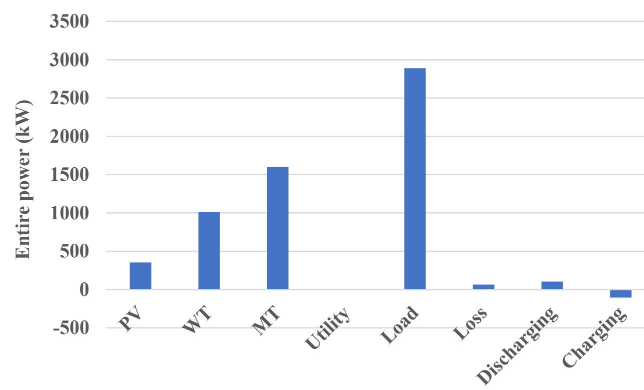

Fig. 7. The power supply model for the stand-alone case study.

quickly.

5.2. *Testing for convergence*

In Table 3, com experiments are shown for the P-IV, Core 2 Duo parisons of genetic algorithm (GA), particle swarm optimization (PSO), and IPIOA under various case studies. Table 3 clearly shows IPIOA's superiority to a variety of algorithms.

5.3. *Testing for robustness*

Table 4 and Table 5 show the results of testing each algorithm in the Islanding and non-Islanding scenarios. A total of one hundred tests were conducted using identical primary parents for all algorithms. A global optimal is more likely to be achieved with IPIOA because it enhances search efficiency. In Table 4 and Table 5, IPIOA shows higher precision compared to GA, PSO, and PIOA, and more tests reach optimal. Despite having a lower average running time compared to GA and a bit longer compared to PSO and PIOA, just 150 productions are needed for convergence. IPIOA, thus, has a shorter actual running time compared to different algorithms.

6. Conclusions

This article proposes a novel sustainable energy management framework for the MGs in an urban area aiming to maximize the sustainability of the system. To this end, digital twin modeling is used for reinforcing the ESS performance through the charging and discharging processes by providing accurate data of the system for the battery.

Due to the model complex structure, the IPIOA method is presented in the study for solving the EM method for MGs using ESSs and RERs over 24 h in several scenarios. The EM method consists of a multi-power

Table 2
The outcomes of the simulations for various case studies.

Item	Mean execution time (s)	Number of trails achieving optimal	Mean number of generations to converge	Worst (NT$)	Best (NT$)	Mean (NT$)
Islandindg case	2.4	46	173	15951.8	15925.3	15,932
Non-Islanding case	0.8	63	150	5048.4	5037	5040.6

Table 3
Comparing the GA, PSO, PIOA and IPIOA.

Algorithm	IPIOA	PIOA	PSO	GA
Islandindg case	15925.3	16078.2	16237.6	16892.4
Non-Islanding case	5037	5038.1	5038.3	5044.9

Table 4
Testing for robustness of the GA, PSO, PIOA and IPIOA for the non-Islanding case study.

Algorithm	IPIOA	PIOA	PSO	GA
Mean execution time (s)	0.8	0.73	0.68	1.52
Number of trails achieving optimal	63	42	45	6
Mean number of generations to converge	150	169	190	193
Mean converged cost (NT$)	5040.6	5047.5	5048.2	5054.1
Minimum converged cost (NT$)	5037	5038.1	5038.3	5044.9
Maximum converged cost (NT$)	5048.4	5052.3	5054.1	5066.9

Table 5
Testing for robustness of the GA, PSO, PIOA and IPIOA for the Islanding case study.

Algorithm	IPIOA	PIOA	PSO	GA
Mean execution time (s)	2.4	2.2	2.2	5.8
Number of trails achieving optimal	46	31	26	2
Mean number of generations to converge	173	187	191	198
Mean converged cost (NT$)	15,932	16163.9	16279.5	17009.8
Minimum converged cost (NT$)	15925.3	16078.2	16237.6	16892.4
Maximum converged cost (NT$)	15951.8	16281.4	16392.7	17192.6

dispatch scheme that uses an electrical connection among the MGs and utilities as a means of exchanging energy. This paper evaluates the two Islanding and non-Islanding case studies under various TOU programs with the aim of minimizing MG operating prices. Here, an IPIOA was employed for analyzing the performance of standard distribution systems, taking various technical limitations into account. A number of optimization problems can be improved by IPIOA. The RER and ESSs are operated in Islanding and non-Islanding scenarios using digital twin simulations in order to optimize the planning of agents in MGs' EM. A lower voltage distribution system has been used to demonstrate and test IPIOA efficiency. MG EM can be effectively carried out based on the outcomes presented here. In addition, it could be followed the suggested methods to improve the financial efficiency of MGs for the energy sector.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was sponsored in part by National Natural Science Foundation of China (51208060)

References

[1] Leitao, J., Gil, P., Ribeiro, B., Cardoso, A., 2020 Jan. A survey on home energy management. IEEE Access 1 (8), 5699–5722.
[2] Wirth H. Recent Facts about Photovoltaics in Germany; Version of May 15, 2021. Fraunhofer Institute for Solar Energy Systems ISE (Fraunhofer ISE). https://www.ise. fraunhofer. de/en/publications/studies/recent-facts-about-pv-in-germany. html. Accessed. 2021 Oct;11.
[3] He, Y., Song, Z., Liu, Z., 2019 Jul. Fast-charging station deployment for battery electric bus systems considering electricity demand charges. Sustain. Cities Soc. 1 (48), 101530.
[4] Gerard, H., Puente, E.I., Six, D., 2018 Feb. Coordination between transmission and distribution system operators in the electricity sector: A conceptual framework. Util. Policy 1 (50), 40–48.
[5] Sarker, E., Halder, P., Seyedmahmoudian, M., Jamei, E., Horan, B., Mekhilef, S., Stojcevski, A., 2021 Jan. Progress on the demand side management in smart grid and optimization approaches. Int. J. Energy Res. 45 (1), 36–64.
[6] B Kazemi, A Kavousi-Fard, M Dabbaghjamanesh, M Karimi, "IoT-Enabled Operation of Multi Energy Hubs Considering Electric Vehicles and Demand Response", IEEE Transactions on Intelligent Transportation Systems, vol. 24 (2), 2023.
[7] Elsayed, A.T., Mohamed, A.A., Mohammed, O.A., 2015 Feb. DC microgrids and distribution systems: An overview. Electr. Pow. Syst. Res. 1 (119), 407–417.
[8] Çimen, H., Bazmohammadi, N., Lashab, A., Terriche, Y., Vasquez, J.C., Guerrero, J. M., 2022 Feb. An online energy management system for AC/DC residential microgrids supported by non-intrusive load monitoring. Appl. Energy 1 (307), 118136.
[9] Ahmethodzic, L., Music, M., 2021 Sep. Comprehensive review of trends in microgrid control. Renew. Energy Focus. 1 (38), 84–96.
[10] Daneshvar, M., Mohammadi-Ivatloo, B., Zare, K., Asadi, S., Anvari-Moghaddam, A., 2020 Jul 28. A novel operational model for interconnected microgrids participation in transactive energy market: A hybrid IGDT/stochastic approach. IEEE Trans. Ind. Inf. 17 (6), 4025–4035.
[11] Gutiérrez-Oliva, D., Colmenar-Santos, A., Rosales-Asensio, E., 2022 Mar 24. A Review of the State of the Art of Industrial Microgrids Based on Renewable Energy. Electronics 11 (7), 1002.
[12] Dabbaghjamanesh, M., Kavousi-Fard, A., Dong, Z.Y., Jolfaei, A., 2022. Guest editorial: Applications of advanced machine learning and big data techniques in renewable energy-based power grids. IET Renew. Power Gener. 16 (16), 3445–3448.
[13] Bahlawan, H., Castorino, G.A., Losi, E., Manservigi, L., Spina, P.R., Venturini, M., 2022 Dec. Optimal management with demand response program for a multi-generation energy system. Energy Convers. Management: X. 1 (16), 100311.
[14] Sobhani, S.O., Sheykhha, S., Azimi, M.R., Madlener, R., 2019 Feb. Two-level distributed demand-side management using the smart energy hub concept. Energy Procedia 1 (158), 3052–3063.
[15] Lu, X., Chen, Y., Fu, M., Wang, H., 2019 Jan. Multi-objective optimization-based real-time control strategy for battery/ultracapacitor hybrid energy management systems. IEEE Access 11 (7), 11640–11650.
[16] Eremia, M., Shahidehpour, M. (Eds.), 2013 Feb 21. Handbook of Electrical Power System Dynamics: Modeling, Stability, and Control. John Wiley & Sons.

[17] Al-Ghussain, L., Ahmad, A.D., Abubaker, A.M., Mohamed, M.A., 2021 Aug. An integrated photovoltaic/wind/biomass and hybrid energy storage systems towards 100% renewable energy microgrids in university campuses. Sustain. Energy Technol. Assess. 1 (46), 101273.

[18] Bhattacharjee, S., Nandi, C., 2021 Jan. Design of a voting based smart energy management system of the renewable energy based hybrid energy system for a small community. Energy 1 (214), 118977.

[19] Dabbaghjamanesh, M., Kavousi-Fard, A., Mehraeen, S., Zhang, J., Dong, Z.Y., 2019. Sensitivity analysis of renewable energy integration on stochastic energy management of automated reconfigurable hybrid AC–DC microgrid considering DLR security constraint. IEEE Trans. Ind. Inf. 16 (1), 120–131.

[20] Jafari, M., Kavousi-Fard, A., Dabbaghjamanesh, M., Karimi, M., 2022. A Survey on Deep Learning Role in Distribution Automation System: A New Collaborative Learning-to-Learning (L2L) Concept. IEEE Access 10, 81220–81238.

[21] Ajeil, F.H., Ibraheem, I.K., Humaidi, A.J., Khan, Z.H., 2021 Feb. A novel path planning algorithm for mobile robot in dynamic environments using modified bat swarm optimization. J. Eng. 2021 (1), 37–48.

[22] Roberts, S., Guilford, T., Rezek, I., Biro, D., 2004 Mar 7. Positional entropy during pigeon homing I: application of Bayesian latent state modelling. J. Theor. Biol. 227 (1), 39–50.

[23] Hussain, A.N., Ismail, A.A., 2020 Apr. Operation cost reduction in unit commitment problem using improved quantum binary PSO algorithm. Int. J. Electr. Comput. Eng. 10, 1149–1155.

[24] Yang, D., Liu, Z., Zhou, J., 2014 Apr 1. Chaos optimization algorithms based on chaotic maps with different probability distribution and search speed for global optimization. Commun. Nonlinear Sci. Numer. Simul. 19 (4), 1229–1246.